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ALGORITHMS FOR FINDING ZEROS AND EXTREMA OF FUNCTIONS
WITHOUT CALCULATING DERIVATIVES

BY

RICHARD P. BRENT

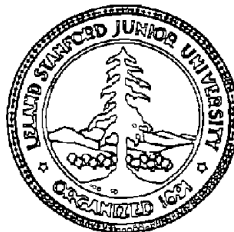
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<p>Theorems are given concerning the order (i.e., rate) of convergence of a successive interpolation process for finding simple zeros of a function or its derivatives, using only function evaluations. Special cases include the successive linear interpolation process for finding zeros, and a parabolic interpolation process for finding turning points. Results on interpolation and finite differences include weakening the hypotheses of a theorem of Ralston on the derivative of the error in Lagrangian interpolation.</p> <p>The theoretical results are applied to given algorithms for finding zeros or local minima of functions of one variable, in the presence of rounding errors. The algorithms are guaranteed to converge nearly as fast as would bisection or Fibonacci search, and in most practical cases convergence is superlinear, and much faster than for bisection or Fibonacci search.</p> <p>The problem of finding a global minimum of a function f, of one variable, is investigated. We give a nearly optimal algorithm which is applicable if an upper bound on f'' is known. A generalization, useful in practice if $n \leq 3$, is given for functions of n variables. The effect of rounding errors in these algorithms can be accounted for.</p> <p>Finally, we present a modification of Powell's algorithm for finding a local minimum of a function of several variables without calculating derivatives. The modification ensures that the search directions can not become linearly dependent, and numerical examples suggest that the algorithm compares favorably with other methods which do not require derivatives.</p> <p>A bibliography on unconstrained minimization is given, and ALGOL implementations</p>		

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Preface

The problem of finding numerical approximations to the zeros and extrema of functions, using hand computation, has a long history. In the last few years, considerable progress has been made in the development of algorithms suitable for use on a digital computer. The aim of this work is to suggest improvements to some of these algorithms, extend the mathematical theory behind them, and describe some new algorithms for approximating local and global minima. The unifying thread is that all the algorithms considered depend entirely on sequential function evaluations: no evaluations of derivatives are required. Such algorithms are very useful if derivatives are difficult to evaluate, and this is often true in practical problems.

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This work is dedicated to Oscar and Nancy, sine quis non.

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Chapter 1.

Introduction and Summary

1. Introduction

Consider the problem of finding an approximate zero or minimum of a function of one real variable, using limited-precision arithmetic on a sequential digital computer. The function f may not be differentiable, or the derivative f' may be difficult to compute, so a method which uses only computed values of f is desirable. Since an evaluation of f may be very expensive in terms of computer time, a good method should guarantee to find a correct solution, to within some prescribed tolerance, using only a small number of function evaluations. Hence, we study algorithms which depend on evaluating f at a small number of points, and for which certain desirable properties are guaranteed, even in the presence of rounding errors.

Slow, safe algorithms are seldom preferred in practice to fast algorithms which may occasionally fail. Thus, we want algorithms which are guaranteed to succeed in a reasonable time even for the most "difficult" functions, yet are as fast as commonly used algorithms for "easy" functions. For example, bisection is a safe method for finding a zero of a function which changes sign in a given interval, but from our point of view it is not an acceptable method, because it is just as slow for any function, no matter how well behaved, as it is in the worst possible case (ignoring the possibility that an exact zero may occasionally be found by chance). As a contrasting example, consider the method of successive linear interpolation, which converges superlinearly to a simple zero of a C^1 function, provided that the initial approximation is good and rounding errors are unimportant. This method is not acceptable either, for, in practice, we may have no way of knowing in

advance if the zero is simple, if the initial approximation is sufficiently good to ensure convergence, or what the effect of rounding errors will be.

In Chapter 4 we describe an algorithm which, by combining some of the desirable features of bisection and successive linear interpolation, does come close to satisfying our requirements: it is guaranteed to converge (i.e., halt) after a reasonably small number of function evaluations, and the rate of convergence for well-behaved functions is so fast that a less reliable algorithm is unlikely to be preferred on grounds of speed.

An analogous algorithm, which finds a local minimum of a function of one variable by a combination of golden section search and successive parabolic interpolation, is described in Chapter 5. This algorithm fails to completely satisfy one of our requirements: in certain applications where repeated one-dimensional minimizations are required, and where accuracy is not very important, a faster (though less reliable) method is preferable. One such application, finding local minima of functions of several variables without calculating derivatives, is discussed in Chapter 7. Note that, wherever we consider minima, we could equally well consider maxima.

Most algorithms for minimizing a nonlinear function of one or more variables find, at best, a local minimum. For a function with several local minima, there is no guarantee that the local minimum found is the global (i.e., true or lowest) minimum. Since it is the global minimum which is of interest in most applications, this is a serious practical disadvantage of most minimization algorithms, and our algorithm given in Chapter 5 is no exception. The usual remedy is to try several

different starting points and, perhaps, vary some of the parameters of the minimization procedure, in the hope that the lowest local minimum found is the global minimum. This approach is inefficient, as the same local minimum may be found several times, and it is also unreliable, for, no matter how many starting points are tried, it is impossible to be quite sure that the global minimum has been found.

In Chapter 6 we discuss the problem of finding the global minimum to within a prescribed tolerance. It is possible to give an algorithm for solving this problem, provided that a little a priori information about the function to be minimized is known. We describe an efficient algorithm, applicable if an upper bound on f is known, and we show how this algorithm can be used recursively to find the global minimum of a function of several variables. Unfortunately, because the amount of computation involved increases exponentially with the number of variables, this is practically useful only for functions of less than four variables. For functions of more variables, we still have to resort to the unreliable "trial and error" method, unless special information about the function to be minimized is available.

Thus, we are led to consider practical methods for finding local (unconstrained) minima of functions of several variables. As before, we consider methods which depend on evaluating the function at a small number of points. Unfortunately, without imposing very strict conditions on the functions to be minimized, it is not possible to guarantee that an n -dimensional minimization algorithm produces results which are correct to within some prescribed tolerance, or that the effect of rounding errors has completely been taken into account. We have to be satisfied with

algorithms which nearly always give correct results for the functions likely to arise in practical applications.

As suggested by the length of our bibliography, there has recently been considerable interest in the unconstrained minimization problem. Thus, we can hardly expect to find a good method which is completely unrelated to the known ones. In Chapter 7 we take one of the better methods which does not use derivatives, that of Powell (1964), and modify it to try to overcome some of the difficulties observed in the literature. Numerical tests suggest that our proposed method is faster than Powell's original method, and just as reliable. It also compares quite well with a different method proposed by Stewart (1967), at least for functions of less than ten variables. (We have no numerical results for non-quadratic functions of more than ten variables.)

ALGOL implementations of all the above algorithms are given. Most testing was done with ALGOL W (Wirth and Hoare (1966)) on IBM 360/67 and 360/91 computers. As ALGOL W is not widely used, we give ALGOL 60 procedures (Naur (1963)), except for the n -dimensional minimization algorithm. FORTRAN subroutines for the one-dimensional zero-finding and local minimization algorithms are also available.

To recapitulate, we describe algorithms, and give ALGOL procedures, for solving the following problems efficiently, using only function (not derivative) evaluations:

1. Finding a zero of a function of one variable, if an interval in which the function changes sign is given;
2. Finding a local minimum of a function of one variable, defined on a given interval;

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3. Finding, to within a prescribed tolerance, the global minimum of a function of one or more variables, given upper bounds on the second derivatives;
4. Finding a local minimum of a function of several variables.

For the first three algorithms, rigorous bounds on the error and the number of function evaluations required are established, taking the effect of rounding errors into account. Some results concerning the order of convergence of the first two algorithms, and preliminary results on interpolation and divided differences, are also of interest.

2. Summary

In this section we summarize the main results of the following chapters. A more detailed discussion is given at the appropriate places in each chapter. This summary is intended to serve as a guide to the reader who is interested in some of our results, but not in others. To assist such a reader, an attempt has been made to keep each chapter as self-contained as possible.

Chapter 2

In Chapter 2 we collect some results on Taylor series, Lagrangian interpolation, and divided differences. Most of these results are needed in Chapter 3, and the casual reader might prefer to skip Chapter 2 and refer back to it when necessary. Some of the results are similar to classical ones, but instead of assuming that f has $n+1$ continuous

1.2

derivatives, we only assume that $f^{(n)}$ is Lipschitz continuous, and the term $f^{(n+1)}(\xi)$ in the classical results is replaced by a number bounded in absolute value by a Lipschitz constant. For example, Lemmas 2.3.1, 2.3.2, 2.4.1, and 2.5.1 are of this nature. Since a Lipschitz continuous function is differentiable almost everywhere, these results are not surprising, although they have not been found in the literature, except where references are given. (Sometimes Lipschitz conditions are imposed on the derivatives of functions of several variables: see, for example, Armijo (1966) and McCormick (1969).) The proofs are mostly similar to those for the classical results.

Theorem 2.6.1 is a slight generalization of some results of Ralston (1963, 1965) on differentiating the error in Lagrangian interpolation. It is included both for its independent interest, and because it may be used to prove a slightly weaker form of Lemma 3.6.1 for the important case $q = 2$. (A similar proof is sketched in Kowalik and Osborne (1968).)

An interesting result of Chapter 2 is Theorem 2.6.2, which gives an expression for the derivative of the error in Lagrangian interpolation at the points of interpolation. A well-known weaker result is that the conclusion of Theorem 2.6.2 holds if f has $n+1$ continuous derivatives, but Theorem 2.6.2 shows that it is sufficient for f to have n continuous derivatives.

Theorem 2.5.1, which gives an expansion of divided differences, may be regarded as a generalization of Taylor's theorem. It is used several times in Chapter 3: for example, see Theorem 3.4.1 and Lemma 3.6.1. Theorem 2.5.1 is useful for the analysis of interpolation processes

whenever the coefficients of the interpolation polynomials can conveniently be expressed in terms of divided differences.

Chapter 3

In Chapter 3 we prove some theorems which provide a theoretical foundation for the algorithms described in Chapters 4 and 5. In particular, we show when the algorithms will converge superlinearly, and what the order (i.e., rate) of convergence will be. Of course, for these results the effect of rounding errors is ignored. The reader whose main interest is the practical applications of our results might omit Chapter 3, except for the numerical examples (Section 3.9) and the summary (Section 3.10).

So that results concerning successive linear interpolation for finding zeros (used in Chapter 4), and successive parabolic interpolation for finding turning points (used in Chapter 5), can be given together, we consider a more general process for finding a zero of $f^{(q-1)}$, for any fixed $q \geq 1$. Successive linear interpolation and successive parabolic interpolation are just the special cases $q = 1$ and $q = 2$. Another case which is of some practical interest is $q = 3$, for finding inflexion points. As the proofs for general q are essentially no more difficult than for $q = 2$, most of our results are for general q .

For the applications in Chapters 4 and 5, the most important results are Theorem 3.4.1, which gives conditions under which convergence is superlinear, and Theorem 3.5.1, which shows when the order is at least 1.618... (for $q = 1$) or 1.324... (for $q = 2$). These numbers are well-known, but our assumptions about the differentiability of f are

weaker than those of previous authors, e.g., Ostrowski (1966) and Jarratt (1967, 1968).

From a mathematical point of view, the most interesting result of Chapter 3 is Theorem 3.7.1. The result for $q = 1$ is given in Ostrowski (1966), except for our slightly weaker assumption about the smoothness of f . For $q = 2$, our result that convergence to ξ with order at least 1.378... is possible, even if $f^{(3)}(\xi) \neq 0$, appears to be new. Jarratt (1967) and Kowalik and Osborne (1968) assume that

$$\lim_{n \rightarrow \infty} \frac{|x_{n+1} - \xi|}{|x_n - \xi|} = 0, \quad (2.1)$$

and then, from Lemma 3.6.1, the order of convergence is 1.324... .

However, even for such a simple function as

$$f(x) = 2x^3 + x^2, \quad (2.2)$$

there are starting points x_0 , x_1 and x_2 such that (2.1) fails to hold, and then the order may be at least 1.378... . We should point out that this exceptional case is unlikely to occur: an interesting conjecture is that the set of starting points for which it occurs has measure zero.

The practical conclusion to be drawn from Theorem 3.7.1 is that, if convergence is to be accelerated, then the result of Lemma 3.6.1 should be used. In Section 3.8 we give one of the many ways in which this may be done. Finally, some numerical examples illustrating both the accelerated and unaccelerated processes are given in Section 3.9.

Chapter 4

In Chapter 4 we describe an algorithm for finding a zero of a function which changes sign in a given interval. The algorithm is based on a combination of successive linear interpolation and bisection, in much the same way as "Dekker's algorithm" (van Wijngaarden, Zonneveld and Dijkstra (1963), Wilkinson (1967), Peters and Wilkinson (1969), Dekker (1969)). Our algorithm never converges much slower than bisection, whereas Dekker's algorithm may converge extremely slowly in certain cases. (Examples are given in Section 4.2.)

It is well-known that bisection is the optimal algorithm, in a minimax sense, for finding zeros of functions which change sign in an interval. (We only consider sequential algorithms: see Robbins (1952), Wilde (1964) and Section 4.5.) The motivation for both our algorithm and Dekker's is that bisection is not optimal if the class of allowable functions is suitably restricted. For example, it is not optimal for convex functions (Bellman and Dreyfus (1962), Gross and Johnson (1959)), or for C^1 functions with simple zeros.

Both our algorithm and Dekker's exhibit superlinear convergence to a simple zero of a C^1 function, for eventually only linear interpolations are performed, and the theorems of Chapter 3 are applicable. Thus, convergence is usually much faster than for bisection. Our algorithm incorporates inverse quadratic interpolation as well as linear interpolation, so it is often slightly faster than Dekker's algorithm on well-behaved functions (see Section 4.4).

Chapter 5

An algorithm for finding a local minimum of a function of one variable is described in Chapter 5. The algorithm combines golden section search (Bellman (1957), Kiefer (1953), Wilde (1964), Witzgall (1969)) and successive parabolic interpolation (the case $q = 2$ of the process analysed in Chapter 3), in the same way as bisection and successive linear interpolation are combined in the zero-finding algorithm of Chapter 4. Convergence in a reasonable number of function evaluations is guaranteed (see Section 5.5), and, for a C^2 function with positive curvature at the minimum, the results of Chapter 3 show that convergence is superlinear, if we ignore rounding errors and suppose that the minimum is at an interior point of the interval. Other algorithms given in the literature either fail to have these two desirable properties, or, when convergence is strictly superlinear, the order of convergence is less than for our algorithm (see Sections 5.4 and 5.5).

In Sections 5.2 and 5.3 we consider the effect of rounding errors. Section 5.2 contains an analysis of the limitations, imposed by rounding errors, on the attainable accuracy of any algorithm which is based entirely on function evaluations, and this section should be studied by the reader who intends to use the ALGOL procedure given in Section 5.8.

If f is unimodal, then our algorithm will find the unique minimum, provided there are no rounding errors. To study the effect of rounding errors, we define " δ -unimodal" functions. A unimodal function is δ -unimodal for all $\delta \geq 0$, but a computed approximation to a unimodal function can not be unimodal: it will be δ -unimodal for some positive δ , depending on the function and on the precision of computation. ($\delta \rightarrow 0$ as the

precision increases indefinitely.) We prove some theorems about δ -unimodal functions, and give a bound for the error in the approximate minimum found by our algorithm when applied to a δ -unimodal function. In this way we can justify the use of our algorithm in the presence of rounding errors, and account for their effect. Our motivation is rather similar to that of Richman (1968) in developing the ϵ -calculus, but we are not concerned with properties that hold as $\epsilon \rightarrow 0$. The reader who is not very interested in the effect of rounding errors might prefer to skip Section 5.3.

Chapter 6

In Chapter 6 we consider the problem of finding an approximation to the global minimum of a function f , defined on a finite interval, if some a priori information about f is known. This interesting problem does not seem to have received much attention, although there have been some empirical investigations, e.g., see Magee (1960). In Section 6.1, we show why some a priori information is necessary, and discuss some of the possibilities. In the remainder of the chapter we restrict our attention to the case where an upper bound on f'' is known.

An algorithm for global minimization of a function of one variable, applicable when such an upper bound on the second derivative is known, is described in Section 6.3. The basic idea of this algorithm is used by Rivlin (1970) to find bounds on a polynomial in a given interval. We pay particular attention to the problem of giving guaranteed bounds in the presence of rounding errors, and the casual reader may find the details in the last half of Section 6.3 rather indigestible.

In Section 6.4, we try to obtain some insight into the behaviour of our algorithm by considering some tractable special cases. Then, in Sections 6.5 and 6.6, we show that no algorithm which uses only function evaluations and an upper bound on f'' could be much faster than our algorithm. Finally, a generalization to functions of several variables is given in Section 6.8. The conditions on f are much weaker than unimodality (Newman (1965)). The generalization is not practically useful for functions of more than three variables, and it is an open question whether a significantly better algorithm is possible.

Chapter 7

In Chapter 7 we describe a modification of Powell's (1964) algorithm for finding a local minimum of a function of several variables, without calculating derivatives. The modification is designed to ensure quadratic convergence, and to avoid the difficulties with Powell's criterion for accepting new search directions.

First, a brief introduction to the problem and a survey of the recent literature are given in Section 7.1. The effect of rounding errors on the limiting accuracy attainable is discussed in Section 7.2. Powell's algorithm is described in Section 7.3, and our main modification is given in Section 7.4. The idea of the modification (finding the principal axes of an approximating quadratic form) is not new: for example, it is used by Greenstadt (1967) in his quasi-Newton method. Unlike Greenstadt, though, we do not use an explicit approximation to the Hessian matrix. An interesting feature of our modification is that it is possible to avoid squaring the condition number of the eigenvalue problem by using a singular value decomposition: see Section 7.4 for the details.

In Sections 7.5 and 7.6 we describe some additional features of our algorithm. Then, in Section 7.7, we give the results of some numerical experiments, and compare our method with those of Powell (1964), Davies, Swann and Campey (Swann (1964)), and Stewart (1967). For the comparison we have used numerical results obtained by Fletcher (1965) and Stewart (1967). The numerical results suggest that our algorithm is competitive with the currently used algorithms which do not require the user to compute derivatives, although it is difficult to reach a definite conclusion without more practical experience.

Finally, we give a bibliography of the recent literature on nonlinear minimization, with the emphasis being on methods for solving unconstrained problems.

Chapter 2.

Some Useful Results on Taylor Series, Divided Differences, and Lagrangian Interpolation

1. Introduction

In this chapter we collect some results which are needed in Chapters 3 and 6. The reader who is mainly interested in the practical applications described in Chapters 4 to 7 might prefer to skip this chapter, except for Section 2, and refer back to it when necessary.

Classical expressions for the error in truncated Taylor series and Lagrangian interpolation often involve a term $f^{(n+1)}(\xi)$, where ξ is an unknown point in some interval. For such expressions to be valid, f must have $n+1$ derivatives. Several of the results of this chapter give expressions which are valid if $f^{(n)}$ satisfies a (possibly one-sided) Lipschitz condition. In these results, the term $f^{(n+1)}(\xi)$ is replaced by a number which is bounded by a Lipschitz constant. It seems unlikely that these results are new, but they have not been found in the literature except where references are given.

The results of Chapter 3 depend heavily on Theorem 5.1, which gives an expansion of the divided difference $f[x_0, \dots, x_n]$ (see Section 2) near the origin. This theorem, and the less cumbersome Corollary 5.1, are useful for the analysis of interpolation processes, for the coefficients of the interpolating polynomials can be expressed in terms of divided differences (see Chapter 3).

Finally, in Section 6, we extend some results of Ralston (1963) on the derivative of the error term in Lagrangian interpolation. These results are relevant to Chapter 3, although they are given mainly for their independent interest. Perhaps the most interesting result is Theorem 6.2, which shows that, if we are only concerned with the points of interpolation, then we can differentiate the classical expression for the error (equation (6.4)), regarding the term $f^{(n)}(\xi(x))$ as constant.

This is well-known if f has $n+1$ continuous derivatives, but Theorem 6.2 shows that it is sufficient for f to have n continuous derivatives.

2. Notation and definitions

Throughout this chapter $[a, b]$ is a nonempty, finite, closed interval, and f is a real-valued function defined on $[a, b]$. n is a nonnegative integer, M a nonnegative real number, and α a number in $(0, 1]$.

Definitions

The modulus of continuity $w(f; \delta)$ of f (in $[a, b]$) is defined by

$$w(f; \delta) = \sup_{\substack{x, y \in [a, b] \\ |x - y| \leq \delta}} |f(x) - f(y)|, \quad (2.1)$$

for all $\delta \geq 0$.

If f has a continuous n -th derivative on $[a, b]$, then we write $f \in C^n[a, b]$. If, in addition, $f^{(n)} \in \text{Lip}_M \alpha$, i.e.,

$$w(f^{(n)}; \delta) \leq M \delta^\alpha \quad (2.2)$$

for all $\delta > 0$, then we write $f \in \text{LC}^n[a, b; M, \alpha]$. (This notation is not standard, but it is convenient if we want to mention the constants M and α explicitly.) If $f \in \text{LC}^n[a, b; M, 1]$ then we write simply $f \in \text{LC}^n[a, b; M]$.

If x_0, \dots, x_n are distinct points in $[a, b]$, then $\text{IP}(f; x_0, \dots, x_n)$ is the Lagrangian interpolation polynomial, i.e., the unique polynomial of degree n or less which coincides with f at x_0, \dots, x_n . The

divided difference $f[x_0, \dots, x_n]$ is defined by

$$f[x_0, \dots, x_n] = \sum_{j=0}^n \left(\frac{f(x_j)}{\prod_{\substack{i=0 \\ i \neq j}}^n (x_j - x_i)} \right) . \quad (2.3)$$

(There are many other notations: see for example, Milne (1949), Milne-Thomson (1933), and Traub (1964).) Note that, although we suppose for simplicity that x_0, \dots, x_n are distinct, nearly all the results given here and in Chapter 3 hold if some of x_0, \dots, x_n coincide. (We then have Hermite interpolation and confluent divided differences: see Traub (1964).) For the statement of these results, the word "distinct" is enclosed in parentheses.

Newton's identities

For future reference, we note the following useful identities (see Cauchy (1840), Isaacson and Keller (1966), or Traub (1964)). The first is often used as the definition of the divided difference $f[x_0, \dots, x_n]$, while the second gives an explicit representation of the interpolating polynomial and remainder.

$$1. \quad f[x_0] = f(x_0)$$

and, for $n \geq 1$,

$$f[x_0, \dots, x_n] = \frac{f[x_0, \dots, x_{n-1}] - f[x_1, \dots, x_n]}{x_0 - x_n} . \quad (2.4)$$

2. If $P = IP(f; x_0, \dots, x_n)$, then

$$f(x) = P(x) + \left(\prod_{i=0}^n (x - x_i) \right) \cdot f[x_0, \dots, x_n, x] , \quad (2.5)$$

and

$$P(x) = f[x_0] + (x - x_0)f[x_0, x_1] + \dots + (x - x_0) \dots (x - x_{n-1})f[x_0, \dots, x_n] . \quad (2.6)$$

3. Truncated Taylor series

In this section we give some forms of Taylor's theorem. Lemma 3.1 is needed in Chapter 6, and applies if $f^{(n)}$ satisfies a one-sided Lipschitz condition.

Lemma 3.1

Suppose that $f \in C^n[0, b]$ for some $b > 0$, and that there is a constant M such that, for all $y \in [0, b]$,

$$f^{(n)}(y) - f^{(n)}(0) \leq My . \quad (3.1)$$

Then, for all $x \in [0, b]$,

$$f(x) = \sum_{r=0}^n \frac{x^r}{r!} f^{(r)}(0) + \frac{x^{n+1}}{(n+1)!} m(x) , \quad (3.2)$$

where

$$m(x) \leq M . \quad (3.3)$$

Remarks

The proof is by induction on n , and is omitted. The corresponding two-sided result is immediate, and is generalized in Lemma 3.2 below. In Lemma 3.2, fractional factorials are defined in the usual way, so

$$(n+\alpha)!/\alpha! = (1+\alpha)(2+\alpha)\dots(n+\alpha) . \quad (3.4)$$

Lemma 3.2

If $f \in LC^n[a, b; M, \alpha]$ and $x, y \in [a, b]$, then

$$f(x) = \sum_{r=0}^n \frac{(x-y)^r}{r!} f^{(r)}(y) + |x-y|^{n+\alpha} m(x, y) \alpha! / (n+\alpha)! \quad (3.5)$$

where

$$|m(x, y)| \leq M \quad (3.6)$$

Remarks

The result is trivial if $n = 0$, and for $n \geq 1$ it follows from Taylor's theorem with the integral form for the remainder, using the integral

$$\int_0^x \frac{t^\alpha (x-t)^{n-1}}{(n-1)!} dt = x^{n+\alpha} \alpha! / (n+\alpha)! \quad (3.7)$$

for $x \geq 0$.

Note that the bound (3.6) is sharp, as can be seen from the example

$$f(x) = x^{n+\alpha}, \quad (3.8)$$

with $y = 0$ and $M = (n+\alpha)!/\alpha!$. Since, for $n \geq 1$,

$$n! < (n+\alpha)!/\alpha! \quad (3.9)$$

the bound obtained from the classical result

$$f(x) = \sum_{r=0}^{n-1} \frac{(x-y)^r}{r!} f^{(r)}(y) + \frac{(x-y)^n}{n!} f^{(n)}(\xi) \quad (3.10)$$

for some ξ between x and y , is not sharp.

4. Lagrangian interpolation

The following lemma, used in Chapter 6, gives a one-sided bound on the error in Lagrangian interpolation, if $f^{(n)}$ satisfies a one-sided Lipschitz condition. Thus, it corresponds to Lemma 3.1. The corresponding two-sided result follows from Theorem 3 of Baker (1970), but the proof given here is simpler, and similar to the usual proof of the classical result that, if $f \in C^{n+1}[a, b]$, then $m(x) = f^{(n+1)}(\xi(x))$, for some $\xi(x) \in [a, b]$. (See, for example, Isaacson and Keller (1966), pg. 190.)

Lemma 4.1

Suppose that $f \in C^n[a, b]$; x_0, \dots, x_n are (distinct) points in $[a, b]$; $P = IP(f; x_0, \dots, x_n)$; and, for all $x, y \in [a, b]$ with $x > y$,

$$f^{(n)}(x) - f^{(n)}(y) \leq M(x-y) \quad (4.1)$$

Then, for all $x \in [a, b]$,

$$f(x) = P(x) + \left(\prod_{r=0}^n (x - x_r) \right) \frac{m(x)}{(n+1)!} \quad (4.2)$$

where

$$m(x) \leq M \quad (4.3)$$

Proof

Suppose that $n > 0$ and $x \neq x_r$ for any $r = 0, \dots, n$, for otherwise the result is trivial. Let

$$w(x) = \prod_{r=0}^n (x - x_r) \quad (4.4)$$

and write

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$$f(x) = P(x) + w(x)S(x) \quad (4.5)$$

Regarding x as fixed, define

$$F(z) = f(z) - P(z) - w(z)S(x) \quad (4.6)$$

for $z \in [a, b]$.

Thus $F \in C^n[a, b]$, and $F(z)$ vanishes at the $n+2$ distinct points x, x_0, \dots, x_n . Applying Rolle's theorem n times shows that there are two distinct points $\xi_0, \xi_1 \in (a, b)$, such that

$$F^{(n)}(\xi_0) = F^{(n)}(\xi_1) = 0 \quad (4.7)$$

Differentiating (4.6) n times gives

$$F^{(n)}(z) = f^{(n)}(z) - (n+1)!S(x)z + c(x), \quad (4.8)$$

where $c(x)$ is independent of z . Thus, from (4.7),

$$S(x) = \frac{1}{(n+1)!} \left[\frac{f^{(n)}(\xi_0) - f^{(n)}(\xi_1)}{\xi_0 - \xi_1} \right], \quad (4.9)$$

so the result follows from condition (4.1).

5. Divided differences

Lemma 5.1 and Theorem 5.1 are needed in Chapter 3. The first part of Lemma 5.1 follows immediately from Lemma 4.1 and the identity (2.5) (we state the two-sided result for variety), while the second part is well-known, and follows similarly. Theorem 5.1 is more interesting, and most of the results of Chapter 3 depend on it. It may be regarded as a generalization of Taylor's theorem (the special case $n = 0$).

2.5

Lemma 5.1

Suppose that $f \in C^n[a, b; M]$ and that x_0, \dots, x_{n+1} are (distinct) points in $[a, b]$. Then

$$f[x_0, \dots, x_{n+1}] = m/(n+1)! \quad (5.1)$$

where

$$|m| \leq M \quad (5.2)$$

Furthermore, if $f \in C^{n+1}[a, b]$, then

$$m = f^{(n+1)}(\xi) \quad (5.3)$$

for some $\xi \in [a, b]$.

Theorem 5.1

Suppose that $k, n \geq 0$; $f \in C^{n+k}[a, b]$; $a \leq 0$; $b \geq 0$; and x_0, \dots, x_n are (distinct) points in $[a, b]$. Then

$$\begin{aligned} f[x_0, \dots, x_n] &= \frac{f^{(n)}(0)}{n!} + \left(\sum_{0 \leq r_1 \leq n} x_{r_1} \right) \frac{f^{(n+1)}(0)}{(n+1)!} + \dots \\ &+ \left(\sum_{0 \leq r_1 \leq r_2 \leq \dots \leq r_k \leq n} x_{r_1} \dots x_{r_k} \right) \frac{f^{(n+k)}(0)}{(n+k)!} + R, \end{aligned} \quad (5.4)$$

where

$$R = \frac{1}{(n+k)!} \left(\sum_{0 \leq r_1 \leq r_2 \leq \dots \leq r_k \leq n} x_{r_1} \dots x_{r_k} [f^{(n+k)}(\xi_{r_1, \dots, r_k}) - f^{(n+k)}(0)] \right) \quad (5.5)$$

for some ξ_{r_1, \dots, r_k} in the interval spanned by x_{r_1}, \dots, x_{r_k} and 0.

Corollary 5.1

If, in Theorem 5.1,

$$\delta = \max_{r=0, \dots, n} |x_r|, \quad (5.6)$$

then

$$|R| \leq \frac{\delta^k}{n!k!} w(f^{(n+k)}; \delta). \quad (5.7)$$

Proof of Theorem 5.1

The result for $k = 0$ is immediate from the second part of Lemma 5.1, so suppose that $k > 0$. Take points y_0, \dots, y_n which are distinct, and distinct from x_0, \dots, x_n . Then

$$\begin{aligned} & f[x_0, \dots, x_n] - f[y_0, \dots, y_n] \\ &= \sum_{r=0}^n \{f[x_0, \dots, x_r, y_{r+1}, \dots, y_n] - f[x_0, \dots, x_{r-1}, y_r, \dots, y_n]\} \end{aligned} \quad (5.8)$$

$$= \sum_{r=0}^n (x_r - y_r) f[x_0, \dots, x_r, y_r, \dots, y_n], \quad (5.9)$$

by the identity (2.4).

We may suppose, by induction on k , that the theorem holds if k is replaced by $k-1$ and n by $n+1$. Use this result to expand each term in (5.9), and consider the limit as y_0, \dots, y_n tend to 0. By the second part of Lemma 5.1, $f[y_0, \dots, y_n]$ tends to $f^{(n)}(0)/n!$, so the result follows. (Strictly, to show the existence of the points $\xi_{r_1}, \dots, \xi_{r_k}$, we must add to the inductive hypothesis the result that $f^{(n+k)}(\xi_{r_1}, \dots, \xi_{r_k})$ is a continuous function of x_{r_1}, \dots, x_{r_k} .)

Corollary 5.1 is immediate, once we note that there are exactly $\frac{(n+k)!}{n!k!}$ terms in the sum (5.5).

6. Differentiating the error

The two theorems in this section are concerned with differentiating the error term for Lagrangian interpolation. These theorems are not needed later, but are included for their independent interest, and also because they may be used to give alternative proofs of some of the results of Chapter 3 (see Kowalik and Osborne (1968), pp. 18-20).

Theorem 6.1 is given by Ralston (1963, 1965) if $f \in C^{n+1}[a, b]$. We state the result under the slightly weaker assumption that $f \in LC^n[a, b; M]$ for some M : the only difference in the conclusion is that Ralston's term $f^{(n+1)}(\eta(x))$ is replaced by $m(x)$, where $|m(x)| \leq M$. The proof is similar to that given by Ralston (1963), and is also similar to the proof of Lemma 6.2 below, so it is omitted.

Theorem 6.2 gives an expression for the derivative of the error at the points of interpolation. If $f \in LC^n[a, b; M]$ then the result follows immediately from Theorem 6.1, but Theorem 6.2 shows that $f \in C^n[a, b]$ is sufficient. This result may be of some independent interest.

Theorem 6.1

Suppose that $n \geq 1$; $f \in LC^n[a, b; M]$; x_0, \dots, x_{n-1} are (distinct) points in $[a, b]$; $w(x) = (x-x_0)\dots(x-x_{n-1})$; $P = IP(f; x_0, \dots, x_{n-1})$; and $f(x) = P(x) + R(x)$. Then there are functions $\xi: [a, b] \rightarrow [a, b]$ and $m: [a, b] \rightarrow [-M, M]$, such that

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1. $f^{(n)}(\xi(x))$ is a continuous function of $x \in [a, b]$ (although $\xi(x)$ is not necessarily continuous);

2. $m(x)$ is continuous on $[a, b]$, except possibly at x_0, \dots, x_{n-1} ;

3. for all $x \in [a, b]$,

$$R(x) = w(x)f^{(n)}(\xi(x))/n! \quad (6.1)$$

and

$$R'(x) = w'(x)f^{(n)}(\xi(x))/n! + w(x)m(x)/(n+1)!; \quad (6.2)$$

and

4. if $x \neq x_r$ for $r = 0, \dots, n-1$, then

$$\frac{d}{dx} f^{(n)}(\xi(x)) = \frac{m(x)}{n+1}. \quad (6.3)$$

Theorem 6.2

Suppose that $n \geq 1$; $f \in C^n[a, b]$; x_0, \dots, x_{n-1} are (distinct) points in $[a, b]$; $w(x) = (x-x_0)\dots(x-x_{n-1})$; $P = IP(f; x_0, \dots, x_{n-1})$; and $f(x) = P(x) + R(x)$. Then there is a function $\xi: [a, b] \rightarrow [a, b]$, such that $f^{(n)}(\xi(x))$ is a continuous function of $x \in [a, b]$; for all $x \in [a, b]$,

$$R(x) = w(x)f^{(n)}(\xi(x))/n!; \quad (6.4)$$

and, for $r = 0, \dots, n-1$,

$$R'(x_r) = w'(x_r)f^{(n)}(\xi(x_r))/n!. \quad (6.5)$$

Before proving Theorem 6.2, we need some lemmas. Note the similarity between Lemma 6.2 and Theorem 6.1.

Lemma 6.1

Suppose that $n \geq 1$; $f \in C^n[a, b]$; x_0, \dots, x_n are distinct points in $[a, b]$; $P = IP(f; x_0, \dots, x_n)$;

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$$\Delta = \max_{x \in [a, b]} |f^{(n)}(x)|, \quad (6.6)$$

and

$$\delta = \max_{0 \leq i < j \leq n} |x_i - x_j|. \quad (6.7)$$

Then, for all $x \in [a, b]$,

$$f(x) = P(x) + \left(\prod_{r=0}^n (x - x_r) \right) S(x), \quad (6.8)$$

where

$$|S(x)| \leq \frac{2\Delta}{\delta \cdot n!}. \quad (6.9)$$

Proof

If $x = x_r$ for some $r = 0, \dots, n$, then we can take $S(x) = 0$.

Otherwise, by the identity (2.5),

$$S(x) = F[x_0, \dots, x_n, x]. \quad (6.10)$$

Write x_{n+1} for x , and reorder x_0, \dots, x_{n+1} (if necessary) so that, if the reordered points are x'_0, \dots, x'_{n+1} , then

$$x'_0 - x'_{n+1} = \max_{0 \leq i < j \leq n+1} |x'_i - x'_j| \geq \delta. \quad (6.11)$$

From (6.10) and the identity (2.4),

$$S(x) = \frac{f[x'_0, \dots, x'_n] - f[x'_1, \dots, x'_{n+1}]}{x'_0 - x'_{n+1}}, \quad (6.12)$$

so, by Lemma 5.1,

$$S(x) = \frac{f^{(n)}(\xi) - f^{(n)}(\xi')}{n!(x'_0 - x'_{n+1})} \quad (6.13)$$

for some ξ and ξ' in $[a, b]$. In view of (6.6) and (6.11), the result follows.

Lemma 6.2

Suppose that $n \geq 2$; $f \in C^n[a, b]$; x_0, \dots, x_{n-1} are distinct points in $[a, b]$; $\Delta = \max_{x \in [a, b]} |f^{(n)}(x)|$; $\delta = \max_{0 \leq i < j < n} |x_i - x_j|$;

$P_n = IP(f; x_0, \dots, x_{n-1})$; $w_n(x) = (x - x_0) \dots (x - x_{n-1})$; and $f(x) = P_n(x) + R(x)$. Then there is a function $\xi: [a, b] \rightarrow [a, b]$ such that, for all $x \in [a, b]$, $f^{(n)}(\xi(x))$ is a continuous function of x ,

$$R(x) = w_n(x) f^{(n)}(\xi(x)) / n! \quad , \quad (6.14)$$

$$|R'(x) - w_n'(x) f^{(n)}(\xi(x)) / n!| \leq \frac{2|w_n'(x)| \Delta}{n! \delta} \quad , \quad (6.15)$$

and, if $x \neq x_r$ for $r = 0, \dots, n-1$, then

$$\left| \frac{d}{dx} f^{(n)}(\xi(x)) \right| \leq \frac{2\Delta}{\delta} \quad . \quad (6.16)$$

Proof

Let x_n be a point in $[a, b]$, distinct from x and x_0, \dots, x_{n-1} . For $k = n$ or $n+1$, define

$$P_k = IP(f; x_0, \dots, x_{k-1}) \quad (6.17)$$

and

$$w_k(x) = (x - x_0) \dots (x - x_{k-1}) \quad . \quad (6.18)$$

By the classical result corresponding to Lemma 4.1, there is a function ξ such that (6.14) holds. Suppose, until further notice, that $x \neq x_r$

for $r = 0, \dots, n$. Then, from (6.14) and the identity

$$P_k(x) = \sum_{r=0}^{k-1} \frac{f(x_r) w_k(x)}{(x - x_r) w_k'(x_r)} \quad , \quad (6.19)$$

we have

$$\frac{f^{(n)}(\xi(x))}{n!} = \frac{f'(x)}{w_n(x)} - \sum_{r=0}^{n-1} \frac{f(x_r)}{(x - x_r) w_n'(x_r)} \quad . \quad (6.20)$$

Since the right side of (6.20) is continuously differentiable at x , so is the left side, and

$$\frac{1}{n!} \frac{d}{dx} f^{(n)}(\xi(x)) = \frac{d}{dx} \left(\frac{f'(x)}{w_n(x)} \right) + \sum_{r=0}^{n-1} \frac{f(x_r)}{(x - x_r)^2 w_n'(x_r)} \quad . \quad (6.21)$$

Define $S(x, x_n)$ by

$$f(x) = P_{n+1}(x) + w_{n+1}(x) S(x, x_n) \quad . \quad (6.22)$$

Since

$$w_{n+1}'(x_r) = \begin{cases} w_n'(x_n) & \text{if } r = n, \\ (x_r - x_n) w_n'(x_r) & \text{if } r = 0, \dots, n-1, \end{cases} \quad (6.23)$$

equation (6.19) gives

$$\frac{P_{n+1}(x)}{w_{n+1}(x)} = \sum_{r=0}^{n-1} \frac{f(x_r)}{(x - x_r)(x_r - x_n) w_n'(x_r)} + \frac{f(x_n)}{(x - x_n) w_n'(x_n)} \quad , \quad (6.24)$$

so

$$S(x, x_n) = \frac{\frac{f(x)}{w_n(x)} - \frac{f(x_n)}{w_n(x_n)}}{x - x_n} + \sum_{r=0}^{n-1} \frac{f(x_r)}{(x - x_r)(x_n - x_r) w_n'(x_r)} \quad . \quad (6.25)$$

2.6

As $x_n \rightarrow x$, the right side of (6.25) tends to the right side of (6.21).

Thus, there exists

$$\lim_{x_n \rightarrow x} S(x, x_n) = \frac{1}{n!} \frac{d}{dx} f^{(n)}(\xi(x)) , \quad (6.26)$$

and, from the definition (6.22) and Lemma 6.1, this proves (6.16). Now,

by differentiating the right side of (6.14) by parts, we see that (6.15)

holds, in fact

$$R'(x) = \frac{w'_n(x) f^{(n)}(\xi(x)) + w_n(x) \frac{d}{dx} f^{(n)}(\xi(x))}{n!} , \quad (6.27)$$

provided that $x \neq x_r$, for $r = 0, \dots, n-1$. Consider (6.27) near one

of the points x_r , $r = 0, \dots, n-1$. $R'(x)$ is continuous at x_r ,

$w_n(x_r) = 0$, $w'_n(x_r) \neq 0$, and, by (6.16), $\frac{d}{dx} f^{(n)}(\xi(x))$ is bounded

for $x \neq x_r$. Thus $f^{(n)}(\xi(x))$ has, at worst, a removable discontinuity

at x_r , and, by the continuity of $f^{(n)}(\xi)$ as a function of ξ ,

a suitable redefinition of $\xi(x_r)$ will ensure that $f^{(n)}(\xi(x))$ is a

continuous function of x , and that

$$R'(x_r) = w'_n(x_r) f^{(n)}(\xi(x_r))/n! . \quad (6.28)$$

This completes the proof of the lemma.

Proof of Theorem 6.2

If $n \geq 2$ then the result follows immediately from Lemma 6.2. If

$n = 1$, choose $\xi(x)$ so that $\xi(x_0) = x_0$ and, for $x \neq x_0$,

$$f'(\xi(x)) = \frac{f(x) - f(x_0)}{x - x_0} . \quad (6.29)$$

Then $f'(\xi(x))$ is a continuous function of $x \in [a, b]$, and, as

2.6

$R(x) = f(x) - f(x_0)$ and $w(x) = x - x_0$, it is easy to see that

equations (6.4) and (6.5) are satisfied. Thus, the theorem holds for

all $n \geq 1$.

Chapter 3.

The Use of Successive Interpolation for Finding Simple

Zeros of a Function and its Derivatives

3.1

1. Introduction

Suppose that $q \geq 1$ and $f \in C^{q-1}[a, b]$. Given (distinct) points x_0, \dots, x_q in $[a, b]$, a sequence (x_n) may be defined in the following way: if x_0, \dots, x_{n+q} are already defined, let $P_n = IP(f; x_n, \dots, x_{n+q})$ be the q -th degree polynomial which coincides with f at x_n, \dots, x_{n+q} , and choose x_{n+q+1} so that

$$P_n^{(q-1)}(x_{n+q+1}) = 0. \quad (1.1)$$

Under certain conditions the sequence (x_n) is well-defined by (1.1), lies in $[a, b]$, and converges to a zero ξ of $f^{(q-1)}$. In this chapter we give sufficient conditions for convergence, and estimate the asymptotic rate of convergence, making various assumptions about the differentiability of f .

Since P_n is a polynomial of degree q , (1.1) is a linear equation in x_{n+q+1} . If

$$f[x_n, \dots, x_{n+q}] \neq 0, \quad (1.2)$$

then Lemma 3.1 shows that the unique solution is

$$x_{n+q+1} = \frac{1}{q} \left(\sum_{i=1}^q x_{n+i} - \frac{f[x_{n+1}, \dots, x_{n+q}]}{f[x_n, \dots, x_{n+q}]} \right), \quad (1.3)$$

and this might be used as an alternative definition. From Section 4 on, our assumptions ensure that x_n, \dots, x_{n+q} are sufficiently close to a simple zero ξ of $f^{(q-1)}$, so (1.2) holds. In Section 3, the assumption that $f^{(q)}(\xi) \neq 0$ is unnecessary: all that is required is that x_{n+q+1} is a (not necessarily unique) solution of (1.1).

The cases of most practical interest are $q = 1, 2$ and 3 . For $q = 1$, our successive interpolation process reduces to the familiar method of

3.1

successive linear interpolation for finding a zero of f , and some of our results are well-known (see Collatz (1964), Householder (1971), Ortega and Rheinboldt (1970), Ostrowski (1966), Schröder (1870), Traub (1964, 1967) etc.). For $q = 2$, we have a process of successive parabolic interpolation for finding a turning point, and, for $q = 3$, a process for finding an inflexion point. These two cases are discussed separately by Jarratt (1967, 1968), who assumes that f is analytic near ξ . By using (1.3) and Theorem 2.5.1, we show that much milder assumptions on the smoothness of f suffice (see Theorems 4.1, 5.1 and 7.1). Also, most of our results hold for any $q \geq 1$, and the proofs are no more difficult than those for the special cases $q = 2$ and $q = 3$.

Some simplifying assumptions

Practical algorithms for finding zeros and extrema, using the results of this chapter, are discussed in Chapters 4 and 5. Until then we ignore the problem of rounding errors, and usually suppose that the initial approximations x_0, \dots, x_q are sufficiently good.

For the sake of simplicity, we assume that any $q+1$ consecutive points x_n, \dots, x_{n+q} are distinct. (This is always true in the applications described in Chapters 4 and 5.) Thus, P_n is just the Lagrange interpolation polynomial, and the results of Chapter 2 are applicable. As in Chapter 2, the assumption of distinct points is not necessary, and the same results hold without this assumption if P_n is the appropriate Hermite interpolation polynomial.

3.1

A preview of the results

The definition of "order of convergence" is discussed in Section 2, and in Section 3 we show that, if a sequence (x_n) satisfies (1.1) and converges to ξ , then $f^{(q-1)}(\xi) = 0$ (Theorem 3.1).

In Sections 4 to 7, we consider the rate of convergence to a simple zero ξ of $f^{(q-1)}$, making increasingly stronger assumptions about the smoothness of f . For practical applications, the most important result is probably Theorem 4.1, which shows that convergence is superlinear if $f \in C^q$ and the starting values are sufficiently good. As in similar results for Newton's method (Collatz (1964), Kantorovich and Akilov (1959), Ortega (1968), Ortega and Rheinboldt (1970) etc.), it is possible to say precisely what "sufficiently good" means. Theorem 5.1 is an easy consequence of Theorem 4.1 and the theory of linear difference equations (Nörlund (1954)), and gives a lower bound on the order of convergence if $f^{(q)}$ is Lipschitz continuous.

The question of when the order of convergence is equal to the lower bound given by Theorem 5.1 is the subject of Sections 6 and 7. Although the results are interesting, they are not of much practical importance, for in practical problems it is merely a pleasant surprise if the iterative process converges faster than expected! Thus, the reader whose main interest is practical applications might prefer to skip Sections 6 and 7 (and also Theorem 3.1), except for Lemma 6.1.

In Section 8, we consider the interesting problem of accelerating the rate of convergence, and Theorem 8.1 shows how this may be done. We make use of Lemma 6.1, which gives a recurrence relation for the error in successive approximations to ξ , and is a generalization of results of Ostrowski (1966) and Jarratt (1967, 1968).

Finally, in Section 9 the theoretical results are illustrated by some numerical examples, and a brief summary of the main theorems is given in Section 10. The reader may find it worthwhile to glance at this summary occasionally in order to see the pattern of the results.

2. The definition of order

Suppose that $\lim_{n \rightarrow \infty} x_n = \xi$. There are many reasonable definitions of the "order of convergence" of the sequence (x_n) . For example, we could say that the order of convergence is ρ if any one of (2.1) to (2.4) holds:

$$\lim_{n \rightarrow \infty} \frac{|x_{n+1} - \xi|}{|x_n - \xi|^\rho} = K > 0, \quad (2.1)$$

$$\lim_{n \rightarrow \infty} \frac{\log|x_{n+1} - \xi|}{\log|x_n - \xi|} = \rho, \quad (2.2)$$

$$\lim_{n \rightarrow \infty} (-\log|x_n - \xi|)^{1/n} = \rho, \quad (2.3)$$

$$\liminf_{n \rightarrow \infty} (-\log|x_n - \xi|)^{1/n} = \rho. \quad (2.4)$$

These conditions are in decreasing order of strength, i.e.,

(2.1) \supset (2.2) \supset (2.3) \supset (2.4), and none of them are equivalent. (2.1) is used by Ostrowski (1966), Jarratt (1967) and Traub (1964, 1967), while (2.2) is used by Wall (1956), Tornheim (1964) and Jarratt (1968). Voigt (1969)

and Ortega and Rheinboldt (1970) give some more possibilities (for example, we may take the supremum of ρ such that the limit K in (2.1) exists and is zero, or the infimum of ρ such that K is infinite). See also Schröder (1870). For our purposes it is convenient to use (2.1) and (2.4), so we make the following definitions.

Definition 2.1

We say $x_n \rightarrow \xi$ with strong order ρ and asymptotic constant K if $x_n \rightarrow \xi$ as $n \rightarrow \infty$ and (2.1) holds.

We say $x_n \rightarrow \xi$ with weak order ρ if $x_n \rightarrow \xi$ as $n \rightarrow \infty$ and (2.4) holds. (If $x_n = \xi$ for all sufficiently large n then we say that $x_n \rightarrow \xi$ with weak order ∞ .)

Definition 2.2

Let

$$c = \limsup_{n \rightarrow \infty} |x_n - \xi|^{1/n}. \quad (2.5)$$

We say $x_n \rightarrow \xi$ sublinearly (or less than linearly) if $x_n \rightarrow \xi$ and $c = 1$. We say $x_n \rightarrow \xi$ linearly if $0 < c < 1$. We say $x_n \rightarrow \xi$ superlinearly if $c = 0$. We say $x_n \rightarrow \xi$ strictly superlinearly if $x_n \rightarrow \xi$ with weak order $\rho > 1$.

Examples

Some remarks and examples may help to clarify the definitions. If $\rho > 1$ and $x_n = \exp(-\rho^n)(1 + o(1))$ as $n \rightarrow \infty$, then $x_n \rightarrow 0$ with strong order ρ and asymptotic constant 1. If $\sigma > 1$ and $x_n = \exp(-\sigma^n)(2 + (-1)^n)$ then $x_n \rightarrow 0$ with weak order σ , but not with any strong order, for the

limit in (2.1) does not exist if $\rho = \sigma$, is zero if $\rho < \sigma$, and is infinite if $\rho > \sigma$. Thus, convergence with strong order ρ implies convergence with weak order ρ , but not conversely.

If the limit in (2.1) or (2.4) exists, and $x_n \rightarrow \xi$, then $\rho \geq 1$.

If the limit (2.1) exists with $\rho = 1$, and $x_n \rightarrow \xi$, then $K \leq 1$ ($K < 1$ for linear convergence, and $K = 1$ for sublinear convergence).

Examples of sublinear, linear, superlinear, and strictly superlinear convergence are $x_n = \frac{1}{n}$, 2^{-n} , n^{-n} , and 2^{-2^n} respectively.

3. Convergence to a zero

In this section we show that, if the sequence (x_n) defined by (1.1) converges, then it must converge to a zero of $f^{(q-1)}$, assuming only that $f \in C^{q-1}[a, b]$. First, we need a lemma which gives a relation between the points x_n, \dots, x_{n+q+1} .

Lemma 3.1

If $x_n, x_{n+1}, \dots, x_{n+q}$ are (distinct) points in $[a, b]$, and x_{n+q+1} satisfies (1.1), then

$$\left(\sum_{i=0}^{q-1} (x_{n+i} - x_{n+q+1}) \right) f[x_n, \dots, x_{n+q}] = f[x_n, \dots, x_{n+q-1}]. \quad (3.1)$$

Proof

By the identity (2.2.6),

$$\begin{aligned} P_n(x) &= f[x_n] + (x - x_n)f[x_n, x_{n+1}] + \dots \\ &\quad + (x - x_n) \dots (x - x_{n+q-1})f[x_n, \dots, x_{n+q}], \end{aligned} \quad (3.2)$$

so

$$\begin{aligned} P_n^{(q-1)}(x) &= (q-1)! \{f[x_n, \dots, x_{n+q-1}] \\ &\quad - \left(\sum_{i=0}^{q-1} (x_{n+i} - x) \right) f[x_n, \dots, x_{n+q}]\}. \end{aligned} \quad (3.3)$$

Thus, the result follows from (1.1).

Theorem 3.1

Suppose that $f \in C^{q-1}[a, b]$; that a sequence (x_n) satisfying (1.1) is defined (see Section 1) in $[a, b]$; and that there exists $\lim_{n \rightarrow \infty} x_n = \xi$. Then $f^{(q-1)}(\xi) = 0$.

Proof

Suppose, by way of contradiction, that

$$f^{(q-1)}(\xi) \neq 0. \quad (3.4)$$

For $0 \leq r < q$, the identity (2.2.4) shows that

$$\begin{aligned} (x_{n+r} - x_{n+q})f[x_n, \dots, x_{n+q}] &= f[x_n, \dots, x_{n+q-1}] - \\ &\quad f[x_n, \dots, x_{n+r-1}, x_{n+r+1}, \dots, x_{n+q}]. \end{aligned} \quad (3.5)$$

Thus, from Lemma 3.1,

$$x_{n+r} - x_{n+q} = \mu_{n,r} \sum_{i=0}^{q-1} (x_{n+i} - x_{n+q+1}), \quad (3.6)$$

where

$$\mu_{n,r} = 1 - \frac{f[x_n, \dots, x_{n+r-1}, x_{n+r+1}, \dots, x_{n+q}]}{f[x_n, \dots, x_{n+q-1}]} \quad (3.7)$$

Both divided differences in (3.7) tend to $f^{(q-1)}(\xi)/(q-1)!$ as $n \rightarrow \infty$,

so there is no loss of generality in assuming that the denominator

3.3

$f[x_n, \dots, x_{n+q-1}]$ is nonzero for all n (on the assumption (3.4)), and we have

$$\lim_{n \rightarrow \infty} \mu_{n,r} = 0 \quad (3.8)$$

Summing (3.6) over $r = 0, \dots, q-1$ and rearranging terms gives

$$\sum_{r=0}^{q-1} (x_{n+r} - x_{n+q+1}) = \mu'_n (x_{n+q} - x_{n+q+1}) \quad (3.9)$$

where

$$\mu'_n = \frac{q}{1 - \sum_{r=0}^{q-1} \mu_{n,r}} \quad (3.10)$$

and, by (3.8), there is no loss of generality in assuming that the denominator in (3.10) is nonzero for all $n \geq 0$. From (3.6), with $r = q-1$, and (3.9), we have

$$x_{n+q-1} - x_{n+q} = \mu_n (x_{n+q} - x_{n+q+1}) \quad (3.11)$$

where

$$\mu_n = \mu_{n,q-1} \mu'_n \quad (3.12)$$

The repeated application of (3.11) gives

$$x_{q-1} - x_q = \mu_0 \mu_1 \dots \mu_n (x_{n+q} - x_{n+q+1}) \quad (3.13)$$

and, by (3.8), (3.10) and (3.12), $\mu_n \rightarrow 0$ as $n \rightarrow \infty$, so the right side of (3.13) tends to zero as $n \rightarrow \infty$. This contradicts the assumption that $x_{q-1} \neq x_q$, so (3.4) must be false, and the proof is complete. (If we do not wish to assume that any $q+1$ consecutive points x_n, \dots, x_{n+q}

3.4

are distinct, then we may argue as follows: on the assumption (3.4), the right side of (3.1) is nonzero for all sufficiently large n , and thus at least two consecutive points from x_n, \dots, x_{n+q+1} are distinct. Taking these two points in place of x_{q-1} and x_q , we get a contradiction in the same way as from (3.13).)

4. Superlinear convergence

If f has one more continuous derivative than required in Theorem 3.1, then Theorem 4.1 shows that convergence to a simple zero of $f^{(q-1)}$ is superlinear, in the sense of Definition 2.2, provided the starting values are sufficiently good. The theorem makes precise what we mean by "sufficiently good". (In equation (4.1), w is the modulus of continuity: see Section 2.2.) Convergence to a multiple zero of $f^{(q-1)}$ is not usually superlinear, even if $q = 1$ (see Section 4.2), and Theorem 3.1 above is the only theorem in this chapter for which we do not need to assume that the zero is simple. Thus, there is no reason to expect that the algorithms described in Chapters 4 and 5 will converge any faster than linearly to multiple zeros of $f^{(q-1)}$.

Theorem 4.1

Suppose that $f \in C^q[a, b]$; $\xi \in [a, b]$; x_0, \dots, x_q are (distinct) points in $[a, b]$; $\delta_0 = \max_{i=0, \dots, q} |x_i - \xi|$; $f^{(q-1)}(\xi) = 0$; $[\xi - \delta_0, \xi + \delta_0] \subseteq [a, b]$; and

$$\beta_w(f^{(q)}; \delta_0) < |f^{(q)}(\xi)| \quad (4.1)$$

3.4

Then a sequence (x_n) is uniquely defined by (1.1), and $x_n \rightarrow \xi$ superlinearly as $n \rightarrow \infty$. Furthermore, if, for $n \geq 0$,

$$\delta_n = \max_{i=0, \dots, q} |x_{n+i} - \xi| \quad (4.2)$$

and

$$\lambda_n = \delta w(f^{(q)}; \delta_n) / |f^{(q)}(\xi)|, \quad (4.3)$$

then the sequence (δ_n) is monotonic decreasing, and

$$\delta_{n+q+1} \leq \lambda_n \delta_{n+1}. \quad (4.4)$$

Proof

Without loss of generality, assume that $\xi = 0$. Let δ_n and λ_n be as in the statement of the theorem (equations (4.2) and (4.3)). Since $f^{(q-1)}(0) = 0$, Corollary 2.5.1 to Theorem 2.5.1 (with $k = 1$, $n = q-1$) gives

$$f[x_1, \dots, x_q] = \left(\sum_{i=1}^q x_i \right) f^{(q)}(0) / q! + R_1, \quad (4.5)$$

where

$$|R_1| \leq \delta' w(f^{(q)}; \delta') / (q-1)!, \quad (4.6)$$

if

$$\delta' = \max_{i=1, \dots, q} |x_i| \leq \delta_0. \quad (4.7)$$

Similarly,

$$f[x_0, \dots, x_q] = \frac{f^{(q)}(0)}{q!} (1 + R_2) = \frac{f^{(q)}(0)}{q!(1 + R_2)}, \quad (4.8)$$

3.4

where

$$|R_2| \leq w(f^{(q)}; \delta_0) / |f^{(q)}(0)| = \lambda_0 / 3 < 1/3, \quad (4.9)$$

so

$$|R_3| = \left| \frac{R_2}{1 + R_2} \right| \leq \lambda_0 / 2 < 1/2. \quad (4.10)$$

(Note that the assumption (4.1) ensures that $f[x_0, \dots, x_q] \neq 0$.)

From (4.5), (4.8), and Lemma 3.1 (with x_0 and x_q interchanged),

$$\left(\sum_{i=1}^q (x_i - x_{q+1}) \right) \frac{f^{(q)}(0)}{q!} = \left(\sum_{i=1}^q x_i \right) \frac{f^{(q)}(0)}{q!} + R_4, \quad (4.11)$$

where

$$R_4 = R_3 \left(\sum_{i=1}^q x_i \right) \frac{f^{(q)}(0)}{q!} + R_1 (1 + R_3). \quad (4.12)$$

From (4.6), (4.7) and (4.10), equation (4.12) gives

$$|R_4| \leq \frac{\lambda_0 \delta' |f^{(q)}(0)|}{2 \cdot (q-1)!} + \frac{3 \delta' w(f^{(q)}; \delta')}{2 \cdot (q-1)!}, \quad (4.13)$$

so, from (4.3) and (4.7),

$$|R_4| \leq \frac{\lambda_0 \delta' |f^{(q)}(0)|}{(q-1)!}. \quad (4.14)$$

Now, from (4.11), we have

$$|x_{q+1}| \leq \lambda_0 \delta'. \quad (4.15)$$

By the assumption (4.1), $\lambda_0 < 1$, so x_{q+1} lies in $[a, b]$, δ_1 and λ_1 are well-defined, $\delta_1 = \delta' \leq \delta_0$, $\lambda_1 \leq \lambda_0$, and

3.4

$$|x_{q+1}| \leq \lambda_0 \delta_1 . \quad (4.16)$$

In the same way, we see that $\delta_0 \geq \delta_1 \geq \delta_2 \geq \dots$,
 $1 > \lambda_0 \geq \lambda_1 \geq \lambda_2 \geq \dots$, and, for $n \geq 0$,

$$|x_{n+q+1}| \leq \lambda_n \delta_{n+1} . \quad (4.17)$$

Thus, the inequality (4.4) holds, and it only remains to show that $x_n \rightarrow 0$ superlinearly. From (4.4) and the above,

$$\delta_{kq+1} \leq \lambda_0 \lambda_q \dots \lambda_{(k-1)q} \delta_1 \leq \lambda_0^k \delta_1 , \quad (4.18)$$

and $\lambda_0 < 1$ by assumption (4.1), so $\delta_n \rightarrow 0$ as $n \rightarrow \infty$. Thus, by the continuity of $f^{(q)}$ and the definition (4.3), $\lambda_n \rightarrow 0$ as $n \rightarrow \infty$.

Take any $\varepsilon > 0$. For all sufficiently large n ,

$$\lambda_n \leq \varepsilon^q , \quad (4.19)$$

so, from (4.4),

$$\limsup_{n \rightarrow \infty} \delta_n^{1/n} \leq \varepsilon . \quad (4.20)$$

As ε is arbitrarily small, this shows that

$$\lim_{n \rightarrow \infty} |x_n|^{1/n} = \lim_{n \rightarrow \infty} \delta_n^{1/n} = 0 . \quad (4.21)$$

Thus, $x_n \rightarrow \xi = 0$ superlinearly, and the proof is complete.

Remarks

The proof of Theorem 4.1 shows that, for $n \geq 0$, $|x_{n+q+1} - \xi|$ is no greater than the second-largest of $|x_n - \xi|, \dots, |x_{n+q} - \xi|$. Thus, if

3.5

$q = 1$, the sequence $(|x_n - \xi|)$ is monotonic decreasing, except perhaps for the first term. In fact, the proof shows that, for $q = 1$ and $n \geq 1$,

$$\frac{|x_{n+1} - \xi|}{|x_n - \xi|} \leq \lambda_{n-1} \rightarrow 0 \text{ as } n \rightarrow \infty \quad (4.22)$$

(provided $x_n \neq \xi$). This is a common definition of "superlinear convergence", stronger than our Definition 2.2.

If $q \geq 2$, the sequence $(|x_n - \xi|)$ need not be eventually monotonic decreasing: monotonicity would follow from strong superlinear convergence with order greater than 1, but more conditions are necessary to ensure this sort of convergence (see Sections 6 and 7).

5. Strict superlinear convergence

Assuming slightly more than in Theorem 4.1, Theorem 5.1 shows that convergence to a simple zero of $f^{(q-1)}$ is strictly superlinear, according to Definition 2.2. Before stating the theorem, we define some constants $\beta_{q,\alpha}$ and $\gamma_{q,\alpha}$ which are needed here and in Sections 6 and 7.

Definition 5.1

For $q \geq 1$ and $\alpha > 0$, let the roots of

$$x^{q+1} = x + \alpha \quad (5.1)$$

be $u_{q,\alpha}^{(i)}$, for $i = 0, \dots, q$, with $|u_{q,\alpha}^{(0)}| \geq |u_{q,\alpha}^{(1)}| \geq \dots \geq |u_{q,\alpha}^{(q)}|$.

Then the constants $\beta_{q,\alpha}$ and $\gamma_{q,\alpha}$ are defined by

$$\beta_{q,\alpha} = |u_{q,\alpha}^{(0)}| \quad \text{and} \quad \gamma_{q,\alpha} = |u_{q,\alpha}^{(1)}| .$$

Since the case $\alpha = 1$ often occurs, we write simply β_q for $\beta_{q,1}$, and γ_q for $\gamma_{q,1}$.

Remarks

$\beta_{q,\alpha}$ is just the positive real root of (5.1), and it is easy to see that, for $0 < \alpha \leq 1$,

$$(1+\alpha)^{\frac{2}{2q+1}} < \beta_{q,\alpha} < (1+\alpha)^{\frac{1}{q}}. \quad (5.2)$$

We are only interested in the constants $\gamma_{q,\alpha}$ when $\alpha = 1$. If $\alpha = 1$ and $q \geq 2$ then there are exactly two complex conjugate roots of (5.1) with modulus γ_q . If $q = 1$ or 2 then $\gamma_q < 1$, but, for $q \geq 3$,

$$1 < \gamma_q < \beta_q.$$

This may be proved by applying the Lehmer-Schur test to show that, for suitable $\epsilon > 0$, exactly $q-2$ roots of

$$x^{q+1} = x+1 \quad (5.3)$$

lie in the circle $|x| < 1+\epsilon$. The details are omitted, for all cases of practical interest are covered by Table 5.1, which gives β_q and γ_q to 12 decimal places for $q = 1, \dots, 10$. The table was computed by finding all roots of (5.3) with the program of Jenkins (1969), and the entries are the correctly rounded values of β_q and γ_q if Jenkin's a posteriori error bounds are correct.

Table 5.1: The constants β_q and γ_q for $q = 1(1)10$ to 120

q	β_q	γ_q
1	1.618033988750	0.618033988750
2	1.324717957245	0.868836961833
3	1.220744084606	1.063336938821
4	1.167303978261	1.099000515146
5	1.134724138402	1.099174913506
6	1.112775684279	1.091953305766
7	1.096981557799	1.083743696285
8	1.085070245491	1.076133134033
9	1.075766066087	1.069448852721
10	1.068297188921	1.063666938404

See Definition 5.1 and the remarks above for a description of the constants β_q and γ_q .

Theorem 5.1

Suppose that $f \in IC^q[a, b; M, \alpha]$ (see Section 2.2); $\xi \in (a, b)$; $f^{(q-1)}(\xi) = 0$; and $f^{(q)}(\xi) \neq 0$. If x_0, \dots, x_q are (distinct and) sufficiently close to ξ , then a sequence (x_n) is uniquely defined by (1.1), and $x_n \rightarrow \xi$ with weak order at least $\beta_{q, \alpha}$, the positive real root of $x^{q+1} = x + \alpha$.

Remark

If $\delta_0 = \max_{i=0, \dots, q} |x_i - \xi|$, then, from Theorem 4.1, x_0, \dots, x_q are "sufficiently close" to ξ if $\delta_0 \leq \xi - a$, $\delta_0 \leq b - \xi$, and

$$3M\delta_0^\alpha < |f^{(q)}(\xi)|. \quad (5.4)$$

If these conditions are satisfied, then an upper bound on $|x_n - \xi|$ follows from equation (5.10) below.

Proof of Theorem 5.1

For $n \geq 0$, let

$$\delta_n = \max_{i=0, \dots, q} |x_{n+1} - \xi|. \quad (5.5)$$

Suppose that x_0, \dots, x_q are so close to ξ that the conditions mentioned in the remark above are satisfied. Then Theorem 4.1 shows that (δ_n) is monotonic decreasing to zero, and

$$\delta_{n+q+1} \leq \frac{3M}{|f^{(q)}(\xi)|} \delta_n^\alpha \delta_{n+1}. \quad (5.6)$$

If eventually $\delta_n = 0$, then the result follows immediately: by our definition, $x_n \rightarrow \xi$ with weak order ∞ . Hence, suppose that

$\delta_n / 0$ for all $n \geq 0$ (and thus, from (5.6), $M > 0$). Let

$$\lambda_n = -\log(\delta_n \left| \frac{3M}{f^{(q)}(\xi)} \right|^{1/\alpha}) \quad (5.7)$$

(not the same λ_n as in Theorem 4.1). From condition (5.4) and the fact that (δ_n) is monotonic decreasing, $0 < \lambda_0 \leq \lambda_1 \leq \lambda_2 \leq \dots$, and, from equation (5.6),

$$\lambda_{n+q+1} \geq \lambda_{n+1} + \alpha \lambda_n. \quad (5.8)$$

Since $\beta_{q, \alpha} > 1$, we have

$$\lambda_n \geq \lambda_0 \beta_{q, \alpha}^{n-q} \quad (5.9)$$

for $n = 0, \dots, q$. Thus, from (5.8) and the definition of $\beta_{q, \alpha}$, the inequality (5.9) holds for all $n \geq 0$, by induction on n . Hence, for all $n \geq 0$,

$$-\log |x_n - \xi| \geq -\log \delta_n \geq \lambda_0 \beta_{q, \alpha}^{n-q} + \frac{1}{\alpha} \log \left| \frac{3M}{f^{(q)}(\xi)} \right|. \quad (5.10)$$

Since $\lambda_0 > 0$ and $\beta_{q, \alpha} > 1$, equation (5.10) shows that

$$\liminf_{n \rightarrow \infty} (-\log |x_n - \xi|)^{1/n} \geq \beta_{q, \alpha}, \quad (5.11)$$

which completes the proof.

Note that, in the important case $\alpha = 1$, there is a simple proof of Theorem 5.1 which does not depend on Theorems 2.5.1 and 4.1. Also, this proof shows that, instead of (5.4), the condition

$$3M\delta_0 < 2|f^{(q)}(\xi)| \quad (5.12)$$

is sufficient. The idea is this: by applying Rolle's Theorem $q-1$ times, we see that $p_n^{(q-1)}(x)$ coincides with f' at points ξ_n and ξ'_n say, with $|\xi_n - \xi| \leq \delta_n$ and $|\xi'_n - \xi| \leq \delta'_n$ = the second largest of $|x_n - \xi|, \dots, |x_{n+q} - \xi|$. Thus, from Lemma 2.4.1,

$$|p_n^{(q-1)}(\xi)| \leq \frac{1}{2} M \delta_n \delta'_n. \quad (5.13)$$

On the other hand, equations (1.1) and (3.3) show that

$$x_{n+q+1} = \xi - \frac{p_n^{(q-1)}(\xi)}{q! f[x_n, \dots, x_{n+q}]}, \quad (5.14)$$

so we can bound $|x_{n+q+1} - \xi|$, and then the result follows in much the same way as above.

6. The exact order of convergence

Theorem 5.1 gives conditions under which $x_n \rightarrow \xi$ with weak order at least β_q . It is natural to ask if the order is exactly β_q . In general, this is true, but some conditions are necessary to ensure that the rate of convergence is not too fast: for example, the successive linear interpolation process ($q = 1$) converges to a simple zero ξ with weak order at least 2 ($> \beta_1 = 1.618 \dots$) if it happens that $f''(\xi) = 0$, for then linear interpolation is more accurate than would normally be expected. Theorem 6.1 gives sufficient conditions for the order to be exactly β_q . Apart from the condition $f^{(q+1)}(\xi) \neq 0$, it is necessary to impose some conditions on the initial points x_0, \dots, x_q . (These extra conditions are superfluous if $q = 1$: see Section 7.)

Before proving Theorem 6.1, we need two lemmas. Lemma 6.2 is concerned with the solution of a certain difference equation, and is closely related to Theorem 12.1 of Ostrowski (1966). (The lemma could easily be generalized, but we only need the result stated.) Lemma 6.1 gives a recurrence relation for the error $x_n - \xi$. Special cases of this lemma have been given by Ostrowski (1966) and Jarratt (1967, 1968). Ostrowski essentially gives the case $q = 1$, and Jarratt gives weaker results for $q = 2$ and $q = 3$. (Our bound on the remainder R_n is sharper than Jarratt's, and we do not assume that f is analytic.) In Section 8, we show how the result of Lemma 6.1 may be used to accelerate convergence of the sequence (x_n) .

Lemma 6.1

Suppose that $f \in C^{q+1}[a, b]$; $\xi \in [a, b]$; $f^{(q-1)}(\xi) = 0$; $f^{(q)}(\xi) \neq 0$; x_n, \dots, x_{n+q} are (distinct) points in $[a, b]$; and x_{n+q+1} satisfies equation (1.1). Let δ_n be the largest of $|x_n - \xi|, \dots, |x_{n+q} - \xi|$; and δ'_n the second largest. Then

$$x_{n+q+1} - \xi = \frac{f^{(q+1)}(\xi)}{q(q+1)f^{(q)}(\xi)} \sum_{0 \leq i < j \leq q} (x_{n+i} - \xi)(x_{n+j} - \xi) + R_n, \quad (6.1)$$

where

$$R_n = O(\delta_n \delta'_n (\delta_n + w(f^{(q+1)}; \delta_n)) |f^{(q+1)}(\xi)|) \quad (6.2)$$

as $\delta_n \rightarrow 0$.

Proof

Without loss of generality, assume that $n = 0$ and $\xi = 0$. Rearrange

3.6

x_0, \dots, x_q , if necessary, so that $|x_0| \leq |x_1| \leq \dots \leq |x_q|$. From

Lemma 3.1,

$$q \cdot x_{q+1} f[x_0, \dots, x_q] = \left(\sum_{i=0}^{q-1} x_i \right) f[x_0, \dots, x_q] - f[x_0, \dots, x_{q-1}]. \quad (6.3)$$

Thus, as $f^{(q-1)}(0) = 0 \neq f^{(q)}(0)$, Theorem 2.5.1 gives

$$\begin{aligned} q \cdot x_{q+1} \frac{f^{(q)}(0)}{q!} (1 + r_1) \\ = \left(\sum_{i=0}^{q-1} x_i \right) \frac{f^{(q)}(0)}{q!} + \left(\sum_{i=0}^q x_i \right) \frac{f^{(q+1)}(0)}{(q+1)!} + r_2 \\ = \left(\sum_{i=0}^{q-1} x_i \right) \frac{f^{(q)}(0)}{q!} + \left(\sum_{0 \leq i \leq j < q} x_i x_j \right) \frac{f^{(q+1)}(0)}{(q+1)!} + r_3, \end{aligned} \quad (6.4)$$

where

$$|r_1| \leq \frac{w(f^{(q)}; \delta_0)}{|f^{(q)}(0)|} = o(\delta_0), \quad (6.5)$$

$$|r_2| \leq \delta_0 w(f^{(q+1)}; \delta_0)/q! = o(\delta_0 w(f^{(q+1)}; \delta_0)), \quad (6.6)$$

and

$$|r_3| \leq \frac{\delta_0^2 w(f^{(q+1)}; \delta_0)}{2(q-1)!} = o(\delta_0^2 w(f^{(q+1)}; \delta_0)) \quad (6.7)$$

as $\delta_0 \rightarrow 0$.

The right side of (6.4) is just

$$\left(\sum_{0 \leq i < j \leq q} x_i x_j \right) \frac{f^{(q+1)}(0)}{(q+1)!} + r_4, \quad (6.8)$$

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where

$$|r_4| \leq q \delta_0 |r_2| + |r_3| = o(\delta_0 \delta_0 w(f^{(q+1)}; \delta_0)) \quad (6.9)$$

as $\delta_0 \rightarrow 0$, so the result follows.

Remarks

From the bounds on r_1, \dots, r_4 , it is easy to derive an explicit bound on $|R_n|$ for sufficiently small δ_n . For our purposes, though, the relation (6.2) is adequate. A simple corollary of (6.2) is that, if $f^{(q+1)} \in \text{Lip}_M \alpha$, then

$$R_n = o(\delta_n^{1+\alpha} \delta_n^t) \quad (6.10)$$

as $\delta_n \rightarrow 0$.

Lemma 6.2

Suppose that $\lambda_n \rightarrow +\infty$ as $n \rightarrow \infty$, and, for $n \geq 0$,

$$\lambda_{n+q+1} - \lambda_{n+1} - \lambda_n = k_n, \quad (6.11)$$

where

$$k_n = o(s^n) \quad (6.12)$$

as $n \rightarrow \infty$, s a constant. If $\gamma_q < s < \beta_q$ then

$$\lambda_n = c \cdot \beta_q^n + o(s^n) \quad (6.13)$$

as $n \rightarrow \infty$, and if $k_n = o(s^n)$ as $n \rightarrow \infty$ then

$$\lambda_n = c \cdot \beta_q^n + o(s^n) \quad (6.14)$$

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as $n \rightarrow \infty$. If $0 \leq s < \gamma_q$ then

$$\lambda_n = c \cdot \beta_q^n + O(n^v \cdot \gamma_q^n) \quad (6.15)$$

as $n \rightarrow \infty$, where

$$v = \begin{cases} 0 & \text{if } q = 1, \\ 1 & \text{if } q > 1, \end{cases} \quad (6.16)$$

and c is a nonnegative constant.

Proof

The restriction $|u_2| < 1$ in Theorem 12.1 of Ostrowski (1966) is unnecessary, for we can choose any λ with $|u_2| < \lambda < |u_1|$ and consider λ_n/λ^n , instead of λ_n , in Ostrowski's proof. Thus, in view of the remarks after Definition 5.1, (6.13) and (6.15) follow from Ostrowski's Theorem 12.1. (6.14) does not follow directly in the same way, but the proof of Ostrowski's Theorem 12.1 goes through, assuming $k_n = o(s^n)$ instead of $k_n = O(s^n)$, and giving a result from which (6.14) follows. The only difficulty is in proving the modified form of Ostrowski's Lemma 12.1, but this follows from the Toeplitz lemma: if $k_n \rightarrow 0$, $|\xi| < 1$, and $z_n = k_n + k_{n-1}\xi + \dots + k_0\xi^n$, then $z_n \rightarrow 0$ as $n \rightarrow \infty$ (see Ortega and Rheinboldt (1970), pg. 399).

Theorem 6.1

Suppose $f \in C^{q+1}[a, b]$; $\xi \in (a, b)$; $f^{(q-1)}(\xi) = 0$; $f^{(q)}(\xi) \neq 0$; and $f^{(q+1)}(\xi) \neq 0$. If $|x_0 - \xi|$ is sufficiently small,

$$|x_{i-1} - \xi| \geq h|x_i - \xi| \quad (6.17)$$

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for $i = 1, 2, \dots, q$, and

$$|x_q - \xi| \geq 6|K(x_0 - \xi)(x_1 - \xi)| > 0, \quad (6.18)$$

where

$$K = \frac{f^{(q+1)}(\xi)}{q(q+1)f^{(q)}(\xi)}, \quad (6.19)$$

then a sequence (x_n) is uniquely defined by (1.1), and $x_n \rightarrow \xi$ with weak order exactly β_q . In fact, if $q = 1$ or 2 then $x_n \rightarrow \xi$ with strong order β_q and asymptotic constant $|K|^{\beta_q^{-1}}$, and if $q \geq 3$ then

$$-\log|x_n - \xi| = c \cdot \beta_q^n + O(n \cdot \gamma_q^n) \quad (6.20)$$

as $n \rightarrow \infty$, for some positive constant c .

Remarks

Condition (6.17) ensures that x_0, \dots, x_q approach ξ sufficiently fast, while (6.18) makes sure that they do not approach ξ too fast. These conditions could be weakened, but Theorem 7.1 shows that some such conditions are necessary if $q \geq 2$. If $q = 1$ then the conditions are superfluous: see Corollary 7.1.

Equation (6.20) implies that (2.2) holds with $\rho = \beta_q$, but (2.1) does not necessarily hold, for $\gamma_q > 1$ if $q \geq 3$.

Proof of Theorem 6.1

$$\text{Let } y_n = |K(x_n - \xi)|. \quad (6.21)$$

From the assumptions (6.17) and (6.18) we have, at least for $n = 0$,

$$y_{n+i-1} \geq 4y_{n+i} \quad (6.22)$$

for $i = 1, 2, \dots, q$, and

$$y_{n+q} \geq 6y_n y_{n+1} > 0. \quad (6.23)$$

We shall show that (6.22) and (6.23) hold for all $n \geq 0$. Suppose, as inductive hypothesis, that they hold for all $n \leq m$. Then, by taking $|x_0 - \xi|$ sufficiently small (independent of m), we may suppose that the remainder R_n of Lemma 6.1 satisfies

$$|KR_n| \leq \frac{1}{13} y_n y_{n+1} \quad (6.24)$$

for all $n \leq m$. Thus, from Lemma 6.1,

$$\begin{aligned} y_{m+q+1} &\leq y_m y_{m+1} \left(1 + \frac{1}{4} + \frac{2}{4^2} + \frac{2}{4^3} + \frac{3}{4^4} + \dots + \frac{1}{13}\right) \\ &\leq \frac{3}{2} y_m y_{m+1}. \end{aligned} \quad (6.25)$$

From (6.23) with $n = m$, this gives

$$y_{m+q} \geq 4y_{m+q+1}. \quad (6.26)$$

Similarly,

$$\begin{aligned} y_{m+q+1} &\geq y_m y_{m+1} \left(1 - \frac{1}{4} - \frac{2}{4^2} - \frac{2}{4^3} - \frac{3}{4^4} - \dots - \frac{1}{13}\right) \\ &\geq \frac{1}{2} y_m y_{m+1} \end{aligned} \quad (6.27)$$

$$\geq 6y_{m+1} y_{m+2}. \quad (6.28)$$

Also, from (6.27), $y_{m+q+1} > 0$, so the right side of (6.28) is positive. From (6.26) and (6.28), we see that (6.22) and (6.23) hold for $n = m+1$, so they hold for all $n \geq 0$, by induction. Thus (6.25) and (6.27) hold for all $m \geq 0$.

Let

$$\lambda_n = -\log y_n \quad (6.29)$$

and

$$k_n = \lambda_{n+q+1} - \lambda_{n+1} - \lambda_n. \quad (6.30)$$

From (6.25) and (6.27),

$$|k_n| \leq \log 2, \quad (6.31)$$

so we may apply Lemma 6.2 with $s = 1$. If $q \geq 3$ then $\gamma_q > 1$, so

$$\lambda_n = c \cdot \beta_q^n + o(n \cdot \gamma_q^n) \quad (6.32)$$

as $n \rightarrow \infty$. From Theorem 5.1, $c > 0$, so the result for $q \geq 3$ follows.

If $q = 1$ or 2 then $\gamma_q < 1$, so

$$\lambda_n = c \cdot \beta_q^n + o(1) \quad (6.33)$$

as $n \rightarrow \infty$. From (6.29), (6.30), (6.33) and Lemma 6.1, we now see that

$$k_n = o(1) \quad (6.34)$$

as $n \rightarrow \infty$, so, by equation (6.14) with $s = 1$,

$$\lambda_n = c \cdot \beta_q^n + o(1) \quad (6.35)$$

as $n \rightarrow \infty$. Thus, there exists

$$\lim_{n \rightarrow \infty} \frac{y_{n+1}}{\beta_q y_n} = 1, \quad (6.36)$$

so the result follows from equation (6.21). (Note that, if $f^{(q+1)} \in \text{Lip}_M \alpha$ for any M and $\alpha > 0$, then (6.34) may be replaced by $k_n = o(s^n)$ for any $s > 0$, so (6.15) holds, and

$$\frac{|x_{n+1} - \xi|}{|x_n - \xi|^q} = |K|^{\beta_q - 1} + O(n^{q-1} \cdot \gamma_q^n) \quad (6.37)$$

as $n \rightarrow \infty$.)

7. Stronger results for $q = 1$ and 2

In this section we restrict our attention to the two cases of the greatest practical interest, $q = 1$ (successive linear interpolation) and $q = 2$ (successive parabolic interpolation for finding an extreme point). Corollary 7.1 shows that the conditions (6.17) and (6.18) of Theorem 6.1 are unnecessary if $q = 1$.

Corollary 7.1

Suppose that $q = 1$; $f \in C^2[a, b]$; $\xi \in (a, b)$; $f(\xi) = 0$; $f'(\xi) \neq 0$; and $f''(\xi) \neq 0$. If x_0, x_1 and ξ are distinct and sufficiently close together, then a sequence (x_n) is uniquely defined by (1.1), and $x_n \rightarrow \xi$ with strong order $\beta_1 = \frac{1}{2}(1 + \sqrt{5})$ and asymptotic constant $\left| \frac{f''(\xi)}{2f'(\xi)} \right|^{\beta_1 - 1}$ as $n \rightarrow \infty$.

Proof

From Lemma 6.1,

$$x_2 - \xi = \frac{f''(\xi)}{2f'(\xi)} (x_0 - \xi)(x_1 - \xi)(1 + o(1)) \quad (7.1)$$

as $\max(|x_0 - \xi|, |x_1 - \xi|) \rightarrow 0$. Thus, Theorem 6.1 is applicable to the sequence (x'_n) , where $x'_n = x_{n+1}$, provided x_0 and x_1 are sufficiently close to ξ .

Remarks

Ostrowski (1966) gives Corollary 7.1 with the stronger assumption that $f \in C^3[a, b]$. He also shows that, if $f \in C^3[a, b]$ and the conditions of Corollary 7.1 are satisfied, then

$$\frac{|x_{n+1} - \xi|}{|x_n - \xi|^{\beta_1}} = \left| \frac{f''(\xi)}{2f'(\xi)} \right|^{\beta_1 - 1} + O(\gamma_1^n) \quad (7.2)$$

as $n \rightarrow \infty$. As we remarked at the end of the proof of Theorem 6.1, the relation (7.2) holds provided that $f \in LC^2[a, b; M, \alpha]$ for some M and α (see equation (6.37)). For an even weaker condition, see (7.7) and (7.8) below.

The following theorem removes the rather artificial restrictions (6.17) and (6.18) of Theorem 6.1, if $f^{(q+1)}$ is Lipschitz continuous and $q = 1$ or 2 . The proof does not extend to $q \geq 3$, because it depends on the assumption that $\gamma_q < 1$, which is only true for $q = 1$ and $q = 2$ (see Table 5.1).

Theorem 7.1

Suppose that $q = 1$ or 2 ; $f \in LC^{q+1}[a, b; M]$; $\xi \in (a, b)$; $f^{(q-1)}(\xi) = 0$; and $f^{(q)}(\xi) \neq 0$. If x_0, \dots, x_q are (distinct and) sufficiently close to ξ , then a sequence (x_n) is uniquely defined by (1.1), and either

1: $x_n \rightarrow \xi$ with strong order β_q and asymptotic constant

$$\left| \frac{f^{(q+1)}(\xi)}{q(q+1)f^{(q)}(\xi)} \right|^{\beta_q - 1}, \text{ in fact}$$

$$\frac{|x_{n+1} - \xi|}{|x_n - \xi|^{\beta_q}} = \left| \frac{f^{(q+1)}(\xi)}{q(q+1)f^{(q)}(\xi)} \right|^{\beta_q - 1} + o(n^{q-1} \gamma_q^n) \quad (7.3)$$

as $n \rightarrow \infty$ (recall that $\beta_1 \simeq 1.618$, $\beta_2 \simeq 1.325$, $\gamma_1 \simeq 0.618$, and $\gamma_2 \simeq 0.869$);

or

2: $x_n \rightarrow \xi$ with weak order at least 2 if $q = 1$, or

$$\left(\frac{3+\sqrt{5}}{2}\right)^{\frac{1}{3}} \simeq 1.378 \quad \text{if } q = 2.$$

Remarks

If $q = 1$ then, by Corollary 7.1, case 2 of Theorem 7.1 is possible only if $f''(\xi) = 0$ (or if one of x_0 and x_1 coincides with ξ , when the weak order is ∞).

If $q = 2$ then case 2 is possible, although unlikely, even if $f^{(3)}(\xi) \neq 0$ and $x_n \neq \xi$ for all n . All that is necessary is that the terms in relation (7.28) repeatedly nearly cancel out. Jarratt (1967) and Kowalik and Osborne (1968) assume that such cancellation will eventually die out, so the order will be β_2 . The conditions (6.17) and (6.18) are sufficient for this to be true, but without some such conditions there is a remote possibility that cancellation will continue indefinitely.

For example, with $f(x) = 2x^3 + x^2$, there are starting values x_0, x_1 and x_2 such that

$$\left. \begin{aligned} x_{2n} &\sim \exp(-2^n) \\ \text{and} \\ x_{2n+1} &\sim -\exp(-2^n) \end{aligned} \right\} \quad (7.4)$$

so $x_n \rightarrow \xi = 0$ with weak order $\sqrt{2}$. Similarly, if

$$\gamma = \frac{1}{2}(3+\sqrt{5}) \simeq 2.618 \dots, \quad (7.5)$$

then there are starting values such that

$$\left. \begin{aligned} x_{3n} &\sim \exp(-\gamma^n) \\ x_{3n+1} &\sim \exp(-(\gamma-1)\gamma^n) \\ \text{and} \\ x_{3n+2} &\sim -\exp(-(\gamma-1)\gamma^{n+1}) \end{aligned} \right\} \quad (7.6)$$

so $x_n \rightarrow 0$ with weak order $\gamma^{1/3} = 1.378 \dots$. The proof is omitted, but the reader may easily verify that (7.4) and (7.6) are compatible with Lemma 7.3 below (this depends on the relation $2\gamma-1 = \gamma(\gamma-1)$).

For the sake of simplicity, we have not stated Theorem 7.1 in the sharpest possible form. If $f^{(q+1)}(\xi) = 0$, then $x_n \rightarrow \xi$ with weak order at least $\beta_{q,1+\alpha} > \beta_q$, provided that $f^{(q+1)} \in \text{Lip}_M \alpha$ for some M and $\alpha > 0$. If $f^{(q+1)}(\xi) \neq 0$, then the theorem holds provided that $f \in C^{q+1}[a,b]$. Equation (7.3) may no longer hold, but if there is an $\epsilon > 0$ such that

$$w(f^{(q+1)}; \delta) = o(|\log \delta|^{-\epsilon/q}) \quad (7.7)$$

as $\delta \rightarrow 0$, then

$$\frac{|x_{n+1} - \xi|}{|x_n - \xi|^{\beta_q}} = \left| \frac{f^{(q+1)}(\xi)}{q(q+1)f^{(q)}(\xi)} \right|^{\beta_q - 1} = \begin{cases} o(n^{q-1} \gamma_q^n) & \text{if } \epsilon > 1, \\ o(n^q \gamma_q^n) & \text{if } \epsilon = 1, \\ o(\gamma_q^{n\epsilon}) & \text{if } \epsilon < 1, \end{cases} \quad (7.8)$$

as $n \rightarrow \infty$. (A condition like (7.7) occurs in some variants of Jackson's theorem: see Meinardus (1967).)

Before proving Theorem 7.1, we need three rather technical lemmas.

Lemma 7.1

Suppose that, for $n \geq 0$,

$$x_{n+3} = x_n x_{n+1} + x_{n+1} x_{n+2} + x_n x_{n+2} + m_n \delta_n^2 \delta'_n, \quad (7.9)$$

where δ_n is the largest of $|x_n|$, $|x_{n+1}|$ and $|x_{n+2}|$, and δ'_n is the second largest. If there is a positive constant L such that $\frac{1}{15L} \geq |x_0| \geq 3|x_1| \geq 9|x_2| \geq 27|x_3|$, and

$$|m_n| \leq L \quad (7.10)$$

for all $n \geq 0$, then $|x_n| \geq 3|x_{n+1}|$ for all $n \geq 0$.

Proof

As in the proof of Theorem 6.1, it follows by induction on n that

$$|x_{n+3}| \geq \frac{22}{45} |x_n x_{n+1}| \geq \frac{22}{9} |x_{n+1} x_{n+2}| \geq 3|x_{n+4}|, \quad (7.11)$$

for all $n \geq 0$.

Lemma 7.2

If the conditions of Lemma 7.1 are satisfied, then either $x_n = 0$

for all sufficiently large n , or

$$\frac{|x_{n+1}|}{|x_n|^2} = 1 + O(n\gamma_2^n)$$

as $n \rightarrow \infty$.

Proof

If $x_n \neq 0$ for infinitely many n then, by Lemma 7.1, $x_n \neq 0$ for all $n \geq 0$. If this is so, define $\lambda_n = -\log|x_n|$ and $k_n = \lambda_{n+3} - \lambda_{n+1} - \lambda_n$. From equation (7.11), k_n is bounded, so Lemma 6.2 with $s = 1$ gives $\lambda_n = c\beta_2^n + O(1)$ as $n \rightarrow \infty$. By Lemma 7.1, $\lambda_n \rightarrow +\infty$, so $c > 0$. Thus, from (7.9),

$$k_n = O(\exp\{-c(\beta_2 - 1)\beta_2^{n+1}\}) \quad (7.12)$$

as $n \rightarrow \infty$ (this is not necessarily true in the proof of Theorem 6.1).

Now, Lemma 6.2 with $s < \gamma_2$ gives

$$\lambda_n = c\beta_2^n + O(n\gamma_2^n) \quad (7.13)$$

as $n \rightarrow \infty$, and the result follows from the definition of λ_n .

Lemma 7.3

Suppose that (7.9) and (7.10) hold. Then there are constants K and N (depending on L) such that if, for some $n \geq N$,

$$\frac{1}{n} \geq |x_n| \geq n|x_{n+2}| \quad (7.14)$$

and

$$\frac{1}{n} \geq |x_{n+1}| \geq n|x_{n+2}|, \quad (7.15)$$

then

$$x_{n+3} = x_n x_{n+1} (1 + v_{1,n}), \quad (7.16)$$

$$x_{n+4} = x_n x_{n+1}^2 (1 + v_{2,n}) + x_{n+1} x_{n+2} (1 + v_{3,n}), \quad (7.17)$$

$$x_{n+5} = x_n^2 x_{n+1}^3 (1 + v_{4,n}) + x_n x_{n+1} x_{n+2} (1 + v_{5,n}), \quad (7.18)$$

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and

$$x_{n+6} = x_n^2 x_{n+1}^5 (1 + v_{6,n}) + x_n x_{n+1}^2 x_{n+2}^2 (1 + v_{7,n}), \quad (7.19)$$

where

$$|v_{i,n}| \leq \frac{K}{n} \quad (7.20)$$

for $i = 1, \dots, 7$.

Proof

The lemma follows by repeated use of the recurrence relation (7.9) and the inequalities (7.10), (7.14) and (7.15).

Proof of Theorem 7.1

Without loss of generality assume that $\xi = 0$. First suppose that $q = 1$. If $f''(0) \neq 0$ then the theorem holds, by Corollary 7.1. If $f''(0) = 0$ then, by Lemma 6.1,

$$x_{n+2} = O(\delta_n^2 \delta'_n) \quad (7.21)$$

as $\delta_n \rightarrow 0$, where δ_n and δ'_n are as in Lemma 6.1. If x_0 and x_1 are sufficiently small, equation (7.21) implies that

$$\delta_n = |x_n| \quad (7.22)$$

and

$$\delta'_n = |x_{n+1}| \quad (7.23)$$

for all $n \geq 1$. Thus $x_n \rightarrow 0$ as $n \rightarrow \infty$, and

$$|x_{n+2}| \leq A^2 |x_n^2 x_{n+1}| \quad (7.24)$$

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for all $n \geq 0$, where A is some positive constant. If some $x_n = 0$ then $x_{n+1} = x_{n+2} = \dots = 0$, and we are finished (weak order ∞). Otherwise, there is no loss of generality in assuming that

$$A|x_n| \leq \exp(-2^n) \quad (7.25)$$

for $n = 0$ and $n = 1$. From (7.24), equation (7.25) holds for all $n \geq 0$, by induction on n . Thus, the weak order of convergence is at least 2, and the proof for $q = 1$ is complete.

From now on, suppose that $q = 2$. By Lemma 6.1,

$$x_{n+3} = \frac{f^{(3)}(0)}{6f''(0)} (x_n x_{n+1} + x_{n+1} x_{n+2} + x_n x_{n+2}) + O(\delta_n^2 \delta'_n) \quad (7.26)$$

as $n \rightarrow \infty$. If $f^{(3)}(0) = 0$ then the weak order of convergence is at least $\beta_{2,2}$, the positive real root of $x^3 = x + 2$, by a proof like that above for $q = 1$, and the theorem holds as $\beta_{2,2} = 1.52 \dots$.

If $f^{(3)}(0) \neq 0$, then we may as well suppose that

$$\frac{f^{(3)}(0)}{6f''(0)} = 1, \quad (7.27)$$

by a change of scale, as in the proof of Theorem 6.1. Thus, we must study the interesting recurrence relation

$$x_{n+3} = x_n x_{n+1} + x_{n+1} x_{n+2} + x_n x_{n+2} + O(\delta_n^2 \delta'_n), \quad (7.28)$$

and, by Theorem 5.1, we can assume that $x_n \rightarrow 0$ with weak order at least β_2 .

First suppose that there is an infinite sequence $N = (n_0, n_1, \dots)$ with the property that, for every $i \geq 0$ and $n = n_i$, either

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$$1: \quad n_{i+1} = n+2 \quad (7.29)$$

and

$$4n|x_n x_{n+1}^2| \leq |x_{n+2}| \leq 2|x_n x_{n+1}|, \quad (7.30)$$

or

$$2: \quad n_{i+1} = n+3 \quad (7.31)$$

and

$$|x_{n+2}| < 4n|x_n x_{n+1}^2|. \quad (7.32)$$

If either (7.30) or (7.32) holds, then Lemma 7.3 is applicable for all sufficiently large $n = n_i$ in the sequence N . To avoid confusion with subscripts, write m for n_{i+1} (so $m = n+2$ or $n+3$). If $n = n_i$ is sufficiently large, and (7.29) and (7.30) hold, then

$$|x_m| \leq 2|x_n x_{n+1}| \quad (7.33)$$

and, by Lemma 7.3,

$$|x_{m+1}| \leq 2|x_n x_{n+1}|. \quad (7.34)$$

If (7.31) and (7.32) hold then, similarly,

$$|x_m| \leq 2|x_n x_{n+1}| \quad (7.35)$$

and

$$|x_{m+1}| \leq 4|x_n x_{n+1}^2|. \quad (7.36)$$

Let

$$y_n = 2|x_n| \quad (7.37)$$

After a fixed $n = n_i$ in N , suppose that the next $r \geq 1$ elements

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of N satisfy (7.31), and then the next $s \geq 1$ satisfy (7.29). Then repeated use of the inequalities (7.33) to (7.36) gives

$$\max(y_{n+3r+2s}, y_{n+3r+2s+1}) \leq \max(y_n, y_{n+1})^{\varphi(r,s)}, \quad (7.38)$$

where

$$\varphi(r,s) = 2^{s-1} \left[\left(\frac{\sqrt{5}+2}{\sqrt{5}} \right) \left(\frac{3+\sqrt{5}}{2} \right)^r + \left(\frac{\sqrt{5}-2}{\sqrt{5}} \right) \left(\frac{3-\sqrt{5}}{2} \right)^r \right]. \quad (7.39)$$

Let

$$\psi(r,s) = \varphi(r,s)^{\frac{1}{3r+2s}}. \quad (7.40)$$

For fixed $s \geq 1$, $\psi(r,s)$ is a decreasing function of r , with limit

$$c = \left(\frac{3+\sqrt{5}}{2} \right)^{\frac{1}{5}} = \inf_{r,s \geq 1} \psi(r,s) \quad (7.41)$$

as $r \rightarrow \infty$. Thus, $x_n \rightarrow 0$ with weak order at least c , so case 2 of the theorem holds.

Now suppose that there is no infinite sequence N as above. By the superlinear convergence of (x_n) , Lemma 7.3 is applicable for infinitely many n . Choose such an n (sufficiently large). There are only three possibilities:

1. Equation (7.30) holds;
2. Equation (7.32) holds; or
3. Neither (7.30) nor (7.32) holds, so

$$|x_{n+2}| > 2|x_n x_{n+1}|. \quad (7.42)$$

In the first case, Lemma 7.3 shows that we can replace n by $n+2$, and continue with one of the three cases (it is crucial to note that Lemma 7.3 is

still applicable). In the second case, Lemma 7.3 shows that we can replace n by $n+3$ and continue. Since no infinite sequence N with the above properties exists, the third case must eventually arise. Then, from (7.42) and Lemma 7.3, we see that Lemma 7.2 is applicable to the sequence (x'_m) , where $x'_m = x_{m+n+3}$. By Lemma 7.2, (x'_m) converges with strong order β_2 and asymptotic constant 1, and hence, so does (x_n) . In view of the assumption (7.27), this completes the proof.

8. Accelerating convergence

If a very accurate solution is required, and high-precision evaluations of f are expensive, then it may be worthwhile to try to increase the order of convergence of the successive approximations by some acceleration technique. For example, we can use Lemma 6.1 to improve the current approximation at each step of the iterative process. Jarratt (1967) suggests one way of doing this if $q = 2$, but the method which we are about to describe seems easier to justify (see Theorem 8.1), and applies for any $q \geq 1$.

Suppose that x_0, \dots, x_{q+1} are approximations to a simple zero ξ of $f^{(q-1)}$. For example, they could be the last $q+2$ approximations generated by the successive interpolation process discussed above. We may define x_{q+2}, x_{q+3}, \dots in the following way: if $n \geq 1$ and x_0, \dots, x_{n+q} are already defined, let $P_n = TP(f; x_n, \dots, x_{n+q})$, and choose y_n such that

$$P_n^{(q-1)}(y_n) = 0, \quad (8.1)$$

i.e., y_n is just the next approximation generated by our usual interpolation process. From Lemma 3.1, y_n is given explicitly by

$$y_n = \frac{1}{q} \left(\sum_{i=1}^q x_{n+i} - \frac{f[x_{n+1}, \dots, x_{n+q}]}{f[x_n, \dots, x_{n+q}]} \right). \quad (8.2)$$

Instead of taking y_n as the next approximation x_{n+q+1} , we use Lemma 6.1 to compute a correction to y_n , and take the corrected value as the next approximation. Formally, we define x_{n+q+1} by

$$x_{n+q+1} = y_n - \frac{f[x_{n-1}, \dots, x_{n+q}]}{q \cdot f[x_n, \dots, x_{n+q}]} \cdot s_n, \quad (8.3)$$

where

$$s_n = \sum_{0 \leq i < j \leq q} (x_{n+i} - y_n)(x_{n+j} - y_n). \quad (8.4)$$

For a justification of equations (8.3) and (8.4), see the proof of Theorem 8.1 below. This theorem shows that, under suitable conditions, the sequence (x_n) is well-defined, and $x_n \rightarrow \xi$ with weak order appreciably greater than β_q , which is the usual order of convergence of the unaccelerated process (see Sections 5 to 7). Note that there is very little extra work involved in computing x_{n+q+1} from equations (8.3) and (8.4) if y_n is computed via (8.2), for $f[x_n, \dots, x_{n+q}]$ and $f[x_{n-1}, \dots, x_{n+q-1}]$ (except at the first iteration) will already be known.

Before stating Theorem 8.1, we define some constants β'_q which take the place of the constants β_q (see Definition 5.1) if the accelerated process is used.

Definition 8.1

For $q \geq 1$, β'_q is the positive real root of

$$x^{q+2} = x^2 + x + 1. \quad (8.5)$$

Remarks

It is easy to see that $\beta'_q > \beta_q$, and, corresponding to the bound (5.2), we have

$$\frac{1}{3^{q+1}} < \beta'_q < \frac{1}{3^q}. \quad (8.6)$$

If $x_n \rightarrow \xi$ with weak order $\beta > 1$ then, by the definition of order (see Section 2), for any $\epsilon > 0$ we eventually have

$$-\log|x_n - \xi| \geq (\beta - \epsilon)^n. \quad (8.7)$$

Thus, the number of function evaluations required to reduce $|x_n - \xi|$ below a very small positive tolerance is inversely proportional to $\log \beta$

(assuming that approximate equality holds in (8.7)), and the ratio

$\frac{\log \beta_q}{\log \beta'_q}$ suggests how much we gain by using the accelerated process,

rather than the unaccelerated process, if very high accuracy is required.

From the bounds (5.2) and (8.6),

$$\lim_{q \rightarrow \infty} \frac{\log \beta_q}{\log \beta'_q} = \log_3 2 = 0.6309 \dots, \quad (8.8)$$

so there is a 37 percent saving for large q . Of course, the only

practical interest is in small values of q , and in Table 8.1 the

values of β'_q , β_q and $\frac{\log \beta_q}{\log \beta'_q}$ are given for $q = 1, 2, \dots, 10$. The

entries for β'_q are correctly rounded to 12 decimal places, and the

Table 8.1: The constants β'_q for $q = 1(1)10$ to 12D

q	β'_q	β_q	$\log \beta_q / \log \beta'_q$
1	1.839286755214	1.6180	0.7897
2	1.465571231877	1.3247	0.7357
3	1.324717957245	1.2207	0.7093
4	1.249851588864	1.1673	0.6936
5	1.203216033518	1.1347	0.6832
6	1.171321856385	1.1128	0.6757
7	1.148113497353	1.0970	0.6702
8	1.130459571864	1.0851	0.6658
9	1.116575158368	1.0758	0.6623
10	1.105367322949	1.0683	0.6595

See Definition 8.1, and the remarks above, for a description of the constants β'_q and the significance of the ratio $\frac{\log \beta_q}{\log \beta'_q}$.

The constants β_q are given to 12D in Table 5.1.

other entries are given to 4 places (they are given for comparison only: see Table 5.1 for the β_q to 12 places). The table suggests that $\beta'_3 = \beta_2$, and this is true, for $x^5 - x^2 - x - 1 = (x^3 - x - 1)(x^2 + 1)$.

Theorem 8.1

Suppose that $f \in LC^{q+1}[a, b; M]$; $\xi \in (a, b)$; $f^{(q-1)}(\xi) = 0$; $f^{(q)}(\xi) \neq 0$; and x_0, \dots, x_{q+1} are (distinct) points in $[a, b]$. If x_0, \dots, x_{q+1} are sufficiently close to ξ , then a sequence (x_n) is uniquely defined by equations (8.2) to (8.4), and $x_n \rightarrow \xi$ with weak order at least β'_q (see Definition 8.1) as $n \rightarrow \infty$.

Proof

For $n \geq 1$, let δ_n be the largest of $|x_n - \xi|, \dots, |x_{n+q} - \xi|$; let δ'_n be the second-largest; and let

$$\hat{\delta}_n = \max(\delta_n, |x_{n-1} - \xi|). \quad (8.9)$$

If y_n is defined by equation (8.2), then Lemma 6.1 shows that

$$y_n - \xi = K \sum_{0 \leq i < j \leq q} (x_{n+i} - \xi)(x_{n+j} - \xi) + O(\delta_n^2 \delta'_n) \quad (8.10)$$

as $\delta_n \rightarrow 0$, where

$$K = \frac{f^{(q+1)}(\xi)}{q(q+1)f^{(q)}(\xi)}. \quad (8.11)$$

In particular, (8.10) implies that

$$y_n - \xi = O(\delta_n \delta'_n) \quad (8.12)$$

as $\delta_n \rightarrow 0$. Thus, for $0 \leq i < j \leq q$,

$$(x_{n+i} - y_n)(x_{n+j} - y_n) = (x_{n+i} - \xi)(x_{n+j} - \xi) + O(\delta_n^2 \delta'_n) \quad (8.13)$$

as $\delta_n \rightarrow 0$.

If δ_n is sufficiently small then, since $f^{(q)}(\xi) \neq 0$, we have $f[x_n, \dots, x_{n+q}] \neq 0$, and, by Theorem 2.5.1,

$$\frac{f[x_{n-1}, \dots, x_{n+q}]}{q \cdot f[x_n, \dots, x_{n+q}]} = K + O(\hat{\delta}_n) \quad (8.14)$$

as $\hat{\delta}_n \rightarrow 0$.

If s_n is as in (8.4), then (8.13) and (8.14) give

$$\frac{f[x_{n-1}, \dots, x_{n+q}]}{q \cdot f[x_n, \dots, x_{n+q}]} \cdot s_n = K \sum_{0 \leq i < j \leq q} (x_{n+i} - \xi)(x_{n+j} - \xi) + O(\hat{\delta}_n \delta_n \delta'_n) \quad (8.15)$$

as $\hat{\delta}_n \rightarrow 0$. Thus, from (8.3) and (8.10),

$$x_{n+q+1} - \xi = O(\hat{\delta}_n \delta_n \delta'_n) \quad (8.16)$$

as $\hat{\delta}_n \rightarrow 0$. This shows that, provided $\hat{\delta}_1$ is sufficiently small, the sequence (x_n) is uniquely defined, lies in $[a, b]$, and $x_n \rightarrow \xi$ as $n \rightarrow \infty$.

From equation (8.16), there is a positive constant A such that, for all $n \geq 1$,

$$|x_{n+q+1} - \xi| \leq A^2 \hat{\delta}_n \delta_n \delta'_n, \quad (8.17)$$

and, if $\hat{\delta}_1$ is sufficiently small, then

$$-\log(A|x_n - \xi|) \geq \beta_q^n \quad (8.18)$$

for $n = 0, \dots, q+1$. From equation (8.17) and the definition of β'_q , we see that (8.18) holds for all $n \geq 0$, by induction on n . Thus

3.9

$$\liminf_{n \rightarrow \infty} (-\log |x_n - \zeta|)^{\frac{1}{n}} \geq \beta'_q, \quad (8.19)$$

i.e., the weak order of convergence is at least β'_q , so the proof is complete.

9. Some numerical examples

To illustrate the theoretical results obtained in Sections 4 to 8, we give the following examples:

1. $q = 1$, $f(x) = x + x^2 + x^3$, $x_0 = 2$, $x_1 = 1$;
2. $q = 2$, $f(x) = 8 + 6x^2 + 4x^3 + 3x^4$, $x_0 = 2$, $x_1 = 1$, $x_2 = 0.5$;
3. $q = 3$, $f(x) = 1 + 40x + 10x^3 + 5x^4 + 3x^5$, $x_0 = 2$, $x_1 = 1$,
 $x_2 = 0.5$, $x_3 = 0.25$; and
4. $q = 4$, $f(x) = 1 + 2x + 40x^2 + 5x^4 + 2x^5 + x^6$, $x_0 = 2$, $x_1 = 1$,
 $x_2 = 0.5$, $x_3 = 0.25$, $x_4 = 0.125$.

In all these examples $\zeta = 0$, and the iterative process defined by (1.1) converges, even though the initial values are not very close to ζ . Apart from constant factors, the polynomials are obtained by differentiating the last one (for $q = 4$) $4-q$ times, so we are solving the same problem in four different ways.

Table 9.1 gives the sequences (x_n) produced by the successive interpolation process, for the functions and starting values given above. To illustrate the superlinear convergence, the entries are given until $|x_n| < 10^{-20}$, although such high precision would seldom be required in practical problems. The table also gives the sequences (x'_n) produced

3.9

by the accelerated interpolation process described in Section 8, with starting values $x'_i = x_i$ for $i = 0, \dots, q+1$. As predicted by Theorem 8.1 and Table 8.1, the accelerated sequences converge appreciably faster than the unaccelerated ones.

To verify relations (8.12) and (8.16), the table also gives

$$r_n = \frac{x_n}{x_{n-q} x_{n-q-1}} \quad (9.1)$$

and

$$r'_n = \frac{x'_n}{x'_{n-q} x'_{n-q-1} x'_{n-q-2}} \quad (9.2)$$

when they are defined. With a few exceptions near the beginning of some of the sequences, both $(|x_n|)$ and $(|x'_n|)$ are monotonic decreasing, so r_n and r'_n should be bounded. From Lemma 6.1, we expect that

$$\lim_{n \rightarrow \infty} r_n = \frac{f^{(q+1)}(\zeta)}{q(q+1)f^{(q)}(\zeta)} \quad (9.3)$$

and this is just $\frac{2}{q(q+1)}$ for our examples. Similarly, from the proof of Theorem 8.1, we expect that

$$\lim_{n \rightarrow \infty} r'_n = - \frac{f^{(q+2)}(\zeta)}{q(q+1)(q+2)f^{(q)}(\zeta)} \quad (9.4)$$

and this is just $\frac{-6}{q(q+1)(q+2)}$. The results support these predictions.

Table 9.1 was computed on an IBM 360/91 computer, with 14 digit truncated floating-point arithmetic to base 16. To minimize the effect of rounding errors, we took advantage of the fact that n -th divided differences of $1, x, x^2, \dots, x^{n-1}$ vanish identically when computing the

divided differences in equations (8.2) and (8.3). Without this device, it is not possible to reduce $|x_n|$ or $|x'_n|$ to 10^{-20} without using higher precision arithmetic, because of the effect of rounding errors (except for $q = 1$).

For $q = 2$, our example is the same as that used by Jarratt (1967), and our results agree with his for $n \leq 9$. For $n = 10$ and 11 our results differ slightly, presumably because of rounding errors. The example given by Jarratt (1968) for $q = 3$ has also been verified.

Table 9.1: Numerical results for $q = 1, 2, 3$ and 4

q	n	x_n	x'_n	r_n	r'_n
1	0	2.000	2.000		
	1	1.000	1.000		
	2	7.273'-1	7.273'-1	0.3636	
	3	3.980'-1	2.100'-1	0.5473	0.1444
	4	1.983'-1	4.389'-2	0.6851	0.2874
	5	6.727'-2	-1.846'-3	0.8523	-0.2755
	6	1.276'-2	1.221'-5	0.9568	-0.7178
	7	8.543'-4	1.035'-9	0.9949	-1.0455
	8	1.090'-5	2.350'-17	0.9998	-1.0066
	9	9.314'-9	-2.982'-31	1.0000	-1.0039
	10	1.015'-13		1.0000	
	11	9.457'-22		1.0000	
2	0	2.000	2.000		
	1	1.000	1.000		
	2	5.000'-1	5.000'-1		
	3	5.162'-1	5.162'-1	0.2581	
	4	2.681'-1	1.219'-1	0.5362	0.1219
	5	1.366'-1	3.271'-2	0.5291	0.1267
	6	6.978'-2	5.618'-3	0.5042	0.1786
	7	2.053'-2	-3.363'-4	0.5607	-0.1634
	8	4.547'-3	-3.484'-6	0.4772	-0.1556
	9	6.154'-4	1.325'-8	0.4296	-0.2144
	10	3.631'-5	-1.728'-12	0.3890	-0.2625
	11	9.956'-7	-3.844'-18	0.3558	-0.2477
	12	7.666'-9	-2.008'-26	0.3430	-0.2518
	13	1.215'-11		0.3360	
	14	2.548'-15		0.3339	
	15	3.104'-20		0.3334	
	16	1.032'-26		0.3333	

Table 9.1 (continued)

q	n	x_n	x'_n	r_n	r'_n
3	0	2.000	2.000		
	1	1.000	1.000		
	2	5.000'-1	5.000'-1		
	3	2.500'-1	2.500'-1		
	4	3.775'-1	3.775'-1	0.1887	
	5	1.814'-1	6.882'-2	0.3628	0.0688
	6	8.574'-2	1.567'-2	0.6860	0.1253
	7	4.214'-2	3.572'-3	0.4465	0.0757
	8	2.268'-2	7.222'-4	0.3313	0.1112
	9	5.580'-3	-3.949'-5	0.3588	-0.0970
	10	1.227'-3	-3.547'-7	0.3395	-0.0921
	11	2.347'-4	-2.893'-9	0.2455	-0.0716
	12	2.809'-5	8.630'-12	0.2219	-0.0847
	13	1.441'-6	-1.067'-15	0.2105	-0.1055
	14	5.518'-8	4.009'-21	0.1917	-0.0989
	15	1.164'-9		0.1766	
	16	7.021'-12		0.1735	
	17	1.354'-14		0.1703	
	18	1.077'-17		0.1677	
	19	1.365'-21		0.1670	
4	0	2.000	2.000		
	1	1.000	1.000		
	2	5.000'-1	5.000'-1		
	3	2.500'-1	2.500'-1		
	4	1.250'-1	1.250'-1		
	5	2.840'-1	2.840'-1	0.1420	
	6	1.258'-1	3.887'-2	0.2517	0.0589
	7	5.453'-2	7.030'-3	0.4362	0.0562
	8	2.492'-2	1.461'-3	0.7975	0.0935
	9	1.274'-2	4.448'-4	0.3588	0.0501
	10	7.507'-3	1.168'-4	0.2101	0.0846
	11	1.564'-3	-4.334'-6	0.2279	-0.0558
	12	3.227'-4	-2.390'-8	0.2374	-0.0598
	13	6.871'-5	-2.370'-10	0.2164	-0.0519
	14	1.360'-5	-2.500'-12	0.1423	-0.0329
	15	1.545'-6	9.027'-15	0.1316	-0.0401
	16	6.639'-8	-6.291'-19	0.1316	-0.0520
	17	2.814'-9	1.243'-24	0.1270	-0.0506
	18	1.067'-10		0.1142	
	19	2.207'-12		0.1050	
	20	1.073'-14		0.1046	
	21	1.944'-17		0.1040	
	22	3.069'-20		0.1022	
	23	2.367'-25		0.1005	

10. Summary

The main results of this chapter for $q = 1$ (successive linear interpolation for finding a zero) and $q = 2$ (successive parabolic interpolation for finding a turning point) are summarized below.

Theorem 3.1

$q = 1$: If $f \in C$ and $x_n \rightarrow \xi$, then $f(\xi) = 0$.

$q = 2$: If $f \in C^1$ and $x_n \rightarrow \xi$, then $f'(\xi) = 0$.

Theorem 4.1

$q = 1$: If $f \in C^1$, $f'(\xi) \neq 0$, and a good start, then superlinear convergence.

$q = 2$: If $f \in C^2$, $f''(\xi) \neq 0$, and a good start, then superlinear convergence.

Theorem 5.1

$q = 1$: If $f \in C^1$, $f'(\xi) \neq 0$, and a good start, then weak order at least $\beta_1 = 1.618 \dots$

$q = 2$: If $f \in C^2$, $f''(\xi) \neq 0$, and a good start, then weak order at least $\beta_2 = 1.324 \dots$

Theorem 7.1

$q = 1$: If $f \in C^2$, $f'(\xi) \neq 0$, and a good start, then either strong order $\beta_1 = 1.618 \dots$ or weak order at least 2.

$q = 2$: If $f \in C^3$, $f'''(\xi) \neq 0$, and a good start, then either strong order $\beta_2 = 1.324 \dots$ or weak order at least $(\frac{3+\sqrt{5}}{2})^{1/3} = 1.378 \dots$

Theorem 8.1

$q = 1$: If $f \in C^2$, $f'(\xi) \neq 0$, and a good start, then the accelerated sequence converges with weak order at least $\beta_1^* = 1.839 \dots$

$q = 2$: If $f \in C^3$, $f'''(\xi) \neq 0$, and a good start, then the accelerated sequence converges with weak order at least $\beta_2^* = 1.465 \dots$

Chapter 4.

An Algorithm with Guaranteed Convergence for Finding a

Zero of a Function

4.1

1. Introduction

Let f be a real-valued function, defined on the interval $[a, b]$, with $f(a)f(b) \leq 0$. f need not be continuous on $[a, b]$: for example, f might be a limited-precision approximation to some continuous function (see Forsythe (1969)). We want to find an approximation $\hat{\xi}$ to a zero ξ of f , to within a given positive tolerance δ , by evaluating f at a small number of points. Of course, there may be no zero in $[a, b]$ if f is discontinuous, so we shall be satisfied if f takes both nonnegative and nonpositive values in $[\hat{\xi} - \delta, \hat{\xi} + \delta] \cap [a, b]$.

Clearly, such a $\hat{\xi}$ may always be found by bisection in about $\log_2[(b-a)/\delta]$ steps, and this is the best that we can do for arbitrary f . In this chapter we describe an algorithm which is never much slower than bisection (see Section 3), but which has the advantage of superlinear convergence to a simple zero of a continuously differentiable function, if the effect of rounding errors is negligible. This means that, in practice, convergence is often much faster than for bisection (see Section 4). There is no contradiction here: bisection is the optimal algorithm (in a minimax sense) for the class of all functions which change sign on $[a, b]$, but it is not optimal for other classes of functions: e.g., C^1 functions with simple zeros, or convex functions (see Gross and Johnson (1959), Bellman and Dreyfus (1962), and Chernousko (1970)).

Dekker's algorithm

The algorithm described here is similar to one, which we call Dekker's algorithm for short, variants of which have been given by van Wijngaarden, Zonneveld and Dijkstra (1963), Wilkinson (1967), Peters and Wilkinson (1969),

and Dekker (1969). We wish to emphasize that, although these variants of Dekker's algorithm have proved satisfactory in most practical cases, none of them guarantees convergence in less than about $(b-a)/\delta$ function evaluations. An example for which this bound is attained is given in Section 2. On the other hand, our algorithm must converge within about $(\log_2[(b-a)/\delta])^2$ function evaluations (see Section 3). Typical values are $b-a = 1$ and $\delta = 10^{-12}$, giving 10^{12} and 1600 function evaluations respectively. Our point of view is that 1600 is a reasonable number, but 10^{12} might as well be ∞ , for a computer program which attempts to evaluate a function 10^{12} times is almost certain to run out of time.

On well-behaved functions, e.g., polynomials of moderate degree with well-separated zeros, both our algorithm and Dekker's are much faster than bisection. Our algorithm is at least as fast as Dekker's, and often slightly faster (see Section 4), so the only price to pay for the improvement in the guaranteed rate of convergence is a slight increase in the complexity of the algorithm.

2. The algorithm

The algorithm is defined precisely by the ALGOL 60 procedure zero given in Section 6. Here we describe the algorithm, but the ALGOL procedure should be referred to for points of detail. For the motivation behind both our algorithm and Dekker's algorithm, see Dekker (1969) or Wilkinson (1967).

At a typical step we have three points a , b and c such that $f(b)f(c) \leq 0$, $|f(b)| \leq |f(c)|$, and a may coincide with c . The points a , b and c change during the algorithm, but there should be no

confusion if we omit subscripts. b is the best approximation so far to ξ , a is the previous value of b , and ξ must lie between b and c . (Initially $a = c$.)

If $f(b) = 0$ then we are finished. The ALGOL procedure given by Dekker (1969) does not recognize this case, and can take a large number of small steps if f vanishes on an interval, which may happen because of underflow. This occurred with $f(x) = x^9$ on an IBM 360 computer.

If $f(b) \neq 0$, let $m = (c-b)/2$. We prefer not to return with $\hat{\xi} = \frac{1}{2}(b+c)$ as soon as $|m| \leq 2\delta$, for if superlinear convergence has set in then b , the most recent approximation, is probably a much better approximation to ξ than $\frac{1}{2}(b+c)$ is. Instead, we return with $\hat{\xi} = b$ if $|m| \leq \delta$ (so the error is no more than δ if, as is often true, f is nearly linear between b and c), and otherwise interpolate or extrapolate f linearly between a and b , giving a new point i . (See later for inverse quadratic interpolation.) To avoid the possibility of overflow or division by zero, we find i as $b + p/q$, and the division is not performed if $2|p| \geq 3|m \cdot q|$, for then i is not needed anyway. The reason why the simpler criterion $|p| \geq |m \cdot q|$ is not used is explained later. Since $0 < |f(b)| \leq |f(a)|$ (see later), we can safely compute $s = f(b)/f(a)$, $p = \pm(a-b)s$, and $q = \mp(1-s)$.

Define $b'' = \begin{cases} i & \text{if } i \text{ lies between } b \text{ and } b + \frac{3}{2}m \text{ ("interpolation"),} \\ b+m & \text{otherwise ("bisection"),} \end{cases}$
and $b' = \begin{cases} b'' & \text{if } |b-b''| > \delta, \\ b+\delta \cdot \text{sign}(m) & \text{otherwise (a "step of } \delta \text{").} \end{cases}$

Dekker's algorithm takes b' as the next point at which f is evaluated, forms a new set $\{a, b, c\}$ from the old set $\{b, c, b'\}$, and continues. Unfortunately, it is easy to construct a function f for which

steps of δ are taken every time, so about $(b-a)/\delta$ function evaluations are required for convergence. For example, let

$$f(x) = \begin{cases} 2^{x/\delta} & \text{for } a+\delta \leq x \leq b, \\ -(\frac{b-a-\delta}{\delta}) \cdot 2^{b/\delta} & \text{for } x = a, \\ \text{arbitrary} & \text{for } a < x < a+\delta. \end{cases} \quad (2.1)$$

The first linear interpolation gives the point $b-\delta$, the next (an extrapolation) gives $b-2\delta$, the next $b-3\delta$, and so on.

Even if steps of δ are avoided, the asymptotic rate of convergence of successive linear interpolation may be very slow if f has a zero of sufficiently high multiplicity. (Note that none of the theorems of Chapter 3, apart from Theorem 3.3.1, apply for a multiple zero.) Suppose that $f \in C^n[a, b]$, $n > 1$, $\xi \in (a, b)$, $f(\xi) = f'(\xi) = \dots = f^{(n-1)}(\xi) = 0$, and $f^{(n)}(\xi) \neq 0$ (i.e., ξ is a root of multiplicity $n > 1$). If $\epsilon > 0$, $(\frac{x_1 - \xi}{x_0 - \xi}) \in (\epsilon, 1-\epsilon)$, and x_0 is sufficiently close to ξ , then successive linear interpolation gives a sequence (x_n) which converges linearly to ξ . In fact, equation (3.2.1) holds with $\rho = 1$ and $K = \beta_{n-1}^{-1}$, where the constants $\beta_q \simeq 2^{2/(2q+1)}$ are defined in Definition 3.5.1. The proof is simple: if

$$y_m = \frac{x_{m+1} - \xi}{x_m - \xi} \quad (2.2)$$

is the ratio of successive errors, then a Taylor series expansion of f about ξ gives

$$y_{m+1} = \left(\frac{1 - y_m^{n-1}}{1 - y_m^n} \right) (1 + o(1)) \quad (2.3)$$

as $x_m \rightarrow \xi$, provided y_m remains bounded away from 1. Since the

iteration

$$z_{m+1} = g(z_m), \quad (2.4)$$

where

$$g(z) = \frac{1 - z^{n-1}}{1 - z^n}, \quad (2.5)$$

has fixed point $z = \beta_{n-1}^{-1}$, and

$$|g'(z)| < 1 \quad (2.6)$$

for $z \in (0, 1)$, the result follows from Ostrowski (1966), Theorem 22.1.

An example for which convergence is sublinear (see Definition 3.2.2)

is

$$f(x) = \begin{cases} 0 & \text{if } x = 0, \\ x \cdot \exp(-x^{-2}) & \text{if } x \neq 0, \end{cases} \quad (2.7)$$

on an interval containing the origin. This is an extreme case, for f and all its derivatives vanish at the origin. (As a function of a complex variable, f has an essential singularity at the origin.) If

$$0 < x_1 < x_0 < \sqrt{2}, \quad (2.8)$$

then (x_n) is a positive, monotonic decreasing sequence, and, by Theorem 3.3.1, its limit must be 0. Thus, successive linear interpolation does converge, but very slowly.

Some of the examples above are rather artificial, and unless an extended exponent range is used (see later) we may be saved by underflow, i.e., the algorithm may terminate with a "zero" as soon as underflow occurs.

Even so, it is clear that convergence may occasionally be very slow if Dekker's algorithm is used.

Our main modification of Dekker's algorithm ensures that a bisection is done at least once in every $2 \log_2(|b-c|/\delta)$ consecutive steps. The modification is this: let e be the value of p/q at the step before the last one. If $|e| < \delta$ or $|p/q| \geq \frac{1}{2}|e|$ then we do a bisection, otherwise we do either a bisection or an interpolation just as in Dekker's algorithm. Thus, $|e|$ decreases by at least a factor of two on every second step, and when $|e| < \delta$ a bisection must be done. (After a bisection we take $e = m$ for the next step.) This is why our algorithm, unlike Dekker's, is never much slower than bisection.

A simpler idea is to take e as the value of p/q at the last step, but practical tests show that this slows down convergence for well-behaved functions by causing unnecessary bisections. With the better choice of e , our experience has been that convergence is always at least as fast as for Dekker's algorithm (see Section 4).

Inverse quadratic interpolation

If the three current points a , b and c are distinct, we can find the point i by inverse quadratic interpolation, i.e., fitting x as a quadratic in y , instead of by linear interpolation using just a and b . Experiments show that, for well-behaved functions, this device saves about 0.5 function evaluations per zero on the average (see Section 4). Inverse interpolation is used because with direct quadratic interpolation we have to solve a quadratic equation for i , and there is the problem of which root should be accepted. Cox (1970) gives another way of avoiding this

problem: fit y as a function of the form $p(x)/q(x)$, where p and q are polynomials and p has degree one. A third possibility is to use the acceleration technique described in Section 3.8. (See also Ostrowski (1966), Chapter 11.)

Care must be taken to avoid overflow or division by zero when computing the new point i . Since b is the most recent approximation to the root ξ , and a is the previous value of b , we do a bisection if $|f(b)| \geq |f(a)|$. Otherwise we have $|f(b)| < |f(a)| \leq |f(c)|$, so a safe way to find i is to compute $r_1 = f(a)/f(c)$, $r_2 = f(b)/f(c)$, $r_3 = f(b)/f(a)$, $p = \frac{1}{r_3}((c-b)r_1(r_1-r_2)-(b-a)(r_2-1))$, and $q = \frac{1}{r_1-1}(r_1-1)(r_2-1)(r_3-1)$. Then $i = b + p/q$, but as before we do not perform the division unless it is safe to do so. (If a bisection is to be done then i is not needed anyway.) When inverse quadratic interpolation is used it is natural to accept the point i if it lies between b and c and up to three-quarters of the way from b to c : consider the limiting case where the interpolating parabola has a vertical tangent at c and $f(b) = -f(c)$. Thus, i will be rejected if $2|p| \geq 3|(\frac{c-b}{2}) \cdot q|$, which explains the criterion discussed above.

The tolerance

As in Peters and Wilkinson (1969), the tolerance (28) is a combination of a relative tolerance (4ε) and an absolute tolerance (2t). At each step we take

$$\delta = 2\varepsilon|b| + t, \quad (2.9)$$

where b is the current best approximation to ξ , $\varepsilon = \text{macheps}$ is the relative machine precision (β^{1-r} for r -digit truncated floating-point

arithmetic with base β , and half this for rounded arithmetic), and t is a positive absolute tolerance. Since δ depends on b , which could lie anywhere in the given interval, we should replace δ by its positive minimum over the interval in the upper bound for the number of function evaluations required. In the ALGOL procedures the variable tol is used for δ .

The effect of rounding errors

The ALGOL procedures given in Section 6 have been written so that rounding errors in the computation of i , m etc. can not prevent convergence with the above choice of δ . The number 2ϵ in (2.9) may be increased if a higher relative error is acceptable, but it should not be decreased, for then rounding errors might prevent convergence.

The bound for $|\hat{\xi} - \xi|$ has to be increased slightly if we take rounding errors into account. Suppose that, for floating-point numbers x and y , the computed arithmetic operations satisfy

$$\text{fl}(x \times y) = x \cdot y(1 + \epsilon_1) \quad (2.10)$$

and

$$\text{fl}(x \pm y) = x(1 + \epsilon_2) \pm y(1 + \epsilon_3), \quad (2.11)$$

where $|\epsilon_i| \leq \epsilon$ for $i = 1, 2, 3$ (see Wilkinson (1963)). Also suppose that $\text{fl}(|x|) = |x|$ exactly, for any floating-point number x . The algorithm computes approximations

$$\tilde{m} = \text{fl}(0.5 \times (c-b)) \quad (2.12)$$

and

$$\tilde{\text{tol}} = \text{fl}(2 \times \epsilon \times |b| + t) \quad (2.13)$$

to m and tol , where ξ lies between $b = \hat{\xi}$ and c , and the algorithm terminates only when

$$|\tilde{m}| \leq \tilde{\text{tol}} \quad (2.14)$$

(unless $f(b) = 0$, when $\hat{\xi} = \xi = b$). Our assumptions (2.10) and (2.11) give

$$|\tilde{m}| \geq \frac{1}{2} (|c-b| - \epsilon(|b| + |c|))(1-\epsilon), \quad (2.15)$$

and, similarly,

$$\tilde{\text{tol}} \leq (2\epsilon|b| + t)(1+\epsilon)^3, \quad (2.16)$$

so (2.14) implies that

$$|c-b| \leq \left(\frac{2}{1-\epsilon}\right)(2\epsilon|b| + t)(1+\epsilon)^3 + \epsilon(|b| + |c|). \quad (2.17)$$

Since $|\hat{\xi} - \xi| \leq |c-b|$ and $b = \hat{\xi}$, this gives

$$|\hat{\xi} - \xi| \leq 6\epsilon|\xi| + 2t, \quad (2.18)$$

neglecting terms of order ϵt and $\epsilon^2|\xi|$. Usually the error is less than half this bound (see above).

Of course, it is the user's responsibility to consider the effect of rounding errors in the computation of f . The ALGOL procedures only guarantee to find a zero ξ of the computed function f to an accuracy given by (2.18), and ξ may be nowhere near a root of the mathematically defined function that the user is really interested in!

Extended exponent range

In some applications the range of f may be larger than is allowed for standard floating-point numbers. For example, $f(x)$ might be $\det(A - xI)$, where A is a matrix whose eigenvalues are to be found. In Section 6 we give an ALGOL procedure (zero2) which accepts $f(x)$ represented as a pair $(y(x), z(x))$, where $f(x) = y(x) \cdot 2^{z(x)}$ (y real, z integer). Thus, zero2 will accept functions in the same representation as is assumed by Peters and Wilkinson (1969), although zero2 does not require that $1/16 \leq |y(x)| < 1$ or $y(x) = 0$, and could be simplified slightly if this assumption were made.

3. Convergence properties

If the initial interval is $[a, b]$, assume that

$$b - a > \delta_m, \quad (3.1)$$

and let

$$k = \lceil \log_2((b-a)/\delta_m) \rceil, \quad (3.2)$$

where δ_m is the minimum over $[a, b]$ of the tolerance

$$\delta(x) = 2 \cdot \text{macheps} \cdot |x| + t \quad (3.3)$$

(see Section 2), and $\lceil x \rceil$ means the least integer $y \geq x$. By assumption (3.1), $k > 0$. (If $k = 0$, procedure zero takes only two function evaluations.)

First consider the bisection process, terminating when the interval known to contain a zero has length $\leq 2\delta_m$ (so the endpoint

minimizing $|f|$ is probably within δ_m of the zero, and certainly within $2\delta_m$). It is easy to see that this process terminates after exactly $k+1$ function evaluations unless, by good fortune, f happens to vanish at one of the points of evaluation.

Now consider procedure zero or zero2. If $k = 1$ then the procedure terminates after 2 function evaluations, one at each end-point of the initial interval, just like bisection. If $k = 2$ then there are 2 initial evaluations, and after no more than 4 more evaluations a bisection must be done, for the reason described in Section 2. After this bisection, which requires one more function evaluation, the procedure must terminate. Thus, at most $2+5 = 7$ evaluations are required. Similarly, for $k \geq 1$, the maximum number of function evaluations required is

$$2 + (5 + 7 + 9 + \dots + (2k+1)) = (k+1)^2 - 2. \quad (3.4)$$

Since Dekker's algorithm may take up to 2^k function evaluations (see Section 2), this justifies the remarks made in Section 1. Also, although the upper bound (3.4) is attainable, it is clear that it is unlikely to be attained except for very contrived examples, and in practical tests our algorithm has never taken more than $3(k+1)$ function evaluations (see Section 4). This justifies the claim that our algorithm is never much slower than bisection.

Superlinear convergence

Ignoring the effect of rounding errors and the tolerance δ , we see, as in Dekker (1969), that the algorithm will eventually stop doing bisections when it is approaching a simple zero ξ of a C^1 function. Thus, temporarily ignoring the improvement described in Section 2, the theorems of Chapter 3 are applicable (with $q = 1$). In particular, convergence is

4.3

superlinear, in the sense that $\limsup_{n \rightarrow \infty} |x_n - \xi|^{1/n} = 0$, provided f is C^1 near the simple zero ξ (Theorem 3.4.1). If f' is Lipschitz continuous near ξ , then the weak order of convergence is at least $\frac{1}{2}(1+\sqrt{5}) = 1.618 \dots$ (Theorem 3.5.1). For a summary of the other results of Chapter 3, see Section 3.10.

If f' is Lipschitz continuous near the simple zero ξ , then, even with the inverse parabolic interpolation modification described in Section 2, the weak order of convergence is still at least $\frac{1}{2}(1+\sqrt{5})$. The idea of the proof is that, by Lemma 2.5.1, the curvature at ξ of the approximating parabolas is bounded, so the inequality (3.5.13) still holds for some M (no longer the Lipschitz constant) and sufficiently small δ_n .

Thus, our procedure always converges in a reasonable number of steps and, under the conditions mentioned above, convergence is superlinear with order at least 1.618 It is well-known that, since $(1.618\dots)^2 = 2.618\dots > 2$, this compares favorably with Newton's method if an evaluation of f' is as expensive as an evaluation of f . In practice, convergence for well-behaved functions is fast, and the stopping criterion is usually satisfied in a few steps once superlinear convergence sets in.

Summary

The results of Sections 2 and 3 above may be summarized in the following "theorem":

If $a < b$, $\epsilon = \text{macheps} \geq 0$, $t > 0$, f is defined on $[a, b]$, $f(a)f(b) \leq 0$, and arithmetic is exact, then the algorithm defined by procedure zero (see Section 6) converges, and returns $\xi \in [a, b]$ such that

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f changes sign in $I_\delta = [\xi - 2\delta, \xi + 2\delta] \cap [a, b]$, where $\delta = 2\epsilon|\xi| + t$, and the number n of times that f is evaluated does not exceed $(k+1)^2 - 2$, where k is given by equation (3.2). Also, if $f \in C^1[a, b]$ has a unique simple zero $\xi \in (a, b)$, then $|\xi - \hat{\xi}|^{1/n} \rightarrow 0$ as macheps and $t \rightarrow 0$. Finally, if arithmetic is approximate, but satisfies (2.10) and (2.11) with $\epsilon \leq 10^{-3}$, then the algorithm still converges, and returns $\hat{\xi}$ such that f changes sign in $I_{\delta'}$, where $\delta' = 1.01(3\epsilon|\hat{\xi}| + t)$. (The factor 1.01 takes care of terms of order ϵt and $\epsilon^2|\hat{\xi}|$.)

4. Practical tests

The ALGOL procedures zero (for standard floating-point numbers) and zero2 (for floating-point with an extended exponent range) have been tested using ALGOL W (Wirth and Hoare (1966), Bauer, Becker and Graham (1968)) on an IBM 360/67 and a 360/91 with machine precision 16^{-13} . The number of function evaluations for convergence has never been greater than three times the number required for bisection, even for the functions mentioned in Section 2, and for the functions given by (2.1) and (2.7) Dekker's algorithm takes more than 10^6 function evaluations. Zero2 has been tested extensively with eigenvalue routines, and in this application it usually takes the same or one less function evaluation per eigenvalue than Dekker's algorithm, and considerably less than bisection.

In Table 4.1, we give the number of function evaluations required for convergence with procedure zero2 and functions x^9 , x^{19} , $f_1(x)$, and $f_2(x)$, where

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$$f_1(x) = \begin{cases} 0 & \text{if } |x| < 3.8 \times 10^{-4}, \\ f_1(x \cdot \exp(-x^{-2})) & \text{otherwise,} \end{cases} \quad (4.1)$$

and

$$f_2(x) = \begin{cases} f_1(\exp(x)) & \text{if } x > -10^6, \\ f_1(\exp(-10^6) - (x + 10^6)^2) & \text{otherwise.} \end{cases} \quad (4.2)$$

The parameters a , b and t of procedure zero2 are given in the table. In all cases $\text{macheps} = 16^{-13}$.

In Table 4.2, we compare the procedure given by Dekker (1969) with procedure zero (procedure zero2 gives identical results as no underflow or overflow occurs) for a typical application: finding the eigenvalues of a symmetric band matrix by repeated determinant evaluation. Let A be the n by n 5-diagonal matrix defined by

$$a_{ij} = \begin{cases} p-r & \text{if } i = j = 1 \text{ or } n, \\ p & \text{if } i = j \neq 1 \text{ or } n, \\ 2q & \text{if } |i-j| = 1, \\ r & \text{if } |i-j| = 2, \\ 0 & \text{if } |i-j| > 2. \end{cases} \quad (4.3)$$

For $n > 2$, A has eigenvalues

$$\lambda_k = p - 4q \cos\left(\frac{k\pi}{n+1}\right) + 2r \cos\left(\frac{2k\pi}{n+1}\right) \quad (4.4)$$

for $k = 1, 2, \dots, n$ (see Ehrlich (1971)). Table 4.2 gives the eigenvalues λ_k , the number n_D of function evaluations per eigenvalue for Dekker's procedure, and the number n_Z of function evaluations for procedure zero.

4.4

Table 4.1: The number of function evaluations for convergence with procedure zero2

$f(x)$	a	b	t	$\hat{\xi} - \xi$	function evals.
x^9	-1.0	+1.1	1'-9	4.99'-10	81
x^9	-1.0	+4.0	1'-20	4.92'-21	189
x^{19}	-1.0	+4.0	1'-20	4.81'-21	195
$f_1(x)$	-1.0	+4.0	1'-20	0*	53
$f_2(x)$	-1001200	0	1'-20	1'-9	79

$$* \hat{\xi} = 2.17'-4 \quad \text{and} \quad f_1(\hat{\xi}) = 0.$$

For a definition of f_1 , f_2 etc., and a discussion, see above.

Table 4.2: Comparison of Dekker's procedure with procedure zero

k	λ_k	n_D	n_Z
1	1.05838256968867	10	10
2	1.23995005360754	10	9
3	1.56239614604727	10	10
4	2.05025253169417	10	10
5	2.72832493649769	11	10
6	3.61410919225782	11	10
7	4.71048821337581	10	10
8	6.00000000000000	9	9
9	7.44175272160161	10	9
10	8.97167724536908	10	10
11	10.5063081987721	10	10
12	11.9497474683058	10	9
13	13.2029707184829	10	9
14	14.1742635087655	10	9
15	14.7893764953339	9	8

For a definition of λ_k , n_D and n_Z , see above. The λ_k have a relative error of less than $5 \cdot 10^{-14}$.

For each eigenvalue, the tolerances for Dekker's procedure and for procedure zero were the same. (The tolerance was adjusted by the eigenvalue program to ensure that the computed eigenvalues had a relative error of less than $5 \cdot 10^{-14}$.) Tests were run for several values of n , p , q and r : the table gives a typical set of results for $n = 15$, $p = 7$, $q = 7/4$, and $r = 1/2$. To obtain the same accuracy with bisection, at least 40 function evaluations per eigenvalue would be required, so both our procedure and Dekker's are at least four times as fast as bisection for this application.

Some more experimental results are given in Chapter 5. (For an illustration of the superlinear convergence, see the examples given in Section 3.9.)

5. Conclusion

Our algorithm appears to be at least as fast as Dekker's on well-behaved functions, and, unlike Dekker's, it is guaranteed to converge in a reasonable number of steps for any function. The ALGOL procedures zero and zero2 given in Section 6 have been written to avoid problems with rounding errors or overflow, and floating-point underflow is not harmful as long as the result is set to zero.

Before giving the ALGOL procedures zero and zero2, we briefly discuss some possible extensions.

Cox's algorithm

A recent paper by Cox (1970) gives an algorithm which combines bisection with interpolation, using both f and f' . This algorithm may fail to converge in a reasonable number of steps in the same way as Dekker's. A simple modification, exactly like the one that we have given in Section 2 for Dekker's algorithm, will remedy this defect without slowing the rate of convergence for well-behaved functions.

Parallel algorithms

In this chapter we have considered only serial algorithms. It is well-known (see, for example, Traub (1964)) that all serial methods which use only function evaluations and Lagrangian interpolation polynomials have weak order less than 2, unless certain relations hold between the derivatives of f at ξ . (Winograd has recently shown that no serial method, using only function evaluations, can have order greater than 2 for all analytic functions with simple zeros.) Thus, nothing much can be gained by going beyond linear or quadratic interpolation. However, Miranker (1969) has shown that, if a parallel computer is available, a class of algorithms using Lagrangian interpolation polynomials gives superlinear convergence with weak order greater than 2 under certain conditions. Also, it is clearly possible to generalize the bisection process to " $(r+1)$ -section" with advantage if a parallel computer with r independent processors is available. See, for example, Wilde (1964). There does not appear to be any fundamental difficulty in combining generalized bisection with one of Miranker's parallel algorithms so that convergence in a reasonable number of steps is guaranteed for any function,

and superlinear convergence with order greater than 2 is likely for well-behaved functions.

Searching an ordered file

A problem which is commonly solved by a binary search (i.e., bisection) method is that of locating an element in a large ordered file. The problem may be formalized in the following way. Let S be a (finite or infinite) totally ordered set, and $\varphi: S \rightarrow \mathbb{R}$ an order-preserving mapping from S into the real numbers. Suppose that $T = \{t_0, t_1, \dots, t_n\}$ is a finite subset of S , with $t_0 < t_1 < \dots < t_n$. Given $c \in [\varphi(t_0), \varphi(t_n)]$, we may define a monotonic function f on $[0, n]$ by

$$f(x) = \varphi(t_i) - c, \quad (5.1)$$

where $x \in [0, n]$ and $i = \lceil x - \frac{1}{2} \rceil$. Thus, finding an index i such that $\varphi(t_i) = c$ is equivalent to finding a zero of f in $[0, n]$, and our zero-finding algorithm could be used instead of the usual bisection algorithm. It might be worthwhile to modify our algorithm slightly, so as to take the discrete nature of the problem into account. A related application of our algorithm is in finding the median (or other percentiles) of a list of numbers, but there are faster ways of doing this.

6. ALGOL 60 procedures

The ALGOL procedures zero (for standard floating-point numbers) and zero2 (for floating-point with an extended exponent range) are given below. For a description of the idea of the algorithm, see Section 2. Some test cases and numerical results are described in Section 4.

Procedure zero

```
real procedure zero (a, b, macheps, t, f);
```

```
value a, b, macheps, t; real a, b, macheps, t;
```

```
real procedure f;
```

```
begin comment:
```

Zero returns a zero x of the function f in the given interval $[a,b]$, to within a tolerance $6 \cdot \text{macheps} \cdot |x| + 2 \cdot t$, where macheps is the relative machine precision and t is a positive tolerance. The procedure assumes that $f(a)$ and $f(b)$ have different signs;

```
real c, d, e, fa, fb, fc, tol, m, p, q, r, s;
```

```
fa := f(a); fb := f(b);
```

```
int: c := a; fc := fa; d := e := b-a;
```

```
ext: if abs(fc) < abs(fb) then
```

```
  begin a := b; b := c; c := a;
```

```
  fa := fb; fb := fc; fc := fa
```

```
  end;
```

```
tol := 2 x macheps x abs(b) + t; m := 0.5 x (c-b);
```

```
if abs(m) > tol  $\wedge$  fb  $\neq$  0 then
```

```
  begin comment: See if a bisection is forced;
```

```
  if abs(e) < tol  $\vee$  abs(fa)  $\leq$  abs(fb) then d := e := m else
```

```
    begin s := fb/fa; if a = c then
```

```
      begin comment: Linear interpolation;
```

```
      p := 2 x m x s; q := 1-s
```

```
    end
```

```
  else
```

```
    begin comment: Inverse quadratic interpolation;
```

```
q := fa/fc; r := fb/fc;
```

```
p := s x (2 x m x q x (q-r) - (b-a) x (r-1));
```

```
q := (q-1) x (r-1) x (s-1)
```

```
end;
```

```
if p > 0 then q := -q else p := -p;
```

```
s := e; e := d;
```

```
if 2 x p < 3 x m x q - abs(tol x q)  $\wedge$  p < abs(0.5 x s x q) then
```

```
  d := p/q else d := e := m
```

```
end;
```

```
a := b; fa := fb;
```

```
b := b + (if abs(d) > tol then d else if m > 0 then
```

```
  tol else -tol);
```

```
fb := f(b);
```

```
go to if fb > 0  $\equiv$  fc > 0 then int else ext
```

```
end;
```

```
zero := b
```

```
end zero;
```

Procedure zero2

```
real procedure zero2 (a, b, macheps, t, f);
```

```
value a, b, macheps, t; real a, b, macheps, t; procedure f;
```

```
begin comment:
```

Zero2 finds a zero of the function \tilde{f} in the same way as procedure zero, except that the procedure $f(x,y,z)$ returns y (real) and z (integer) so that $\tilde{f}(x) = y \cdot 2^z$. Thus underflow and overflow can be avoided with a very large function range;


```

real procedure pwr2 (x,n); value x, n; real x; integer n;

comment: The procedure is machine-dependent. It computes  $x \cdot 2^n$  for
n ≤ 0, avoiding underflow in the intermediate results;

pwr2 := if n > -200 then x x 2 ↑ n else
if n > -400 then (x x 2 ↑ (-200)) x 2 ↑ (n+200) else
if n > -600 then ((x x 2 ↑ (-200)) x 2 ↑ (-200)) x 2 ↑ (n+400) else 0;

integer ea, eb, ec;

real c, d, e, fa, fb, fc, tol, m, p, q, r, s;

f(a,fa,ea); f(b,fb,eb);

int: c := a; fc := fa; ec := ea; d := e - b-a;
ext: if (ec ≤ eb ∧ pwr2(abs(fc), ec-eb) < abs(fb))
      ∨ (ec > eb ∧ pwr2(abs(fb), eb-ec) ≥ abs(fc)) then
  begin a := b; fa := fb; ea := eb;
        b := c; fb := fc; eb := ec;
        c := a; fc := fa; ec := ea
  end;

tol := 2 x macheps x abs(b) + t; m := 0.5 x (c-b);

if abs(m) > tol ∧ fb ≠ 0 then
  begin if abs(e) < tol ∨
        (ea ≤ eb ∧ pwr2(abs(fa), ea-eb) ≤ abs(fb)) ∨
        (ea > eb ∧ pwr2(abs(fb), eb-ea) ≥ abs(fa)) then
    d := e := m else
      begin s := pwr2(fb, eb-ea)/fa; if a = c then
        begin p := 2 x m x s; q := 1-s end
      else
        begin q := pwr2(fa, ea-ec)/fc;

```

```

r := pwr2(fb, eb-ec)/fc;
p := s x (2 x m x q x (q-r) - (b-a) x (r-1));
q := (q-1) x (r-1) x (s-1)
end;

if p > 0 then q := -q else p := -p; s := e; e := d;
if 2 x p < 3 x m x q - abs(tol x q) ∧ p < abs(0.5 x s x q) then
  d := p/q else d := e := m
end;

a := b; fa := fb; ea := eb;
b := b + (if abs(d) > tol then d else if m > 0 then
  tol else -tol);
f(b, fb, eb);
go to if fb > 0 ≡ fc > 0 then int else ext
end;

zero2 := b
end zero2;

```

Chapter 5

An Algorithm with Guaranteed Convergence for Finding a Minimum of a Function of One Variable

5.1

1. Introduction

A common computational problem is finding an approximation to the minimum or maximum of a real-valued function f in some interval $[a, b]$. This problem may arise directly or indirectly. For example, many methods for minimizing functions $g(\underline{x})$ of several variables need to minimize functions of one variable of the form

$$\gamma(\lambda) = g(\underline{x}_0 + \lambda \underline{s}) \quad , \quad (1.1)$$

where \underline{x}_0 and \underline{s} are fixed (a "one-dimensional search" from \underline{x}_0 in the direction \underline{s}). In this chapter, we give an algorithm which finds an approximate local minimum of f by evaluating f at a small number of points. There is a clear analogy between this algorithm and the algorithm described in Chapter 4 for root-finding (see Diagram 4.1). Unless f is unimodal (Section 3), the local minimum may not be the global minimum of f in $[a, b]$, and the problem of finding global minima is left until Chapter 6.

The algorithm described in this chapter could be used to solve the problem (1.1), but, for this application, it may be more economical to use special algorithms which make use of any extra information which is available (e.g., estimates of the second derivative of γ), and which do not attempt to find the minimum very accurately. This is discussed in Chapter 7. Thus, a more likely practical use for our algorithm is to find accurate minima of naturally arising functions of one variable.

In Section 2 we consider the effect of rounding errors on any minimization algorithm based entirely on function evaluations. Unimodality is defined in Section 3, and we also define "δ-unimodality" in an attempt

to explain why methods like golden section search work even for functions which are not quite unimodal (because of rounding errors in their computation, for example). In Sections 4 and 5 we describe a minimization algorithm analogous to the zero-finding algorithm of Chapter 4, and some numerical results are given in Section 6. Finally, some possible extensions are described in Section 7, and an ALGOL 60 procedure is given in Section 8.

Reduction to a zero-finding problem

If f is differentiable in $[a, b]$, a necessary condition for f to have a local minimum at an interior point $\mu \in (a, b)$ is

$$f'(\mu) = 0 \quad (1.2)$$

There is also the possibility that the minimum is at a or b : for example, this is true if f' does not change sign on $[a, b]$. If we are prepared to check for this possibility, one approach is to look for zeros of f' . If f' has different signs at a and b , then the algorithm of Chapter 4 might be used to approximate a point μ satisfying (1.2).

Since f' vanishes at any stationary point of f , it is possible that the point found is a maximum, or even an inflexion point, rather than a minimum. Thus, it is necessary to check whether the point found is a true minimum, and continue the search in some way if it is not.

If it is difficult or impossible to compute f' directly, we could approximate f' numerically (e.g., by finite differences), and search for a zero of f' as above. However, a method which does not need f'

seems more natural, and could be preferred for the following reasons:

1. It may be difficult to approximate f' accurately because of rounding errors;
2. A method which does not need f' may be more efficient (see below); and
3. Whether f' can be computed directly or not, a method which avoids difficulty with maxima and inflexion points is clearly desirable.

Jarratt's method

Jarratt (1967) suggests a method, using successive parabolic interpolation, which is a special case of the iteration analyzed in Chapter 3. With arbitrary starting points Jarratt's method may diverge, or converge to a maximum or inflexion point, but this need not be fatal if the method is used in combination with a safe method such as golden section search, in the same way as, in Chapter 4, we used a combination of successive linear interpolation and bisection for finding a zero. Theorem 3.5.1 shows that, if f has a Lipschitz continuous second derivative which is positive at an interior minimum μ , then Jarratt's method gives superlinear convergence to μ with weak order at least $\beta_2 = 1.3247...$ (see Definitions 3.2.1 and 3.5.1), provided the initial approximation is good and rounding errors are negligible.

Let us compare Jarratt's method with one of the alternatives: estimating f' by finite differences, and then using successive linear interpolation to find a zero of f' . (This process may also diverge, or converge to a maximum.) Suppose that $f''(\mu) > 0$ and $f^{(3)}(\mu) \neq 0$, to

avoid exceptional cases (see Sections 3.6, 3.7 and 4.2). Since at least two function evaluations are needed to estimate f' at any point, and $\sqrt{1.618\dots} = 1.272\dots < 1.324\dots$, Jarratt's method has a slightly higher order of convergence. (The comparison is similar to that between Newton's method and successive linear interpolation if an evaluation of f' is as expensive as an evaluation of f : see Golab (1966) or Ostrowski (1966).)

2. Fundamental Limitations because of rounding errors

Suppose that $f \in C^2[a, b; M]$ has a minimum at $\mu \in (a, b)$. Since $f'(\mu) = 0$, Lemma 2.3.1 gives, for $x \in [a, b]$,

$$f(x) = f_0 + \frac{1}{2} f_0'' (x-\mu)^2 + \frac{m_x}{6} (x-\mu)^3, \quad (2.1)$$

where $|m_x| \leq M$, $f_0 = f(\mu)$, and $f_0'' = f''(\mu)$. Because of rounding errors, the best that can be expected if single-precision floating-point numbers are used is that the computed value $fl(f(x))$ of $f(x)$ satisfies the (nearly attainable) bound

$$fl(f(x)) = f(x)(1 + \varepsilon_x), \quad (2.2)$$

where

$$|\varepsilon_x| \leq \varepsilon, \quad (2.3)$$

and ε is the relative machine precision (see Section 4.2). The error bound is unlikely to be as good as this unless f is a very simple function, or is evaluated using double-precision, and then rounded or

truncated to single-precision.

Let δ be the largest number such that, according to equations (2.2) and (2.3), it is possible that

$$fl(f(\mu + \delta)) \leq f_0. \quad (2.4)$$

It is unreasonable to expect any minimization procedure, based on single-precision evaluations of f , to return an approximation $\hat{\mu}$ to μ with a guaranteed upper bound for $|\hat{\mu} - \mu|$ less than δ . This is so, regardless of whether the computed values of f are used directly, as in Jarratt's method, or indirectly, as in the other method suggested in Section 1. The reason is simply that the minimum of the computed function $fl(f(x))$ may lie up to δ from the minimum μ of $f(x)$: see Diagram 2.1.

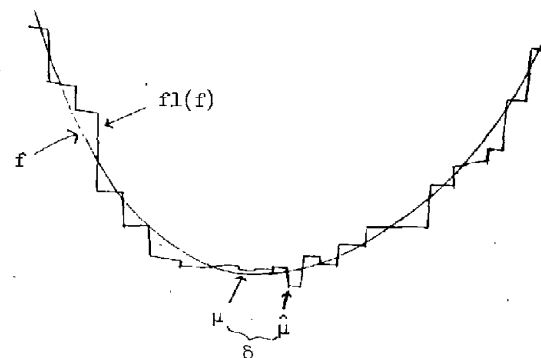


Diagram 2.1: The effect of rounding errors

If $f''_0 > 0$, equations (2.1) to (2.4) give

$$\delta \geq \sqrt{\frac{2|f_0|\epsilon}{f''_0}} \left(1 - \epsilon - \frac{M\delta}{6f''_0}\right) \quad (2.5)$$

Thus, if $\mu \neq 0$ and the term $\frac{M\delta}{6f''_0}$ is negligible, an upper bound for the relative error $\left|\frac{\hat{\mu}-\mu}{\mu}\right|$ could hardly be less than $\sqrt{\frac{2|f_0|\epsilon}{\mu^2 f''_0}}$, and full single-precision accuracy in $\hat{\mu}$ is unlikely unless $\frac{|f_0|}{\mu^2 f''_0}$ is of order ϵ or less, although $\text{fl}(f(\hat{\mu}))$ may agree with $f(\mu)$ to full single-precision accuracy. (See also Pike, Hill, and James (1967).)

If f' has a simple analytic representation, then it may be easy to compute f' accurately. For example, perhaps

$$\text{fl}(f'(x)) = f'(x(1+\epsilon'_x))(1+\epsilon''_x) \quad (2.6)$$

where $|\epsilon'_x| \leq \epsilon$ and $|\epsilon''_x| \leq \epsilon$, so we can expect to find a zero of f' with a relative error bounded by ϵ (see Lancaster (1966) and Ostrowski (1967b)). If (2.6) holds it might be worthwhile to use the algorithm described in Chapter 4 to search for a zero of f' , or at least use it to refine the approximation $\hat{\mu}$ given by a procedure using only evaluations of f . However, this is not so if f' has to be approximated by differences, for then (2.6) can not be expected to hold.

Even if $f(x)$ is a unimodal function, the computed approximation $\text{fl}(f(x))$ will not be unimodal, because of rounding errors. Note that $\text{fl}(f(x))$ must be constant over small intervals of real numbers x which have the same floating-point approximation $\text{fl}(x)$. In the next section

we define " δ -unimodality" to circumvent this difficulty.

From now on, we consider the problem of approximating the minimum of the computed function, or, equivalently, we ignore rounding errors in the computation of f . The user should bear in mind that the minimum of the computed function may differ from the minimum that he is really interested in by as much as δ (see equation (2.5) above). In particular, there is no point in wasting function evaluations by finding the minimum of the computed function to excessive accuracy, and our procedure `localmin` (Section 8) should not be called with the parameter "eps" much less than $\sqrt{\frac{2|f_0|\epsilon}{\mu^2 f''_0}}$.

3. Unimodality and δ -unimodality

There are several different definitions of a unimodal function in the literature. One source of confusion is that the definition may depend on whether the function is supposed to have a unique minimum or a unique maximum (we always consider minima). Kowalik and Osborne (1968) say that f is unimodal on $[a,b]$ if f has only one (no more than one?) stationary value on $[a,b]$. This definition has two disadvantages: first, it is meaningless unless f is differentiable on $[a,b]$, but we would like to say that $|x|$ is unimodal on $[-1,1]$. Second, functions which have inflexion points with a horizontal tangent are prohibited, but we would like to say that $f(x) = x^6 - 3x^4 + 3x^2$ is unimodal on $[-2,2]$ (here $f'(+1) = f'(-1) = 0$).

Wilde (1964) gives another definition: f is unimodal on $[a,b]$ if, for all $x_1, x_2 \in [a,b]$,

5.3

$$x_1 < x_2 \supset (x_2 < x^* \supset f(x_1) > f(x_2)) \wedge (x_1 > x^* \supset f(x_1) < f(x_2)) , \quad (3.1)$$

where x^* is a point at which f attains its least value in $[a, b]$.

(We have reversed some of Wilde's inequalities as he considers maxima rather than minima.) Wilde's definition does not assume differentiability, or even continuity, but to verify that a function f satisfies (3.1) we need to know the point x^* (and such a point must exist). Hence, we prefer the following definition, which is nearly equivalent to Wilde's (see Lemma 3.1), but avoids any reference to the point x^* . The definition is not as complicated as it looks: it merely says that f can not have a "hump" between any two points x_0 and x_2 in $[a, b]$. Two possible configurations of the points x_0, x_1, x_2 and x^* in (3.1) and (3.2) are illustrated in Diagram 3.1.

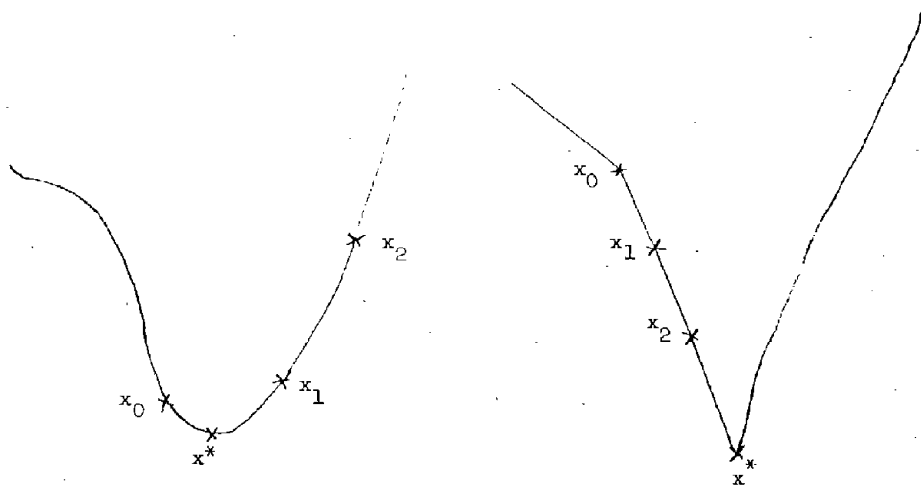


Diagram 3.1: Unimodal functions

5.3

Definition 3.1

f is unimodal on $[a, b]$ if, for all x_0, x_1 and $x_2 \in [a, b]$,

$$x_0 < x_1 \wedge x_1 < x_2 \supset (f(x_0) \leq f(x_1) \supset f(x_1) < f(x_2)) \wedge (f(x_1) \geq f(x_2) \supset f(x_0) > f(x_1)) . \quad (3.2)$$

Lemma 3.1

If a point x^* at which f attains its minimum in $[a, b]$ exists, then Wilde's definition of unimodality and Definition 3.1 are equivalent.

Proof

Suppose that f is unimodal according to Definition 3.1. If $x_1 < x_2$ and $x_2 < x^*$, take $x'_0 = x_1$, $x'_1 = x_2$, and $x'_2 = x^*$. Since f attains its least value at x^* ,

$$f(x'_1) \geq f(x^*) = f(x'_2) , \quad (3.3)$$

so equation (3.2) with primed variables gives

$$f(x'_0) > f(x'_1) , \quad (3.4)$$

and thus

$$f(x_1) > f(x_2) . \quad (3.5)$$

Similarly, if $x_1 < x_2$ and $x_1 > x^*$, equation (3.2) gives

$$f(x_1) < f(x_2) . \quad (3.6)$$

Thus, from (3.5) and (3.6), equation (3.1) holds.

Conversely, suppose that (3.1) holds and $x_0 < x_1 < x_2$. If $f(x_0) \leq f(x_1)$ then there are three possibilities, depending on the position of x^* :

1. $x_1 > x^*$. Thus, by (3.1),

$$f(x_1) < f(x_2). \quad (3.7)$$

2. $x_1 = x^*$. Take $x'_1 = \frac{1}{2}(x_1 + x_2)$, and $x'_2 = x_2$.

Since $x^* < x'_1 < x'_2$, equation (3.1) with primed variables gives

$$f(x'_1) < f(x'_2), \quad (3.8)$$

so

$$f(x_1) = f(x^*) \leq f(x'_1) < f(x'_2) = f(x_2). \quad (3.9)$$

3. $x_1 < x^*$. Take $x'_1 = x_0$ and $x'_2 = x_1$. Since $x'_1 < x'_2 < x^*$, equation (3.1) gives $f(x'_1) > f(x'_2)$, contradicting the assumption that $f(x_0) \leq f(x_1)$. Hence case 3 is impossible, and, by (3.7) and (3.9), we always have $f(x_1) < f(x_2)$. Similarly, if $f(x_1) \geq f(x_2)$ then $f(x_0) > f(x_1)$, so equation (3.2) holds, and the proof is complete.

A simple corollary of Lemma 3.1 is that, if f is continuous, then Wilde's definition of unimodality and ours are equivalent. For arbitrary f the definitions are not equivalent. For example,

$$f(x) = \begin{cases} 1-x & \text{if } x \leq 0, \\ x & \text{if } x > 0 \end{cases} \quad (3.10)$$

is unimodal on $[-1,1]$ by our definition, but not by Wilde's, for x^* does not exist.

The following theorem gives a simple characterization of unimodality. There is no assumption that f is continuous. Since a strictly monotonic function (e.g., x^3) may have stationary points, the theorem shows that both our definition and Wilde's are essentially different from Kowalik and Osborne's, even if f is continuously differentiable. (Although this point is obvious, it is sometimes overlooked! See also Corollary 3.3.)

Theorem 3.1

f is unimodal on $[a,b]$ (according to Definition 3.1) iff, for some (unique) $\mu \in [a,b]$, either f is strictly monotonic decreasing in $[a,\mu]$ and strictly monotonic increasing in $[\mu,b]$, or f is strictly monotonic decreasing in $[a,\mu]$ and strictly monotonic increasing in $(\mu,b]$.

The theorem is a special case of Theorem 3.2 below, so the proof is omitted. The following corollaries are immediate.

Corollary 3.1

If f is unimodal on $[a,b]$, then f attains its least value at most once on $[a,b]$. (If f attains its least value, then it must attain it at the point μ given by Theorem 3.1.)

Corollary 3.2

If f is unimodal and continuous on $[a,b]$, then f attains its least value exactly once on $[a,b]$.

Corollary 3.3

If $f \in C^1[a, b]$ then f is unimodal iff, for some $\mu \in [a, b]$, $f' < 0$ almost everywhere on $[a, \mu]$ and $f' > 0$ almost everywhere on $[\mu, b]$. (Note that f' may vanish at a finite number of points.)

Fibonacci and golden section search

If f is unimodal on $[a, b]$, then the minimum of f (or, if the minimum is not attained, the point μ given by Theorem 3.1) can be located to any desired accuracy by the well-known methods of Fibonacci search or golden section search. The reader is referred to Wilde (1964) for an excellent description of these methods. (See also Boothroyd (1965a, b), Johnson (1955), Krolak (1968), Newman (1965), Pike and Pixner (1967), and Witzgall (1969).) Care should be taken to ensure that the coordinates of the points at which f is evaluated are computed in a numerically stable way (see Overholt (1965)). Fibonacci and golden section search, as well as similar but less efficient methods, are based on the following result, which shows how the interval known to contain μ may be reduced in size.

Corollary 3.4

Suppose that f is unimodal on $[a, b]$, μ is the point given by Theorem 3.1, and $a \leq x_1 < x_2 \leq b$. If $f(x_1) \leq f(x_2)$ then $\mu \leq x_2$, and if $f(x_1) \geq f(x_2)$ then $\mu \geq x_1$.

Proof

If $x_2 < \mu$ then, by Theorem 3.1, $f(x_1) > f(x_2)$. Thus, if $f(x_1) \leq f(x_2)$ then $\mu \leq x_2$. The other half follows similarly.

If the reader is prepared to ignore the problem of computing "unimodal" functions using limited-precision arithmetic, he may skip the rest of this section.

 δ -unimodality

As was pointed out at the end of Section 2, functions computed using limited-precision arithmetic will not be unimodal because of rounding errors. Thus, the theoretical basis for Fibonacci search, golden section search, and similar methods, is irrelevant, and it is not clear that these methods will give even approximately correct results in the presence of rounding errors. To analyze this problem, we generalize the idea of unimodality to δ -unimodality. Intuitively, δ is a nonnegative number such that Fibonacci or golden section search will give correct results, even though f is not necessarily unimodal (unless $\delta = 0$), provided that the distance between points at which f is evaluated is always greater than δ . The results of Section 2 indicate how large δ is likely to be in practice. (Our aim differs from that of Richman (1968) in defining the ϵ -calculus, for he is interested in properties that hold as $\epsilon \rightarrow 0$.) For another approach to the problem of rounding errors, see Overholt (1967).

In the remainder of this section, δ is a fixed nonnegative number. As well as δ -unimodality, we need to define δ -monotonicity. If $\delta = 0$ then δ -unimodality and δ -monotonicity reduce to unimodality (Definition 3.1)

and monotonicity.

Definition 3.2

Let I be an interval and f a real-valued function on I . We say that f is strictly δ -monotonic increasing on I if, for all

$$x_1, x_2 \in I,$$

$$x_1 + \delta < x_2 \supset f(x_1) < f(x_2). \quad (3.11)$$

As an abbreviation, we shall write simply " f is δ - \uparrow on I ".

Strictly δ -monotonic decreasing functions (abbreviated δ - \downarrow) are defined in the obvious way.

Definition 3.3

Let I be an interval and f a real-valued function on I . We say that f is δ -unimodal on I if, for all $x_0, x_1, x_2 \in I$,

$$\begin{aligned} x_0 + \delta < x_1 \wedge x_1 + \delta < x_2 \supset (f(x_0) \leq f(x_1) \supset f(x_1) < f(x_2)) \\ \wedge (f(x_1) \geq f(x_2) \supset f(x_0) > f(x_1)) \end{aligned} \quad (3.12)$$

The following theorem gives a characterization of δ -unimodal functions.

It reduces to Theorem 3.1 if $\delta = 0$.

Theorem 3.2

f is δ -unimodal on $[a, b]$ iff there exists $\mu \in [a, b]$ such that either f is δ - \downarrow on $[a, \mu]$ and δ - \uparrow on $[\mu, b]$, or f is δ - \uparrow on $[a, \mu]$ and δ - \downarrow on $(\mu, b]$. Furthermore, if f is δ -unimodal on

$[a, b]$, then there is a unique interval $[\mu_1, \mu_2] \subseteq [a, b]$ such that the points μ with the above properties are precisely the elements of $[\mu_1, \mu_2]$, and $\mu_2 \leq \mu_1 + \delta$.

Proof

Suppose μ exists so that f is δ - \downarrow on $[a, \mu]$ and δ - \uparrow on $[\mu, b]$. Take any x_0, x_1, x_2 in $[a, b]$ with $x_0 + \delta < x_1$ and $x_1 + \delta < x_2$. If $f(x_0) \leq f(x_1)$ then, since f is δ - \downarrow on $[a, \mu]$, $\mu \leq x_1$. As f is δ - \uparrow on $[\mu, b]$, it follows that $f(x_1) < f(x_2)$. The other cases are similar, so f is δ -unimodal.

Conversely, suppose that f is δ -unimodal on $[a, b]$. Let

$$\mu_1 = \inf\{x \in [a, b] \mid f \text{ is } \delta\text{-}\uparrow \text{ on } [x, b]\}, \quad (3.13)$$

(so $\mu_1 \leq \max(a, b - \delta)$), and

$$\mu_2 = \sup\{x \in [a, b] \mid f \text{ is } \delta\text{-}\downarrow \text{ on } [a, x]\}, \quad (3.14)$$

(so $\mu_2 \geq \min(a + \delta, b)$).

It is immediate from the definitions (3.13) and (3.14) that f is δ - \uparrow on $(\mu_1, b]$ and f is δ - \downarrow on $[a, \mu_2]$. We shall show that

$$\mu_1 \leq \mu_2. \quad (3.15)$$

Suppose, by way of contradiction, that

$$\mu_1 > \mu_2. \quad (3.16)$$

This implies that $\mu_1 > a$ and $\mu_2 < b$, so, from the definitions of μ_1 and μ_2 , there are points x' and x'' with

$$\mu_2 \leq x'' < \left(\frac{\mu_1 + \mu_2}{2} \right) < x' \leq \mu_1, \quad (3.17)$$

such that f is not δ - \uparrow on $[x', b]$ and f is not δ - \downarrow on $[a, x'']$.

Thus, there are points y', y'', z', z'' in $[a, b]$ such that

$$z'' + \delta < y'' \leq x'' < x' \leq y' < z' - \delta, \quad (3.18)$$

$$f(z'') \leq f(y''), \quad (3.19)$$

and

$$f(y') \geq f(z'). \quad (3.20)$$

Let $x_0 = z''$, $x_2 = z'$, and

$$x_1 = \begin{cases} y' & \text{if } f(y') \geq f(y'') \\ y'' & \text{otherwise} \end{cases}, \quad (3.21)$$

From relations (3.18) to (3.21), the points x_0, x_1 and x_2 contradict δ -unimodality (equation (3.12)). Thus (3.16) is impossible, (3.15) must hold, and $[\mu_1, \mu_2]$ is nonempty.

Choose any μ in $[\mu_1, \mu_2]$. From the definitions of μ_1 and μ_2 , f is δ - \downarrow on $[a, \mu]$ and δ - \uparrow on $(\mu, b]$. Suppose, by way of contradiction, that f is neither δ - \downarrow on $[a, \mu]$ nor δ - \uparrow on $(\mu, b]$. Then there are points y_1 and y_2 in $[a, b]$ such that

$$y_2 + \delta < \mu < y_1 - \delta, \quad (3.22)$$

$$f(y_1) \leq f(\mu), \quad (3.23)$$

and

$$f(y_2) \leq f(\mu). \quad (3.24)$$

Thus, the points y_2, μ , and y_1 contradict the δ -unimodality of f , so f is either δ - \downarrow on $[a, \mu]$ or δ - \uparrow on $(\mu, b]$. This completes the proof of the first part of the theorem.

Finally, by the definitions (3.13) and (3.14), the set of points μ satisfying the conditions of the theorem is precisely $[\mu_1, \mu_2]$. Since f is both δ - \uparrow and δ - \downarrow on (μ_1, μ_2) , we have $\mu_2 \leq \mu_1 + \delta$, and the proof is complete.

Remarks

The interval $[\mu_1, \mu_2]$ depends on δ . Suppose that f attains its minimum in $[a, b]$ at $\bar{\mu}$. By Theorem 3.2, f is δ - \uparrow on $(\mu_1, b]$ and δ - \downarrow on $[a, \mu_2]$, so $\bar{\mu} \in [\mu_2 - \delta, \mu_1 + \delta]$, an interval of length at most 2δ .

As an example, consider

$$f(x) = x^2 + \epsilon \cdot g(x) \quad (3.25)$$

on $[-1, 1]$, where g is any function (not necessarily continuous) with $|g(x)| \leq 1$, and $\epsilon \geq 0$. Since $f(x)$ is bounded above and below by the unimodal functions $x^2 + \epsilon$ and $x^2 - \epsilon$, we see that f is δ -unimodal if $\delta \geq \sqrt{2\epsilon}$. In a practical case ϵ might be (a small multiple of) the relative machine precision, and the fact that the least δ for which f is δ -unimodal is of order $\epsilon^{1/2}$, rather than ϵ , is to be expected from the discussion in Section 2.

5.3

The following theorem is a generalization of Corollary 3.4 (which is just the special case $\delta = 0$), and shows why methods like Fibonacci search and golden section search work on δ -unimodal functions while the distance between points at which f is evaluated is greater than δ .

Theorem 3.3

Suppose that f is δ -unimodal on $[a, b]$, μ_1 and μ_2 are the points given by Theorem 3.2, x_1 and x_2 are in $[a, b]$, and $x_1 + \delta < x_2$. If $f(x_1) \leq f(x_2)$ then $\mu_2 \leq x_2$, and if $f(x_1) \geq f(x_2)$ then $\mu_1 \geq x_1$.

Proof

If $x_2 < \mu_2$ then $f(x_1) > f(x_2)$ for, by Theorem 3.2 with $\mu = \mu_2$, f is δ - \downarrow on $[a, \mu_2]$. Hence, if $f(x_1) \leq f(x_2)$ then $\mu_2 \leq x_2$. The second half is similar.

Remarks

Theorems 3.2 and 3.3 show that, provided δ is known, methods like Fibonacci search and golden section search can locate the interval $[\mu_1, \mu_2]$ in an interval of length as close to δ as desired. Since the minimum $\bar{\mu} \in [\mu_2 - \delta, \mu_1 + \delta]$ (see the remarks above), this means that $\bar{\mu}$ can be located in an interval of length as close to 3δ as desired.

In practice f may be δ -unimodal for all $\delta \geq \delta_0$, but a sharp upper bound for δ_0 may be difficult to obtain. If the usual golden section search method is used, giving a nested sequence of intervals I_j with limit $\hat{\mu}$, then Theorem 3.3 shows that $[\mu_1, \mu_2] \subseteq I_j$ as long as the

5.4

two function evaluations giving I_j were at points separated by more than δ_0 . The smallest such interval I_j has length no greater than $(2 + \sqrt{5})\delta_0$, so

$$|\hat{\mu} - \bar{\mu}| \leq (3 + \sqrt{5})\delta_0 \approx 5.236\delta_0. \quad (3.26)$$

Thus, golden section search gives an approximation $\hat{\mu}$ which is nearly as good as could be expected if we knew δ_0 . This may be regarded as a justification for using golden section (or Fibonacci) search to approximate minima of functions which, because of rounding errors, are only "approximately" unimodal.

4. An algorithm analogous to Dekker's algorithm

For finding a zero of a function f , the bisection process has the advantage that linear convergence is guaranteed, as the interval known to contain a zero is halved at each evaluation of f after the first. However, if f is sufficiently smooth and we have a good initial approximation to a simple zero, then a process with superlinear convergence will be much faster than bisection. This is the motivation for the algorithm, described in Chapter 4, which combines bisection and successive linear interpolation in a way which retains the advantages of both.

There is a clear analogy between methods for finding a minimum and for finding a zero. The Fibonacci and golden section search methods have guaranteed linear convergence, and correspond to bisection. Processes like successive parabolic interpolation, which do not always converge, but under certain conditions converge superlinearly, correspond to successive

linear interpolation. In this section we describe an algorithm which combines golden section search and successive parabolic interpolation in a way which retains the advantages of both. The analogy with the algorithm of Chapter 4 is illustrated in Diagram 4.1.

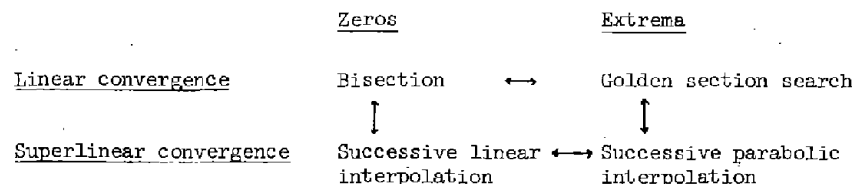


Diagram 4.1: The analogy between algorithms for finding zeros and extrema

Many more or less "ad hoc" algorithms have been proposed for one-dimensional minimization, particularly as components of n-dimensional minimization algorithms. See Box, Davies and Swann (1969), Flanagan, Vitale and Mendelsohn (1969), Fletcher and Reeves (1964), Jacoby, Kowalik and Pizzo (1971), Kowalik and Osborne (1968), Pierre (1969), Powell (1964), etc. The algorithm presented here might be regarded as an unwarranted addition to this list, but it seems to us to be more natural than these algorithms, which involve arbitrary prescriptions like "if ... fails then halve the step-size and try again". Of course, our algorithm is not quite free of arbitrary prescriptions either, so a more objective criticism of the "ad hoc" algorithms is that for many of them convergence to a local minimum in a reasonable number of function evaluations can not be guaranteed, and, for the exceptions, the asymptotic rate of convergence if f is sufficiently smooth is less than for our algorithm

(see Section 5). Note that we do not claim that our algorithm is suitable for use in an n-dimensional minimization procedure: an "ad hoc" algorithm may be more efficient (see Sections 1 and 7.1).

A description of the algorithm

Here we give an outline which should make the main ideas of the algorithm clear. For questions of detail the reader should refer to Section 8, where the algorithm is described formally by the ALGOL 60 procedure localmin.

The algorithm finds an approximation to the minimum of a function f defined on the interval $[a,b]$. Unless a is very close to b , f is never evaluated at the endpoints a and b , so f need only be defined on (a,b) , and if the minimum is actually at a or b then an interior point distant no more than $2 \cdot \text{tol}$ from a or b will be returned, where tol is a tolerance (see equation (4.2) below). The minimum found may be local, but non-global, unless f is δ -unimodal for some $\delta < \text{tol}$.

At a typical step there are six significant points a, b, u, v, w , and x , not all distinct. The positions of these points change during the algorithm, but there should be no confusion if we omit subscripts. Initially, (a,b) is the interval on which f is defined, and

$$v = w = x = a + \left(\frac{3 - \sqrt{5}}{2}\right)(b-a) \quad (4.1)$$

(The magic number $\frac{3 - \sqrt{5}}{2} = 0.381966\dots$ is rather arbitrarily chosen so that the first step is the same as for a golden section search.)

At the start of a cycle (label "loop" of procedure localmin) the points a, b, u, v, w , and x always serve as follows: a local

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minimum lies in $[a,b]$; of all the points at which f has been evaluated, x is the one with the least value of f , or the point of the most recent evaluation if there is a tie; w is the point with the next lowest value of f ; v is the previous value of w ; and u is the last point at which f has been evaluated (undefined the first time). One possible configuration is shown in Diagram 4.2.

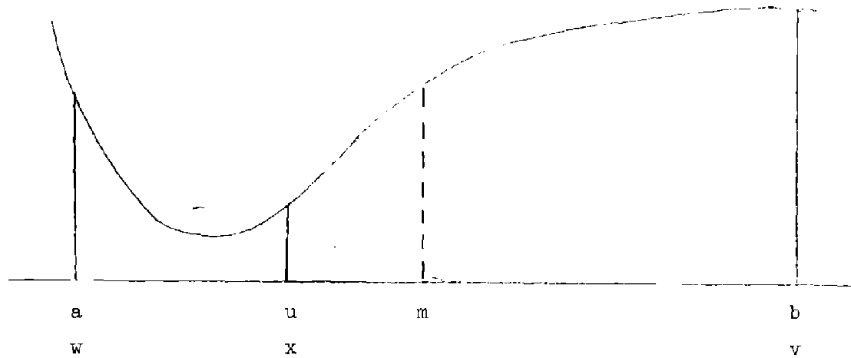


Diagram 4.2: A possible configuration

As in procedure zero (Chapter 4), the tolerance is a combination of a relative and an absolute tolerance. If

$$\text{tol} = \text{eps} \cdot |x| + t, \quad (4.2)$$

then the point x returned approximates a minimum to an accuracy of $2.\text{tol} + \delta < 3.\text{tol}$, if f is δ -unimodal near x and $\delta < \text{tol}$. The user must provide the positive parameters eps and t . In view of the discussion in Section 2, it is generally unreasonable to take eps much less than $\epsilon^{1/2}$, where ϵ is the machine-precision (see Section 4.2).

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t should be positive in case the minimum is at 0. It is possible that the error may exceed $2.\text{tol} + \delta$ because of the effect of rounding errors in determining if the stopping criterion is satisfied, but the additional error is of order $\epsilon|x|$, which is negligible if tol is of order $\epsilon^{1/2}|x|$ or greater.

Let $m = \frac{1}{2}(a+b)$ be the midpoint of the interval known to contain the minimum. If $|x-m| \leq 2.\text{tol} - \frac{1}{2}(b-a)$, i.e., if $\max(x-a, b-x) \leq 2.\text{tol}$, then the procedure terminates with x as the approximate position of the minimum. Otherwise, numbers p and q ($q \geq 0$) are computed so that $x + p/q$ is the turning point of the parabola passing through $(v, f(v))$, $(w, f(w))$, and $(x, f(x))$. If two or more of these points coincide, or if the parabola degenerates to a straight line, then $q = 0$.

p and q are given by

$$p = \frac{1}{2}[(x-v)^2(f(x)-f(w)) - (x-w)^2(f(x)-f(v))] \quad (4.3)$$

$$+ (x-v)(x-w)(w-v)[(x-w)f[v,w,x] + f[w,x]], \quad (4.4)$$

and

$$q = \frac{1}{2}[(x-v)(f(x)-f(w)) - (x-w)(f(x)-f(v))] \quad (4.5)$$

$$= \frac{1}{2}(x-v)(x-w)(w-v)f[v,w,x]. \quad (4.6)$$

From (4.4) and (4.6), the correction p/q should be small if x is close to a minimum where the second derivative is positive, so the effect of rounding errors in computing p and q is minimized. (Golub and Smith (1967) compute a correction to $\frac{1}{2}(v+w)$ for the same reason.)

As in procedure zero, let e be the value of p/q at the second-last cycle. If $|e| \leq \text{tol}$, $q = 0$, $x + p/q \notin (a,b)$, or $|p/q| \geq \frac{1}{2}|e|$, then

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a "golden section" step is performed, i.e., the next value of u is

$$u = \begin{cases} \left(\frac{\sqrt{5}-1}{2}\right)x + \left(\frac{3-\sqrt{5}}{2}\right)a & \text{if } x \geq m, \\ \left(\frac{\sqrt{5}-1}{2}\right)x + \left(\frac{3-\sqrt{5}}{2}\right)b & \text{if } x < m. \end{cases} \quad (4.7)$$

(An optimal choice in the limit: see Witzgall (1969).) Otherwise u is taken as $x+p/q$ (a "parabolic interpolation" step), except that the distances $|u-x|$, $u-a$ and $b-u$ must be at least tol . Then f is evaluated at the new point u , the points a , b , v , w and x are updated as necessary, and the cycle is repeated (the procedure returns to the label "loop"). We see that f is never evaluated at two points closer together than tol , so δ -unimodality for some $\delta < \text{tol}$ is enough to ensure that the global minimum is found to an accuracy of $2.\text{tol}+\delta$ (see Theorem 3.3 and the following remarks).

Typically the algorithm terminates in the following way: $x = b - \text{tol}$ (or, symmetrically, $a + \text{tol}$) after a parabolic interpolation step has been performed with the condition $|u-x| \geq \text{tol}$ enforced. The next parabolic interpolation point lies very close to x and b , so u is forced to be $x - \text{tol}$. If $f(u) > f(x)$ then a moves to u , $b-a$ becomes $2.\text{tol}$, and the termination criterion is satisfied (see Diagram 4.3). Note that two consecutive steps of tol are done just before termination. If a golden section search were done whenever the last, rather than second-last, value of $|p/q|$ was tol or less, then termination with two consecutive steps of tol would be prevented, and unnecessary golden section steps would be performed.

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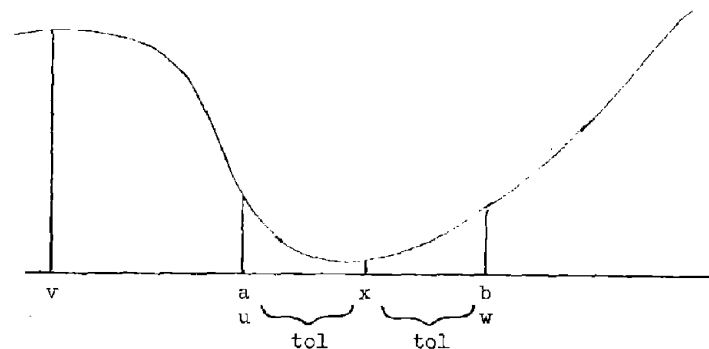


Diagram 4.3: A typical situation after termination

5. Convergence properties

There can not be more than about $2.\log_2((b-a)/\text{tol})$ consecutive parabolic interpolation steps (with the current a and b , and the minimum of tol over the interval), for while parabolic interpolation steps are being performed $|p/q|$ decreases by a factor of at least two on every second cycle of the algorithm, and when $|e| \leq \text{tol}$ a golden section step is performed. (In this section, "about" means we are not distinguishing between a real number and its integer part.) A golden section step does not necessarily decrease $b-a$ significantly, e.g., if $x = b - \text{tol}$ and $f(u) < f(x)$, then $b-a$ is only decreased by tol , but two golden section steps must decrease $b-a$ by a factor of at least $\frac{1+\sqrt{5}}{2} = 1.618\dots$. As in Section 4.3, we see that convergence can not require more than about

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$$2K(\log_2(\frac{b-a}{\text{tol}}))^2 \quad (5.1)$$

function evaluations, where

$$K = 1/\log_2(\frac{1+\sqrt{5}}{2}) = 1.44... \quad (5.2)$$

By comparison, a golden section or Fibonacci search would require about

$$K \cdot \log_2(\frac{b-a}{\text{tol}}) \quad (5.3)$$

function evaluations, and a brute-force search about $\frac{b-a}{2 \cdot \text{tol}}$.

The analogy with procedure zero of Chapter 4 should be clear, and essentially the same remarks apply here as were made in Chapter 4. In practical tests convergence has never been more than 5 percent slower than for a Fibonacci search (see Section 6).

In deriving (5.1) we have ignored the effect of rounding errors inside the procedure, but it is easy to see (as in Section 4.2) that they can not prevent convergence if floating-point operations satisfy (4.2.10) and (4.2.11), provided the parameter eps of procedure localmin is at least 2ϵ .

Superlinear convergence

If f is C^2 near an interior minimum μ with $f''(\mu) > 0$, then Theorem 3.4.1 shows that, while rounding errors are negligible, convergence will be superlinear. Usually the algorithm stops doing golden section steps, and eventually does only parabolic interpolation steps, with $f(x)$ decreasing at each step, until the tolerance comes into play just before termination. This is certainly true if the successive parabolic interpolation process

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converges with strong order $\beta_2 = 1.3247...$ (sufficient conditions for this are given in Sections 3.6 and 3.7).

For most of the "ad hoc" methods given in the literature, convergence with a guaranteed error bound of order tol in the number of steps given by (5.1) is not certain, and, even if convergence does occur, the order is no greater than for our algorithm. For example, the algorithm of Davies, Swann and Campey (see Box, Davies and Swann (1969)) evaluates f at two or more points for each parabolic fit, so the order of convergence is at most $\sqrt{\beta_2} = 1.150...$ (excluding exceptional cases).

6. Practical tests

The ALGOL procedure localmin given in Section 8 has been tested using ALGOL W (Wirth and Hoare (1966), Bauer, Becker and Graham (1968)) on an IBM 360/67 and a 360/91 with a machine precision of 16^{-13} . Although it might be possible to contrive an example where the bound (5.1) on the number of function evaluations is nearly attained, for our test cases convergence never requires as many as 5 percent more function evaluations than would be needed to guarantee the same accuracy using Fibonacci search. In most practical cases superlinear convergence sets in after a few golden section steps, and the procedure is much faster than Fibonacci search.

As an example, in Table 6.1 we give the number of function evaluations required to find the minima of the function

$$f(x) = \sum_{i=1}^{20} \left(\frac{2i-1}{x-i^2} \right)^2 \quad (6.1)$$

This function has poles at $x = 1^2, 2^2, \dots, 20^2$. Restricted to the open

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interval $(i^2, (i+1)^2)$ for $i = 1, 2, \dots, 19$ it is unimodal (ignoring rounding errors) with an interior minimum. The fourth column of Table 6.1 gives the number n_L of function evaluations required to find this minimum μ_1 , using procedure localmin with $\text{eps} = 16^{-7}$ and $t = 10^{-10}$ (so the error bound is less than $3.\text{tol}$, where $\text{tol} = 16^{-7} \cdot |x| \cdot 10^{-10}$).

The last column of the table gives the number n_Z of function evaluations required to find the zero of

$$f'(x) = -2 \cdot \sum_{i=1}^{20} \frac{(2i-5)^2}{(x-i)^3} \quad (6.2)$$

in the interval $[i^2 + 10^{-9}, (i+1)^2 - 10^{-9}]$, using procedure zero (Section 4.6) with $\text{macheps} = 16^{-7}$ and $t = 10^{-10}$, so the guaranteed accuracy is nearly the same as for localmin. Of course, in practical cases we would seldom be lucky enough to have such a simple analytic expression for f' , so procedure zero could not easily be used to find minima of f in this manner. Also, procedure zero could find a maximum rather than a minimum.

Table 6.1 shows that the number of function evaluations required by procedure localmin compares favorably with the number required by procedure zero. Both are much faster than Fibonacci search, which would require 45 function evaluations to find the minimum for $i = 10$ to the same accuracy.

For some numerical results illustrating the superlinear convergence of the successive parabolic interpolation process, see Section 3.9.

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Table 6.1: Comparison of procedures localmin and zero

i	μ_1	$f(\mu_1)$	n_L	n_Z
1	3.0229153	3.6766990169	12	14
2	6.6837536	1.1118500100	11	8
3	11.2387017	1.2182217637	13	14
4	19.6760001	2.1621103109	10	12
5	29.8282273	3.0322905193	11	12
6	41.9061162	3.7583856477	11	11
7	55.9535958	4.3554103836	10	11
8	71.9856656	4.8482959563	10	11
9	90.0088685	5.2587585400	10	10
10	110.0265327	5.6036524295	10	10
11	132.0405517	5.8956037976	10	10
12	156.0521144	6.1438861542	9	10
13	182.0620604	6.3550764593	9	10
14	210.0711010	6.5333662003	9	10
15	240.0800483	6.6803639849	9	10
16	272.0902669	6.7938538365	9	10
17	306.1051233	6.8634981053	9	10
18	342.1369454	6.8539024631	9	9
19	380.2687097	6.6008470481	9	9

For a discussion and definition of the terms, see above.

7. Conclusion

The algorithm given in this chapter has the same advantages as the algorithm described in Chapter 4 for finding zeros: convergence in a reasonable number of steps is guaranteed for any function (see equation (5.1)), and on well-behaved functions convergence is superlinear, with order at least $1.3247\dots$, and thus much faster than Fibonacci search. There is no contradiction here: Fibonacci search is the fastest method for the worst possible function, but our algorithm is faster on a large class of functions (including, for example, C^2 functions with positive second derivatives at interior minima).

A similar algorithm using derivatives

We pointed out in Section 4.5 that bisection could be combined with interpolation formulas which use both f and f' . We could combine golden section search with an interpolation method using both f and f' in a similar way. Davidon (1959) suggests fitting a cubic polynomial to agree with f and f' at two points, and taking a turning point of the cubic as the next approximation. (See also Johnson and Myers (1967).) This method, which gives the possibility of superlinear convergence, could well replace successive parabolic interpolation (using f at three points) in our algorithm if f' is easy to compute. If the cubic has no real turning point, or if the turning point which is a local minimum lies outside the interval known to contain a minimum of f , then we can resort to golden section search.

Parallel algorithms

So far we have considered only serial (i.e., sequential) algorithms for finding minima. If a parallel computer is available, more efficient algorithms which take advantage of the parallelism are possible, just as in the analogous zero-finding problem (see Section 4.5). Karp and Miranker (1968) give a parallel search method which is a generalization of Fibonacci search (and optimal in the same sense, if a sufficiently parallel processor is available). See also Wilde (1964) and Avriel and Wilde (1966). Miranker (1969) gives parallel methods for approximating the root of a function, and these could be used to find a root of f' (or parallel methods for finding a root of f' , using only evaluations of f , could be used). These parallel methods could be combined, in much the same way as we have combined golden section search and successive parabolic interpolation, to give a parallel method with guaranteed convergence, and often superlinear convergence with a higher order than for our serial method.

8. An ALGOL 60 procedure

The ALGOL procedure localmin for finding a local minimum of a function of one variable is given below. The algorithm and some numerical results are described in Sections 4 to 6.

Procedure localmin

```
real procedure localmin (a, b, eps, t, f, x);
value a, b, eps, t; real a, b, eps, t, x; real procedure f;
```

begin comment:

If the function f is defined in the interval (a,b) , then `localmin` finds an approximation x to the point at which f attains its minimum (or the appropriate limit point), and returns the value of f at x . t and eps define a tolerance $\text{tol} = \text{eps} \cdot |x| + t$, and f is never evaluated at two points closer together than tol . If f is δ -unimodal (see Definition 3.3), for some $\delta < \text{tol}$, then x approximates the global minimum of f with an error of less than $3 \cdot \text{tol}$ (see Section 4). If f is not δ -unimodal on (a,b) , then x may approximate a local, but non-global, minimum. eps should be no smaller than $2 \cdot \text{macheps}$, and preferably not much less than $\text{sqrt}(\text{macheps})$, where macheps is the relative machine precision (Section 4.2). t should be positive. For further details, see Section 2.

The method used is a combination of golden section search and succession parabolic interpolation. Convergence is never much slower than for a Fibonacci search (see Sections 5 and 6). If f has a continuous second derivative which is positive at the minimum (not at a or b) then, ignoring rounding errors, convergence is superlinear, and usually the order is at least 1.3247...;

real $c, d, e, m, p, q, r, \text{tol}, t2, u, v, w, fu, fv, fw, fx$;

$c := 0.381966011250105151795413165634$; comment: $c = (3 - \text{sqrt}(5))/2$;

$v := w := x := a + c \times (b-a)$; $e := 0$;

$fv := fw := fx := f(x)$;

comment: Main loop;

loop: $m := 0.5 \times (a+b)$;

$\text{tol} := \text{eps} \times \text{abs}(x) + t$; $t2 := 2 \times \text{tol}$;

comment: Check stopping criterion;

if $\text{abs}(x-m) > t2 - 0.5 \times (b-a)$ then

begin $p := q := r := 0$;

if $\text{abs}(e) > \text{tol}$ then

begin comment: Fit parabola;

$r := (x-w) \times (fx-fv)$; $q := (x-v) \times (fx-fw)$;

$p := (x-v) \times q - (x-w) \times r$; $q := 2 \times (q-r)$;

if $q > 0$ then $p := -p$ else $q := -q$;

$r := e$; $e := d$

end;

if $\text{abs}(p) < \text{abs}(0.5 \times q \times r) \wedge p > q \times (a-x) \wedge p < q \times (b-x)$ then

begin comment: A "parabolic interpolation" step;

$d := p/q$; $u := x+d$;

comment: f must not be evaluated too close to a or b ;

if $u-a < t2 \vee b-u < t2$ then $d :=$ if $x < m$ then tol else $-\text{tol}$

end

else

begin comment: A "golden section" step;

$e := (\text{if } x < m \text{ then } b \text{ else } a) - x$; $d := c \times e$

end;

comment: f must not be evaluated too close to x ;

$u := x + (\text{if } \text{abs}(d) \geq \text{tol} \text{ then } d \text{ else if } d > 0 \text{ then } \text{tol} \text{ else } -\text{tol})$;

$fu := f(u)$;

comment: Update a, b, v, w and x ;

if $fu \leq fx$ then

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```

begin if u < x then b := x else a := x;
v := w; fv := fw; w := x; fw := fx; x := u; fx := fu
end
else
begin if u < x then a := u else b := u;
if fu < fw v w = x then
begin v := w; fv := fw; w := u; fw := fu end
else if fu < fv v = x v = w then
begin v := u; fv := fu
end
end;
go to loop
end;
localmin := fx
end localmin;

```

Chapter 6.

Global Minimization Given an Upper Bound on the
Second Derivative

6.1

1. Introduction

Minimization procedures like the one described in Chapter 5 can only guarantee to find a local, not necessarily global, minimum of a function $f \in C[a, b]$. If f happens to be unimodal then a local minimum must be the global minimum in $[a, b]$, but in practical problems it often happens that f is not unimodal, or that unimodality is difficult to prove. In this chapter we investigate the problem of finding a good approximation to the global minimum, given weaker conditions on f than unimodality. As usual, we consider methods which depend on the sequential evaluation of f at a finite number of points, and our aim is to reduce, as far as possible, the number of function evaluations required to give an answer which is guaranteed to be accurate to within some prescribed tolerance.

In Sections 2 to 6 we describe an efficient algorithm for approximating the global minimum of a function of one variable, given an upper bound on the second derivative. There are many obvious applications for this algorithm. For example, when finding a posteriori error bounds for the approximate solution of elliptic partial differential equations, we may need to find the maximum of $|f(x)|$ (Fox, Henrici and Moler (1967)). Instead of working with $|f(x)|$, which may have discontinuous derivatives, it is probably better to use the relation

$$\max_x |f(x)| = -\min(\min_x(f(x)), \min_x(-f(x))) \quad (1.1)$$

In Sections 7 and 8 we show how to extend the method to functions of several variables, and ALGOL 60 procedures are given in Section 10.

6.1

Some fundamental limitations

If $f \in C[a, b]$, let

$$\varphi_f = \inf \{f(x) \mid x \in [a, b]\} \quad (1.2)$$

and

$$\mu_f = \inf \{x \in [a, b] \mid f(x) = \varphi_f\} \quad (1.3)$$

Even if f satisfies very stringent smoothness conditions, the problem of finding μ_f is improperly posed, in the sense that μ_f is not a continuous function of f (with the uniform topology on $C[a, b]$). For example, consider

$$f_\delta(x) = \cos(\pi x) - \delta x \quad (1.4)$$

on $[-2, 2]$. If $\delta > 0$ then $\mu_f \simeq 1$, but if $\delta \leq 0$ then $\mu_f \simeq -1$, so a very small change in f can cause a large change in μ_f .

Instead of trying to approximate μ_f , we should seek to approximate $\varphi_f = f(\mu_f)$. Since

$$|\varphi_f - \varphi_g| \leq \|f - g\|_\infty \quad (1.5)$$

for all f and g in $C[a, b]$, φ_f is a continuous function on $C[a, b]$, so the problem of finding φ_f is properly posed. However, given $t > 0$, it is still impossible to find $\hat{\varphi}$ such that

$$|\hat{\varphi} - \varphi_f| \leq t \quad (1.6)$$

with a finite number N_t of function evaluations, unless we have some a priori information about f .

priori conditions on f

If $f \in C[a, b]$, the modulus of continuity $w(f; \delta)$ is defined (as in Section 2.2) by

$$w(f; \delta) = \sup_{\substack{|x-y| \leq \delta \\ x, y \in [a, b]}} |f(x) - f(y)| \quad (1.7)$$

For $\delta \geq 0$. Suppose that a function $W(\delta)$ is given such that

$$\lim_{\delta \rightarrow 0^+} W(\delta) = 0, \quad (1.8)$$

and

$$w(f; \delta) \leq W(\delta) \quad (1.9)$$

for all $\delta > 0$. Given $t > 0$, choose $\delta > 0$ such that

$$W(\delta) \leq t \quad (1.10)$$

(always possible by (1.8)), and evaluate f at points x_0, \dots, x_n in $[a, b]$ such that

$$\max_{x \in [a, b]} \min_{0 \leq i \leq n} |x - x_i| \leq \delta. \quad (1.11)$$

(For example, we might choose $x_0 = a + \delta$, $x_1 = a + 3\delta$, $x_2 = a + 5\delta$, etc.)

If

$$\hat{\phi} = \min_{0 \leq i \leq n} f(x_i), \quad (1.12)$$

then, from (1.7), (1.9), (1.10) and (1.11),

$$0 \leq \hat{\phi} - \phi_f \leq t. \quad (1.13)$$

Thus, a quite weak condition on f , enabling us to approximate ϕ_f with a finite number of evaluations of f , is that we have a bound $W(\delta)$, satisfying (1.8), on the modulus of continuity $w(f; \delta)$ of f . For example, if $f \in C^1[a, b]$ and

$$\|f'\|_{\infty} \leq M, \quad (1.14)$$

then we can take

$$W(\delta) = M\delta. \quad (1.15)$$

Unfortunately, the procedure suggested above will be very slow if t is small: in fact, about $(b-a)M/(2t)$ function evaluations will be required. In the worst case, though, it is impossible to do much better than this without knowing more about f . To see this, consider minimizing a function which is known to be in the class

$$\{f_c(x) = \min(1.01t, M|x-c|) \mid c \in [a, b]\}. \quad (1.16)$$

If

$$\delta = 1.01t/M, \quad (1.17)$$

and $\hat{\phi}$ is computed from (1.12) for some set of points x_0, \dots, x_n , then there is a choice of $c \in [a, b]$ for which $\hat{\phi}$ fails to satisfy (1.13) unless (1.11) holds, so at least $\lceil (b-a)M/(2.02t) \rceil$ function evaluations are required. In some cases less function evaluations will be required: for example, if

$$f(x) = Mx, \quad (1.18)$$

then it is enough to evaluate f at a and b . (See also Section 5.)

Instead of having an a priori bound on $\|f'\|_\infty$, we could have a bound

$$\|f^{(r)}\|_\infty \leq M \quad (1.19)$$

on $\|f^{(r)}\|_\infty$, for some $r \geq 1$. We show below that, with such a bound, the maximum number of function evaluations required to find \hat{q} satisfying (1.13) is of order $(M/t)^{1/r}$.

The case $r = 1$ is discussed above, so suppose $r \geq 2$, and let

$$n = \left\lceil \frac{(b-a)}{4 \cos(\frac{\pi}{2r})} \left(\frac{4M}{r!t} \right)^{\frac{1}{r}} \right\rceil. \quad (1.20)$$

Define $\delta = \frac{b-a}{n}$, $a_i = a + i\delta$ for $i = 0, \dots, n$ (so $a_n = b$), and

$$a_{i,j} = a_i + \frac{\delta}{2} \left\{ 1 - \frac{\cos((j - \frac{1}{2})\pi/r)}{\cos(\frac{1}{2}\pi/r)} \right\} \quad (1.21)$$

for $i = 0, \dots, n-1$ and $j = 1, \dots, r$ (so $a_{i,1} = a_i$, $a_{i,r} = a_{i+1}$). Let $P_i = IP(f; a_{i,1}, \dots, a_{i,r})$ be the polynomial of degree $r-1$ which coincides with f at $a_{i,1}, \dots, a_{i,r}$. Then, Lemma 2.4.1 and the bound (1.19) show that, for all $x \in [a_i, a_{i+1}]$,

$$|f(x) - P_i(x)| \leq |(x - a_{i,1}) \dots (x - a_{i,r})| M/r! \quad (1.22)$$

The right side of (1.22) is no greater than $\left(\frac{\delta}{2 \cos(\frac{\pi}{2r})} \right)^r \frac{M}{r!2^{r-1}}$,

and, by (1.20) and the choice of δ , this is no greater than $t/2$. Thus, we need only find the minimum of each polynomial $P_i(x)$ in $[a_i, a_{i+1}]$ to within a tolerance $t/2$. This is easy if $r = 2$, for then each

polynomial $P_i(x)$ is linear. If $r > 2$ then we can bound $|P_i''(x)|$ in $[a_i, a_{i+1}]$, and apply the procedure for $r = 2$ to minimize $P_i(x)$. (This idea for finding bounds on polynomials in an interval was suggested by Rivlin (1970).) Because successive intervals $[a_i, a_{i+1}]$ are adjacent, the number of function evaluations required to find \hat{q} satisfying (1.13) does not exceed

$$N = (r-1)n + 2, \quad (1.23)$$

where n is given by (1.20).

Since N is of order $(M/t)^{1/r}$, the method described above is not likely to be practical for small t unless $r \geq 2$. On the other hand, in practical problems it is usually difficult to obtain good bounds on the third or higher derivatives of f (if they exist). Thus, in the rest of this chapter we suppose that $r = 2$. It turns out that a one-sided bound

$$f''(x) \leq M \quad (1.24)$$

is sufficient, instead of the two-sided bound (1.19). If $f''(x)$ has a physical interpretation (e.g., as an acceleration), then a bound of the form (1.24) can sometimes be obtained from physical considerations.

2. The basic theorems

The global minimization algorithm which is described in the next section depends on the simple Theorems 2.1, 2.2 and 2.3. Theorem 2.1 is related to the maximum principle for elliptic difference operators, and also to some results in Davis (1965). We assume that $f \in C^1[a, b]$, and

$$f'(x) - f'(y) \leq M(x-y), \quad (2.1)$$

for all x, y in $[a, b]$ with $x > y$. (Weaker conditions suffice: see Section 7.) If $f \in C^2[a, b]$ then the one-sided Lipschitz condition (2.1) is equivalent to

$$f''(x) \leq M \quad (2.2)$$

for all $x \in [a, b]$.

Theorem 2.1

Suppose (2.1) holds. Then, for all $x \in [a, b]$,

$$f(x) \geq \frac{(b-x)f(a) + (x-a)f(b)}{b-a} - \frac{1}{2} M(x-a)(b-x). \quad (2.3)$$

Proof

The proof is immediate from Lemma 2.4.1.

Lemma 2.1

Suppose (2.1) holds and $a < 0 \leq b$. Then

$$f'(0) \leq \frac{f(a) - f(0)}{a} - \frac{1}{2} Ma. \quad (2.4)$$

Proof

Applying Lemma 2.3.1 to $f(-x)$, we have

$$f(a) \leq f(0) + af'(0) + \frac{1}{2} Ma^2, \quad (2.5)$$

so the result follows.

Theorem 2.2

Suppose (2.1) holds, $M > 0$, $a < c \leq b$, $f(a) \geq f(c)$, and $f'(c) = 0$. Then

$$c - a \geq \sqrt{\frac{f(a) - f(c)}{\frac{1}{2} M}}. \quad (2.6)$$

Proof

Applying Lemma 2.1 with a suitable translation of the origin gives

$$0 = f'(c) \leq \frac{f(a) - f(c)}{a - c} - \frac{1}{2} M(a - c), \quad (2.7)$$

so

$$f(a) - f(c) \leq \frac{1}{2} M(c - a)^2, \quad (2.8)$$

and the result follows.

Lemma 2.2

Suppose (2.1) holds, $M > 0$, and $a < 0 \leq b \leq -f'(0)/M$. Then $f'(b) \leq 0$.

Proof

By condition (2.1),

$$f'(b) \leq f'(0) + Mb, \quad (2.9)$$

and, as

$$b \leq -f'(0)/M, \quad (2.10)$$

the result follows.

Theorem 2.3

Suppose (2.1) holds, $M > 0$, $a < c \leq b$, and

$$c \leq x \leq \min \left(b, \frac{a+c}{2} - \frac{f(a)-f(c)}{M(a-c)} \right). \quad (2.11)$$

Then

$$f'(x) \leq 0. \quad (2.12)$$

Proof

There is no loss of generality in assuming that $c = 0$ and $b = x$.

By condition (2.11),

$$b = x \leq \frac{1}{2}a - \frac{f(a)-f(0)}{Ma} - \frac{1}{M} \left(\frac{f(a)-f(0)}{a} - \frac{1}{2}Ma \right), \quad (2.13)$$

so, by Lemma 2.1, we have

$$b \leq -f'(0)/M. \quad (2.14)$$

Now the result follows from Lemma 2.2.

Remarks

Theorems 2.1, 2.2 and 2.3 are sharp, as can easily be seen by taking $f(x)$ as a suitable parabola with leading term $\frac{1}{2}Mx^2$. The theorems are generalized in Section 7, and the proofs given there show that everything needed to justify our minimization algorithm follows from the fundamental inequality (2.3). The proofs given in this section are, however, simpler and more intuitive than those in Section 7.

3. An algorithm for global minimization

Suppose that $f \in C^2[a, b]$ and, for all $x \in [a, b]$,

$$f''(x) \leq M. \quad (3.1)$$

We want to find $\hat{\mu} \in [a, b]$ and $\hat{\phi} = f(\hat{\mu})$ satisfying

$$|\hat{\phi} - \phi_f| \leq t, \quad (3.2)$$

where t is a given positive tolerance, and

$$\phi_f = \min_{x \in [a, b]} f(x). \quad (3.3)$$

If $M \leq 0$ the problem is quite trivial, for Theorem 2.1 says that $f(x)$ can not lie below the straight line interpolating f at a and b , so

$$\phi_f = \min (f(a), f(b)). \quad (3.4)$$

If $M > 0$ the problem is not trivial, although we saw in Section 1 that there does exist an algorithm to solve it.

The basic algorithm

The algorithm described in this section is an elaboration and refinement of the following basic algorithm. (The notation is consistent with that of the ALGOL procedure glomin (Section 10), except that we write M for m , $\hat{\mu}$ for x , $\hat{\phi}$ for y (= glomin), and ε for macheps.)

1. Set $\hat{\phi} \leftarrow \min (f(a), f(b))$,
 $\hat{\mu} \leftarrow$ if $\hat{\phi} = f(a)$ then a else b ,
 and $a_2 \leftarrow a$.

6.3

2. If $M \leq 0$ or $a_2 \geq b$ then halt. Otherwise set $a_3 \leftarrow$ some point in $(a_2, b]$ (e.g., b : see below for a better choice).
3. If $f(a_3) < \hat{\phi}$ then set $\hat{\mu} \leftarrow a_3$ and $\hat{\phi} \leftarrow f(a_3)$.
4. If the parabola $y = P(x)$, with $P''(x) = M$, $P(a_2) = f(a_2)$, and $P(a_3) = f(a_3)$, satisfies $P(x) \geq \hat{\phi} - t$ for all x in $[a_2, a_3]$, then go on to 5. Otherwise set $a_3 \leftarrow \frac{1}{2}(a_2 + a_3)$ and go back to 3.
5. Set $a_2 \leftarrow a_3$ and go back to 2.

We shall see shortly that (with a sensible choice of a_3 at step 2) the basic algorithm must terminate in a finite number of steps. In view of Theorem 2.1 and step 4, it is clear that, when the algorithm terminates, it does so with $\hat{\phi}$ satisfying (3.2).

Refinements of the basic algorithm

The crux of the problem is how to make a good choice of a_3 at step 2 of the basic algorithm. We want to choose a_3 as large as possible, but not so large that it has to be reduced at step 4.

Theorems 2.2 and 2.3 provide useful lower bounds. If the global minimum μ_f lies outside (a_2, b) , or if $\phi_f \geq \hat{\phi} - t$, then the algorithm may halt, for $\hat{\phi}$ already satisfies (3.2). Otherwise

$$f'(\mu_f) = 0 \quad (3.5)$$

and

$$f(\mu_f) < \hat{\phi} - t, \quad (3.6)$$

so, from Theorem 2.2 with a replaced by a_2 and c by μ_f ,

6.3

$$\mu_f - a_2 > \sqrt{\frac{f(a_2) - \hat{\phi} + t}{\frac{1}{2}M}}. \quad (3.7)$$

Thus, at step 2 it is safe to take $a_3 = a_3'$, where

$$a_3' = \min \left\{ b, a_2 + \sqrt{\frac{f(a_2) - \hat{\phi} + t}{\frac{1}{2}M}} \right\}, \quad (3.8)$$

and with this choice there is no risk that a_3 will have to be reduced at step 4. Since the right side of (3.7) is at least $(2t/M)^{1/2}$, the basic algorithm must converge in a finite number of steps if, in step 2, we choose any a_3 in the range $[a_3', b]$.

If f is decreasing rapidly at a_2 , then Theorem 2.3 may give a better bound than (3.7). Apply Theorem 2.3 with c replaced by a_2 and a replaced by a point $a_2 - d_0$ (with $d_0 > 0$) where f has already been evaluated. (This is not possible if $a_2 = a$.) Combining the result with (3.8), we see that it is safe to choose $a_3 = a_3''$ at step 2, where

$$a_3'' = \min \left(b, \max \left\{ a_2 + \sqrt{\frac{f(a_2) - f(\hat{\mu}) + t}{\frac{1}{2}M}}, a_2 - \frac{1}{2} \left(d_0 + \frac{f(a_2) - f(a_2 - d_0) + 2.01e}{\frac{1}{2}M \cdot d_0} \right) \right\} \right). \quad (3.9)$$

Here e is a positive tolerance, and the term $2.01e$ is introduced to combat the effect of rounding errors (see equations (3.41) and (3.52)).

The choice $a_3 = a_3''$ is safe, but it is possible to speed up the algorithm by sometimes choosing $a_3 > a_3''$. Because we want to avoid

having to decrease a_3 at step 4, the best choice would be to take $a_3 = \min(b, a_3^*)$, where a_3^* is the abscissa of the point to the right of a_2 where the curve $y = f(x)$ intersects the parabola P , with second derivative M , which passes through $(a_2, f(a_2))$ and attains its minimum value $\varphi' - t$ to the right of a_2 . Here

$$\varphi' = \min(\hat{\varphi}, f(a_3)) \quad (3.10)$$

is the value of $\hat{\varphi}$ after step 3 has been executed, and we can extend the domain of f by defining $f(x) = f(b)$ for $x > b$ if this is necessary. A typical situation is illustrated in Diagram 3.1.

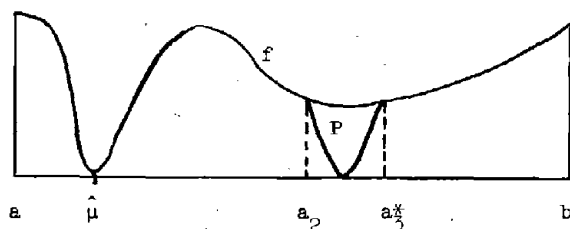


Diagram 3.1: The points a_2 and a_3^*

It is not practical to choose $a_3 = a_3^*$, for, although a_3^* exists, several function evaluations are needed to approximate it accurately. Procedure glomin (Section 10) finds a rough approximation a_3^{**} to a_3^* , without any extra function evaluations, by assuming that f can be approximated sufficiently well by the parabola which interpolates f at

the last three points at which f has been evaluated. To avoid overstepping a_3^* too often, because of the inadequacy of the parabolic approximation to f , the procedure uses a heuristic "safety factor" $hc(0,1)$. If

$$\hat{a}_3 = \min(b, a_2 + h(a_3^{**} - a_2)) \quad (3.11)$$

then at step 2 we choose

$$a_3 = \max(a_3'', \hat{a}_3) \quad (3.12)$$

and if it necessary to reduce a_3 at step 4 then we set $a_3 = \max(a_3'', \frac{1}{2}(a_2 + a_3))$. Procedure glomin also makes a rather primitive attempt to adjust h , the adjustment depending on the outcome of step 4.

Some details of procedure glomin

The ALGOL 60 procedure glomin given in Section 10 uses the basic algorithm with the refinements suggested above. From equation (3.8) and the criterion in step 4 of the basic algorithm, it is clear that, to speed up convergence, we want to find a rough approximation to the global minimum as soon as possible. In other words, $\hat{\varphi}$ should be nearly at its final value as soon as possible. For this reason, procedure glomin incorporates several strategies which are designed to reduce $\hat{\varphi}$ quickly. We emphasize that the global minimum would be found without using these strategies: the strategies merely reduce the number of function evaluations required (see Sections 5 and 6).

The first strategy for reducing $\hat{\varphi}$ quickly is a pseudo-random

search. About 10 percent of the function evaluations are used to evaluate f at "random" points uniformly distributed in (a_2, b) . (f is not evaluated at the random point a_3 if Theorem 2.1, with a replaced by a_2 and x by a_3 , indicates that $f(a_3) \geq \hat{\phi} - t$, for such an evaluation would be a waste of time.) At worst, this strategy wastes 10 percent of the function evaluations, but in practice the saving in function evaluations caused by quickly finding a good value of $\hat{\phi}$ is often much more than 10 percent. (The choice of 10 percent is, of course, rather arbitrary.)

By comparison with the random search strategy, the second strategy is a highly "non-random" search. f is evaluated at the minimum a_3 of the parabola which interpolates f at the last three points at which f has been evaluated, provided that this point a_3 lies in (a_2, b) and Theorem 2.1 does not show that the evaluation is futile for the purpose of reducing $\hat{\phi}$. The details are similar to those of procedure localmin (see Chapter 5). This strategy helps to locate the local minima of f which are in the interior of $[a, b]$, and, unless the global minimum is at a or b , one of these local minima is the global minimum. A bonus is that, if f is sufficiently well-behaved near the global minimum (see Chapter 5 for more precise conditions), then the minimum will be found more accurately than would be expected with the basic algorithm. The numerical examples given in Sections 6 and 8 illustrate this. To avoid wasting function evaluations by repeatedly finding the same local minimum, this strategy is only used about once in every tenth cycle, although it is always used if $\hat{\phi} = f(a_2)$, for then there is a good chance that $f(a_3) < \hat{\phi}$.

Finally, the user may be able to make a good guess at the global minimum. For example, he may know a local minimum which is likely to be the global minimum, or he may know the global minimum of a slightly different function (see the application discussed in Section 8). Thus, procedure glomin has an input parameter c which may be set by the user at the suspected position of the global minimum, and on entry the procedure evaluates f at c in an attempt to reduce $\hat{\phi}$. If the user knows nothing about the likely position of the global minimum, he can set $c = a$ or b .

We can now summarize procedure glomin (for points of detail, see Section 10). Step 1 of the basic algorithm is performed, and the algorithm terminates immediately unless $M > 0$ and $a < b$. Before choosing $a_3 \in (a_2, b]$ at step 2, the strategies described above are used to try to reduce $\hat{\phi}$. Then a_3 is chosen, and perhaps reduced at step 4, as described above.

The reader who is not very interested in the murky details of procedure glomin, or in the effect of rounding errors, would be well advised to skip the rest of this section.

Some of the formulas used by procedure glomin need an explanation. When either the random or non-random search strategy is performed, we have numbers q and r , and wish to determine if the relation

$$q \neq 0 \wedge (a_2 < a_2 + r/q < b) \wedge$$

$$\frac{(b - (a_2 + r/q))f(a_2) + (r/q)f(b)}{b - a_2} - \frac{1}{2} M(r/q)(b - (a_2 + r/q)) < \hat{\phi} - t \quad (3.13)$$

is true. If $m_2 = \frac{1}{2} M > 0$, $z_2 = b - a_2 > 0$, $y_b = f(b)$, and $y_2 = f(a_2)$, then (3.13) is equivalent to

$$q[r(y_b - y_2) + z_2 q(y_2 - \hat{\phi} + t)] < z_2 m_2 r(z_2 q - r), \quad (3.14)$$

which is the condition tested after label "retry" of procedure glomin.

(If $q = 0$ then (3.14) is false, and it is also false if $a_2 + r/q$ lies outside (a_2, b) , since $m_2 > 0$ and $\hat{\phi} - t < \min(y_2, y_b)$.)

To approximate a_3^* , we need the point a_3^{**} where the parabola $y = P(x)$, passing through (a_i, y_i) for $i = 0, 1, 2$, intersects the parabola

$$y = m_2 \left(x - a_2 - \sqrt{\frac{y_2 - \hat{\phi} + t}{m_2}} \right)^2 + \hat{\phi} - t. \quad (3.15)$$

(In procedure glomin we use c in place of a_1 to save a storage location.) Let $z_0 = y_2 - y_1$, $z_1 = y_2 - y_0$, $d_0 = a_2 - a_1$, $d_1 = a_2 - a_0$, and $d_2 = a_1 - a_0$. In the non-random search we have already computed numbers p and q_s (r and q above) with

$$p = d_1^2 z_0 - d_0^2 z_1 \quad (3.16)$$

and

$$q_s = 2(d_0 z_1 - d_1 z_0), \quad (3.17)$$

in order to find the turning point $a_2 + p/q_s$ of $P(x)$. By forming the quadratic equation for a_3^{**} , and dividing out the unwanted root a_2 , we find that

$$a_3^{**} = a_2 + p'/q', \quad (3.18)$$

where

$$p' = p + 2rs, \quad (3.19)$$

$$q' = r + \frac{1}{2} q_s, \quad (3.20)$$

$$r = d_0 d_1 d_2 m_2, \quad (3.21)$$

and

$$s = \sqrt{\frac{y_2 - \hat{\phi} + t}{m_2}}. \quad (3.22)$$

Finally, there is the inspection of the lower bound on f in (a_2, a_3) given by the parabola

$$y = \frac{(a_3 - x)y_2 + (x - a_2)y_3}{d_0} - m_2(x - a_2)(a_3 - x), \quad (3.23)$$

where $m_2 = \frac{1}{2} M > 0$ and

$$d_0 = a_3 - a_2 > 0. \quad (3.24)$$

If

$$p = \frac{y_2 - y_3}{m_2 d_0}, \quad (3.25)$$

then the parabola (3.23) is monotonic increasing or decreasing in

(a_2, a_3) provided

$$|p| \geq d_0. \quad (3.26)$$

Otherwise, the parabola (3.23) attains its minimum in (a_2, a_3) , and the minimum value is $\frac{1}{2}(y_2 + y_3) - \frac{1}{4}m_2(d_0^2 + p^2)$ at $x = \frac{1}{2}(a_2 + a_3 + p)$. Thus, at step 4 of the basic algorithm, a_3 must be reduced if

6.3

$$|p| < d_0 \wedge \frac{1}{2} (y_2 + y_3) - \frac{1}{4} m_2 (d_0^2 + p^2) < \hat{\phi} - t, \quad (3.27)$$

i.e., if

$$|p| < d_0 \wedge \frac{1}{4} M(d_0^2 + p^2) > (y_2 - \hat{\phi}) + (y_3 - \hat{\phi}) + 2t. \quad (3.28)$$

The effect of rounding errors

So far we have ignored the effect of rounding errors, which actually occur both in the computation of $f(x)$ and in the internal computations of procedure glomin. Now we show how these rounding errors can be accounted for.

Let ϵ be the relative machine precision (parameter macheps of procedure glomin), i.e.,

$$\epsilon = \begin{cases} \beta^{1-\tau} & \text{(truncated arithmetic),} \\ \frac{1}{2} \beta^{1-\tau} & \text{(rounded arithmetic),} \end{cases}$$

for τ -digit floating-point arithmetic to base β . We suppose, following Wilkinson (1963), that

$$fl(x \# y) = (x \# y)(1 + \delta), \quad (3.29)$$

where $\#$ stands for any of the arithmetic operations $+$, $-$, \times , $/$, and

$$|\delta| \leq \epsilon. \quad (3.30)$$

On machines without guard digits, the relations (3.29) and (3.30) may fail to hold for addition and subtraction: we may only have the weaker relation

6.3

$$fl(x \pm y) = x(1 + \delta_1) \pm y(1 + \delta_2),$$

where

$$|\delta_i| \leq \epsilon \quad \text{for } i = 1, 2.$$

(3.31)

With these machines it seems difficult to be sure that rounding errors committed inside procedure glomin are harmless. At any rate, our analysis depends heavily on relation (3.29). (See equation (3.52) and the following analysis.)

We also suppose that square roots are computed with a small relative error, say

$$fl(\sqrt{x}) = \sqrt{x}(1 + \delta),$$

where

$$|\delta| \leq \epsilon.$$

(3.32)

(Any good square root routine should satisfy (3.32) very easily. The library routines for the IBM 360 certainly do: see Clark, Cody, Hillstom and Thieleker (1967).)

Let us first consider the effect of rounding errors in the computation of f , supposing for the moment that the internal computations of procedure glomin are done exactly. The user has to provide procedure glomin with a positive tolerance ϵ which gives a bound on the absolute error in computing f . More precisely, we assume that, for all δ and x with $|\delta| \leq \epsilon$ and $x, x(1 + \delta)$ in $[a, b]$, we have

$$|fl(f(x(1 + \delta))) - f(x)| \leq \epsilon, \quad (3.33)$$

where $f(x)$ is the exact mathematical function (satisfying condition (P.1)), and $fl(f(x))$ is its computed floating-point approximation. The

reason for condition (3.33) will be apparent later: at present we only need the special case with $\delta = 0$, i.e.,

$$|fl(f(x)) - f(x)| \leq e \quad (3.34)$$

for all $x \in [a, b]$.

We have seen that, without rounding errors, procedure glomin would return $\hat{\phi}$ (or $y = \text{glomin}$) and $\hat{\mu}$ (or x) satisfying

$$\phi_f \leq \hat{\phi} = f(\hat{\mu}) \leq \phi_f + t \quad (3.35)$$

With rounding errors, (3.35) no longer holds, but we shall show that

$$\phi_f \leq f(\hat{\mu}) \leq \phi_f + t + 2e \quad (3.36)$$

and

$$\phi_f - e \leq \hat{\phi} = fl(f(\hat{\mu})) \leq \phi_f + t + e \quad (3.37)$$

If the error e in computing f is much less than the tolerance t , then (3.36) and (3.37) are much the same as (3.35), so rounding errors have little effect on the accuracy of $\hat{\phi}$.

The left hand inequality in (3.36) is obvious from the definition of ϕ_f . To prove the right hand inequality, we must look closely at the "critical" sections of procedure glomin, i.e., the sections where rounding errors could make an essential difference. (Examples of non-critical sections are the random and non-random searches.)

In computing the safe choice a_3'' for a_3 according to equation (3.9), we compute

$$s = \sqrt{\frac{y_2 - \hat{\phi} + t}{m_2}} \quad (3.38)$$

and

$$r = -\frac{1}{2} \left(d_0 + \frac{(z_0 + 2.01e)}{d_0 m_2} \right) \quad (3.39)$$

where $d_0 = a_2 - a_1$, $z_0 = y_2 - y_1$, $m_2 = \frac{1}{2} M$, $\hat{\phi} = fl(f(\hat{\mu}))$, and $y_i = fl(f(a_i))$ for $i = 1, 2$. Thus

$$s \leq \sqrt{\frac{f(a_2) - f(\hat{\mu}) + (t + 2e)}{m_2}} \quad (3.40)$$

so, as far as the computation of s is concerned, everything said above holds if t is replaced by $t + 2e$. (Remember that we are regarding all computations inside the procedure as exact.) We are only interested in r when $d_0 > 0$ and $m_2 > 0$, and as

$$z_0 + 2.01e \geq z_0 + 2e \geq f(a_2) - f(a_1) \quad ,$$

we have

$$r \leq -\frac{1}{2} \left(d_0 + \frac{f(a_2) - f(a_1)}{d_0 m_2} \right) \quad (3.41)$$

(The reason for the extra 0.01e will be apparent later.) Thus, the computed a_3'' will not exceed the correct value given by (3.9), if t is replaced by $t + 2e$.

The other point where rounding errors in the computation of f are critical is when we determine whether the parabola $y = P(x)$, with $P''(x) = M$, $P(a_2) = y_2$, and $P(a_3) = y_3$, lies above the line $y = \hat{\phi} - t$ in the interval (a_2, a_3) . Let $y = Q(x)$ be the parabola with $Q''(x) = M$, $Q(a_2) = f(a_2)$, and $Q(a_3) = f(a_3)$. Since

$$y_i = \text{fl}(f(a_i)) \leq f(a_i) + e \quad \text{for } i = 2, 3,$$

it is clear that

$$P(x) \leq Q(x) + e \quad (3.42)$$

in (a_2, a_3) . Thus, if

$$P(x) \geq \hat{\phi} - t \quad (3.43)$$

in (a_2, a_3) , then

$$Q(x) \geq \hat{\phi} - t - e \geq f(\hat{\mu}) - t - 2e \quad (3.44)$$

in (a_2, a_3) , so again everything is accounted for by changing t to $t + 2e$. This completes the proof of (3.36). The left inequality in (3.37) is obvious, and the right inequality follows from the above argument if we note that it is sufficient to replace t by $t + (f(\hat{\mu}) - \hat{\phi})$.

Now, let us consider the effect of rounding errors committed inside procedure glomin. We shall show that (3.36) and (3.37) still hold, provided some minor modifications are made in the algorithm. These modifications are included in procedure glomin, but, to avoid confusion, they were not mentioned in the description above. The most important modification is that, instead of having $m_2 = \frac{1}{2} M$, procedure glomin has

$$m_2 = \text{fl}\left(\frac{1}{2}(1 + 16\varepsilon)M\right), \quad (3.45)$$

where the factor $1 + 16\varepsilon$ is introduced purely to nullify the effect of rounding errors.

For the sake of simplicity, terms of order ε^2 are ignored in the rest of this section. Because of the slack in some of our inequalities,

these terms may be accounted for if $\varepsilon \leq \frac{1}{400}$. From (3.45) and the assumption (3.29), we certainly have

$$m_2 \geq \frac{1}{2} (1 + 13\varepsilon)M. \quad (3.46)$$

In the computation of a_3'' according to (3.9), procedure glomin actually computes

$$\tilde{s} = \text{fl}\left(\frac{(y_2 - \hat{\phi}) + t}{m_2}\right)^{\frac{1}{2}}, \quad (3.47)$$

and as errors in the computation of f have already been accounted for, we can assume that y_2 and $\hat{\phi}$ are exact floating-point numbers. From (3.46) and the assumptions (3.29) and (3.32),

$$\tilde{s} \leq (1 + 3\delta_4) \left(\frac{((y_2 - \hat{\phi})(1 + \delta_1) + t)(1 + \delta_2)(1 + \delta_3)}{\frac{1}{2} M(1 + 13\varepsilon)} \right)^{\frac{1}{2}}, \quad (3.48)$$

where $|\delta_i| \leq \varepsilon$ for $i = 1, \dots, 4$. Since $y_2 - \hat{\phi}$ and t are both nonnegative,

$$(y_2 - \hat{\phi})(1 + \varepsilon) + t \leq (y_2 - \hat{\phi} + t)(1 + \varepsilon), \quad (3.49)$$

so

$$\tilde{s} \leq s = \left(\frac{y_2 - \hat{\phi} + t}{\frac{1}{2} M} \right)^{\frac{1}{2}}. \quad (3.50)$$

Thus, the slight modification of m_2 has ensured that the computed s is no greater than the exact s . Note that, in the derivation of (3.50), it was essential that $y_2 - \hat{\phi}$ was computed with a small relative error, so the assumption (3.29) was necessary: (3.31) would not be enough.

Similarly, to find a_3'' , we actually compute

$$\tilde{r} = \text{fl} \left[-\frac{1}{2} \left((a_2 - a_1) + \frac{(y_2 - y_1) + 2.01e}{(a_2 - a_1)m_2} \right) \right], \quad (3.51)$$

where $e > 0$, $m_2 > 0$, and $a_2 > a_1$. We are only interested in \tilde{r} if $\tilde{r} > 0$, so

$$\begin{aligned} 0 &> \text{fl}((y_2 - y_1) + 2.01e) \\ &\geq ((y_2 - y_1)(1 + \epsilon) + 2.01e(1 - \epsilon))(1 + \epsilon) \\ &\geq (y_2 - y_1 + 2e)(1 + \epsilon)^2, \end{aligned} \quad (3.52)$$

assuming that $\epsilon \leq \frac{1}{400}$. (The reason for the extra 0.01e in (3.49) is now clear.) Thus

$$\tilde{r} = \text{fl}(-\frac{1}{2}(r_1 + r_2)), \quad (3.53)$$

where

$$0 < (a_2 - a_1)(1 - \epsilon) \leq r_1 \leq (a_2 - a_1)(1 + \epsilon) \quad (3.54)$$

and

$$0 > r_2 \geq \frac{(y_2 - y_1 + 2e)(1 - 9\epsilon)}{\frac{1}{2}M(a_2 - a_1)}. \quad (3.55)$$

Since $\tilde{r} > 0$, (3.53) shows that $|r_1| < |r_2|$, so, from (3.53) to (3.55),

$$\tilde{r} \leq r \leq -\frac{1}{2} \left[(a_2 - a_1) + \left(\frac{y_2 - y_1 + 2e}{\frac{1}{2}M(a_2 - a_1)} \right) \right]. \quad (3.56)$$

As before, the computed \tilde{r} is no greater than the correct r . The same is not true for \tilde{a}_3'' , the computed value of a_3'' , but \tilde{a}_3'' is either b , $\text{fl}(a_2 + \tilde{r})$, or $\text{fl}(a_2 + \tilde{s})$. Suppose, for example, that

$$\tilde{a}_3'' = \text{fl}(a_2 + \tilde{s}). \quad (3.57)$$

Then

$$\text{fl}(f(\tilde{a}_3'')) = \text{fl}(f((a_2 + \tilde{s})(1 + \delta))) \quad (3.58)$$

where $|\delta| \leq \epsilon$, so, from (3.33),

$$|\text{fl}(f(\tilde{a}_3'')) - f(a_2 + \tilde{s})| \leq e. \quad (3.59)$$

(This is why we required (3.33) instead of the weaker (3.34).) Thus, the error in computing $a_2 + \tilde{s}$ or $a_2 + \tilde{r}$ can be ignored, for it has been absorbed into the assumption (3.33) on e .

Finally, we have to consider the effect of rounding errors when testing the condition (3.28). First

$$\tilde{p} = \text{fl} \left(\frac{y_2 - y_3}{\frac{1}{2}M(a_3 - a_2)} \right) \quad (3.60)$$

is computed. It is important to note that we use $\frac{1}{2}M$, not the slightly different m_2 (given by (3.45)) here. Thus

$$\tilde{p} = \frac{y_2 - y_3}{\frac{1}{2}M(a_3 - a_2)} \cdot (1 + 5\delta_1), \quad (3.61)$$

and

$$\tilde{d}_0 = \text{fl}(a_3 - a_2) = (a_3 - a_2)(1 + \delta_2), \quad (3.62)$$

6.3

where $|\delta_i| \leq \epsilon$ for $i = 1, 2$.

The test actually made by procedure glomin is whether

$$|\tilde{p}| < fl((1+9\epsilon)\tilde{d}_0) \wedge fl(\frac{1}{2}m_2(\tilde{d}_0^2 + \tilde{p}^2)) > fl[(y_2 - \hat{\phi}) + (y_3 - \hat{\phi}) + 2t], \quad (3.63)$$

and we shall show that (3.63) is true whenever the condition (3.28) is

true. First, $|p| < d_0$ implies that $|\tilde{p}| < d_0(1+5\epsilon)$, and thus

$$|\tilde{p}| < fl((1+9\epsilon)\tilde{d}_0). \quad (3.64)$$

Similarly, if $|p| < d_0$ and

$$\frac{1}{4}M(d_0^2 + p^2) > (y_2 - \hat{\phi}) + (y_3 - \hat{\phi}) + 2t, \quad (3.65)$$

then

$$\tilde{d}_0^2 + \tilde{p}^2 \geq (d_0^2 + p^2)(1 - 6\epsilon), \quad (3.66)$$

so

$$\begin{aligned} fl(\frac{1}{2}m_2(\tilde{d}_0^2 + \tilde{p}^2)) &\geq \frac{1}{4}M(d_0^2 + p^2)(1 + 4\epsilon) \\ &> ((y_2 - \hat{\phi}) + (y_3 - \hat{\phi}) + 2t)(1 + 3\epsilon) \\ &\geq fl((y_2 - \hat{\phi}) + (y_3 - \hat{\phi}) + 2t). \end{aligned} \quad (3.67)$$

(Note the importance of grouping the terms: since $y_2 - \hat{\phi}$, $y_3 - \hat{\phi}$ and $2t$ are all nonnegative, their sum can be computed with a small relative error.)

From (3.64) and (3.67), the inexact test (3.63) results in a_3 being reduced whenever the exact test (3.28) says that it must be. a_3 may occasionally be reduced unnecessarily because of rounding errors, but this does not invalidate the bounds (3.36) and (3.37), it merely causes some unnecessary function evaluations.

6.4

We should mention a remote possibility that rounding errors can prevent convergence. This is only possible if $fl(a_2 + \tilde{s}) = a_2$, and, as $\tilde{s} \geq (1 - 14\epsilon)(2t/M)^{1/2}$, there is no chance of it happening provided

$$t \geq M\epsilon^2 \max(a^2, b^2). \quad (3.68)$$

Thus, convergence can only be prevented by rounding errors if t is unreasonably small.

In conclusion, procedure glomin is guaranteed to return $\hat{\phi}$ and $\hat{\mu}$ satisfying the bounds (3.36) and (3.37), provided the input parameters macheps, t and ϵ are set correctly.

4. The rate of convergence in some special cases

It is difficult to say much in general about the number of function evaluations required by the algorithm described in Section 3. In the next section we compare the algorithm with the best possible one for given M and t . In this section, we try to gain some insight into the dependence of the number of function evaluations on the bound M and the tolerance t , by looking at some simple special cases.

The worst case

As pointed out above (equation (3.4)), two function evaluations are enough to determine $\hat{\mu}$ and $\hat{\phi}$ if $M \leq 0$, so suppose that $M > 0$, and let

$$\delta = \sqrt{\frac{2t}{M}}. \quad (4.1)$$

We showed above that, if the last function evaluation was at $a_2 c[a, b]$, we could safely choose

$$a_3 = \min(b, a_2 + \delta) \quad (4.2)$$

for the next evaluation (step 2 of the basic algorithm). With this simple choice of a_3 , about $(b-a)/\delta$ function evaluations would be required. Procedure glomin tries to do better than this, and is nearly always successful (see Section 6), but the worst that can happen is that a_3 will be chosen to be b , and then a_3 will be reduced several times at step 4 of the basic algorithm. As $a_3 - a_2$ is halved at each such reduction of a_3 , there can be at most

$$\left\lceil \log_2 \left(\frac{b - a_2}{\delta} \right) \right\rceil \leq \left\lceil \log_2 \left(\frac{b - a}{\delta} \right) \right\rceil \quad (4.3)$$

consecutive reductions of a_3 at step 4. Thus, at worst, about

$$\left(\frac{b - a}{\delta} \right) \log_2 \left(\frac{b - a}{\delta} \right) \quad (4.4)$$

function evaluations will be required. We have ignored the random and nonrandom searches, but these can only add about $2(\frac{b-a}{\delta})$ extra function evaluations.

If δ is given by (4.1), the term $\log_2(\frac{b-a}{\delta})$ in (4.4) varies only slowly with M and t , so the upper bound is roughly proportional to $(b-a)(M/t)^{1/2}$. In particular, the upper bound is roughly proportional to \sqrt{M} , and it seems to be a good general rule that the number of function evaluations is roughly proportional to \sqrt{M} , even when the upper bound (4.4) is not attained (see below and Section 6).

A straight line

If the global minimum of f occurs at an endpoint $\mu = a$ or b , and $f'(\mu) \neq 0$, we can gain an insight into the behaviour of the algorithm near μ by considering the linear approximation $f(\mu) + (x-\mu)f'(\mu)$ to $f(x)$. Suppose, for example, that

$$f(x) = k(x-a) + t \quad (4.5)$$

for some $k > 0$, so $\mu = a$. Ignoring the random searches, the algorithm will evaluate f at the points a, b, c , and then at points $x_1 < x_2 < x_3 < \dots < x_{N-1}$ say, where $x_0 = a < x_1$, $x_N \geq b$, and the points $(x_n, f(x_n))$ and $(x_{n+1}, f(x_{n+1}))$ lie on the parabola $y = P_n(x)$ which touches the line $y = 0$ and has $P_n''(x) = M$. (See Diagram 4.1.) If $P_n(x)$ touches $y = 0$ at $x = \alpha_n$, then

$$P_n(x) = \frac{1}{2}M(x - \alpha_n)^2, \quad (4.6)$$

so

$$\alpha_n = x_n + \sqrt{\frac{2}{M}(k(x_n - a) + t)} = x_{n+1} - \sqrt{\frac{2}{M}(k(x_{n+1} - a) + t)}. \quad (4.7)$$

If

$$z_n = \sqrt{x_n - a + t/k}, \quad (4.8)$$

then (4.7) gives

$$z_{n+1} = z_n + \sqrt{\frac{2k}{M}}, \quad (4.9)$$

so

$$z_n = \sqrt{\frac{t}{k}} + n \sqrt{\frac{2k}{M}}. \quad (4.10)$$

Thus

$$x_n = a + n \sqrt{\frac{8t}{M}} + n^2 \cdot \left(\frac{2k}{M}\right), \quad (4.11)$$

and as N is the least positive n such that $x_n \geq b$, this gives

$$N = \left\lceil \frac{\sqrt{\frac{1}{2}M}}{k} \left(\sqrt{k(b-a) + t} - \sqrt{t} \right) \right\rceil. \quad (4.12)$$

(4.12) shows that N is essentially proportional to \sqrt{M} .

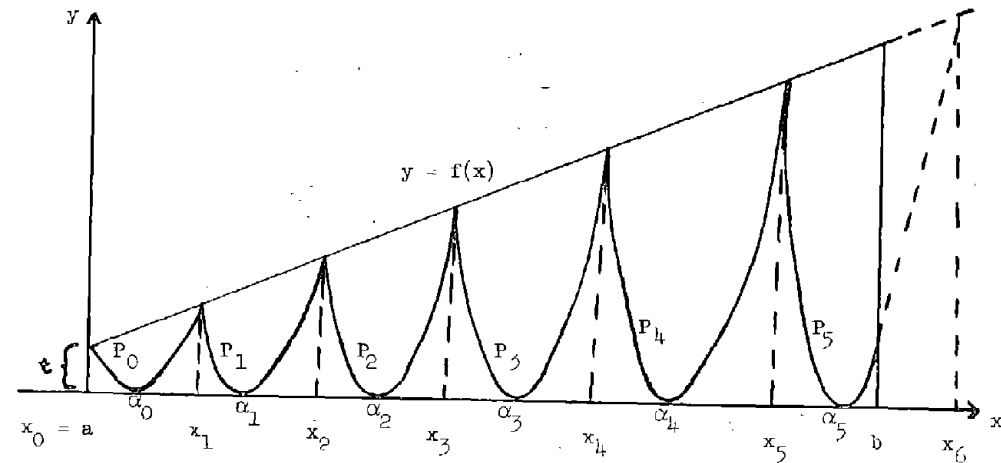


Diagram 4.1: A straight line, $f(x) = k(x-a) + t$ (for $N = 6$)

Two limiting cases of (4.12) are interesting. If t is small and k not too small, so that $k(b-a) \gg t$, then

$$N \simeq \sqrt{\frac{M(b-a)}{2k}}, \quad (4.13)$$

which is independent of t . (In this section we are neglecting the

effect of rounding errors, but these should not be important if t satisfies the weak condition (3.68).)

If k is very small, so that $k(b-a) \ll t$, then (4.12) gives

$$N \simeq \frac{1}{2} (b-a)/\delta, \quad (4.14)$$

and the algorithm proceeds in steps of size about 2δ , where δ is given by (4.1).

A parabola

If the global minimum of f occurs at an interior point μ , then $f'(\mu) = 0$, so if $f''(\mu) \neq 0$ we may analyse the behaviour of the algorithm near μ by considering the parabolic approximation $f(\mu) + \frac{1}{2} f''(\mu)(x-\mu)^2$ to $f(x)$. Thus, suppose that

$$M > m > 0 \quad (4.15)$$

and

$$f(x) = \frac{1}{2} m(x-\mu)^2 + t, \quad (4.16)$$

where $\mu \in (a, b)$. The nonrandom search will quickly locate μ , so we may suppose that $\hat{\mu} = \mu$, and, without loss of generality, $\mu = 0$. The algorithm will call for the evaluation of f at points to the left, and then to the right, of μ . As these two cases are similar, let us define $x_0 = \mu = 0$, and study the points x_1, x_2, \dots defined above, except that now f is given by (4.16) instead of by (4.5). In place of (4.7), we find that

$$\alpha_n = x_n + \sqrt{\frac{m}{M} \left(x_n^2 + \frac{2t}{m} \right)} = x_{n+1} - \sqrt{\frac{m}{M} \left(x_{n+1}^2 + \frac{2t}{m} \right)}. \quad (4.17)$$

It does not seem to be possible to give a simple expression like (4.11) for x_n , defined by the recurrence relation (4.17), but we may solve for x_{n+1} in terms of x_n , obtaining

$$x_{n+1} = \left(\frac{M+m}{M-m} \right) x_n + \left(\frac{2M}{M-m} \right) \sqrt{\frac{m}{M} \left(x_n^2 + \frac{2t}{m} \right)}. \quad (4.18)$$

If

$$\rho = (M/m)^{1/2}, \quad (4.19)$$

this may be written as

$$x_{n+1} = \left(\frac{\rho+1}{\rho-1} \right) x_n + \left(\frac{2\rho}{\rho^2-1} \right) \left(\sqrt{x_n^2 + \frac{2t}{m}} - x_n \right). \quad (4.20)$$

Suppose that ρ is close to 1, i.e., M is not much larger than $m = f''(\mu)$. Then

$$x_1 = \left(\frac{2\rho}{\rho^2-1} \right) \sqrt{\frac{2t}{m}}. \quad (4.21)$$

For $n \geq 1$, the first term in (4.20) dominates the second, and

$$x_{n+1} = \left(\frac{\rho+1}{\rho-1} \right) x_n (1 + O((\rho-1)^2)) \quad \text{as } \rho \rightarrow 1. \quad (4.22)$$

Thus, if ρ is close to 1, then

$$x_n \approx \left(\frac{\rho+1}{\rho-1} \right)^n \sqrt{\frac{2t}{m}} \quad (4.23)$$

for $n \geq 1$, and, as the factor $\frac{\rho+1}{\rho-1}$ is large, only a few function evaluations will be required.

5. A lower bound on the number of function evaluations required

Suppose that a positive tolerance t and bound M are given, that f attains its global minimum ϕ_f in $[a, b]$ at μ_f , and that

$$f''(x) < M \quad (5.1)$$

for all $x \in [a, b]$. (Similar results to those below hold if equality is allowed, but the definitions and proofs have to be modified slightly.)

First, we need a lemma.

Lemma 5.1

If $x' \in [a, b]$, then there is at most one point $x'' \in (x', b]$, such that the parabola $y = P(x)$, with $P'(x) = M$, $P(x') = f(x')$, and touching the line $y = \phi_f - t$, satisfies $P(x'') = f(x'')$.

Proof

Suppose, by way of contradiction, that two such distinct points x'' and x''' exist. Then

$$M = 2f[x', x'', x'''] = f''(\xi) \quad (5.2)$$

for some $\xi \in (x', b]$ (see Chapter 2), contradicting

$$f''(\xi) < M. \quad (5.3)$$

Definition 5.1

For $x' \in [a, b]$, define

$$s(x') = \begin{cases} x'' & \text{if the point } x'' \text{ of Lemma 5.1 exists,} \\ b & \text{otherwise.} \end{cases}$$

Lemma 5.2

If $x \in [a, b]$ and $s(x) \neq b$, then

$$s(x) - x \geq \sqrt{\frac{8t}{M}}. \quad (5.4)$$

Proof

This follows by considering the parabola, with second derivative M , which passes through $(x, f(x))$ and $(s(x), f(s(x)))$, and touches the line $y = \varphi_f - t$, since $f(x) \geq \varphi_f$ and $f(s(x)) \geq \varphi_f$.

Definition 5.2

An integer N and points $a = x_1 < x_2 < x_3 < \dots < x_N = b$ are defined thus:

$$x_1 = a,$$

and, for $n \geq 2$ and $x_{n-1} < b$,

$$x_n = s(x_{n-1}). \quad (\text{See Diagram 5.1.})$$

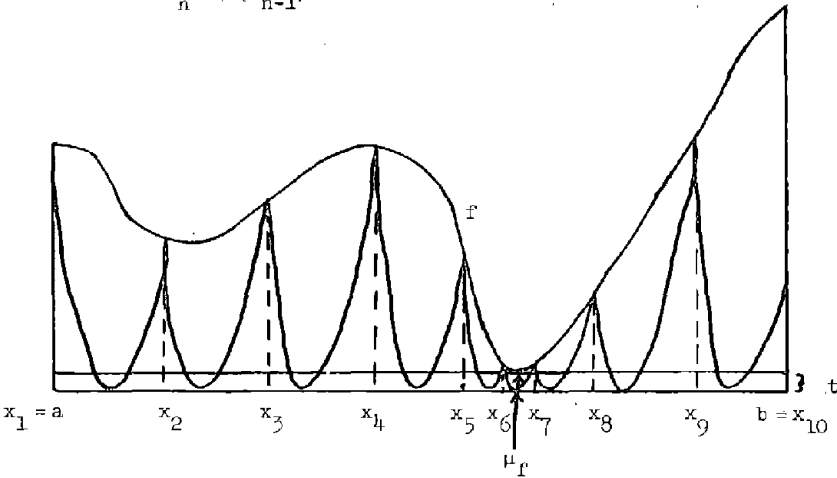


Diagram 5.1: The points x_1, \dots, x_N (for $N = 10$)

Lemma 5.2 shows that N is finite, in fact

$$N \leq 1 + \lceil (b-a)(M/(8t))^{1/2} \rceil. \quad (5.5)$$

The following lemma shows that, in order to prove that $f(x) \geq \varphi_f - t$ for all $x \in [a, b]$, given only condition (5.1), it is sufficient to evaluate f at x_1, x_2, \dots, x_N .

Lemma 5.3

If $g \in C^2[a, b]$, $g''(x) \leq M$ for all $x \in [a, b]$, and

$$g(x_n) = f(x_n) \quad (5.6)$$

for $n = 1, 2, \dots, N$ and the points x_n defined above, then

$$\varphi_g \geq \varphi_f - t. \quad (5.7)$$

Proof

The lemma follows immediately from the definitions and Theorem 2.1. (Clearly, weaker conditions on g , e.g. condition (2.1), are sufficient.)

Our interest in the points x_1, \dots, x_N stems from the following theorem, which complements Lemma 5.3.

Theorem 5.1

Let $x'_1 < x'_2 < \dots < x'_v$ be any v points in $[a, b]$, with $v < N$. Then there is a function $g \in C^\infty[a, b]$, satisfying

$$g''(x) < M \quad (5.8)$$

for all $x \in [a, b]$, and

$$g(x'_n) = f(x'_n) \quad (5.9)$$

for $n = 1, 2, \dots, v$, such that

$$\varphi_g < \varphi_f - t. \quad (5.10)$$

Proof

Suppose, by way of contradiction, that

$$\varphi_g \geq \varphi_f - t \quad (5.11)$$

for all such g . Then $x'_1 = a$, for otherwise $-g(a)$ can be arbitrarily large, and, similarly, $x'_v = b$. Since $v < N$, there is an n , $1 \leq n < v$, such that $x'_n \leq x_n$ and $x'_{n+1} > x_{n+1}$. Thus, the parabola $y = P(x)$, with $P'(x) = M$, $P(x'_n) = f(x'_n)$, and $P(x'_{n+1}) = f(x'_{n+1})$, is such that

$$\min_{x \in [x'_n, x'_{n+1}]} P(x) < \varphi_f - t. \quad (5.12)$$

Since there is a function g as above which is arbitrarily close to $P(x)$ in $[x'_n, x'_{n+1}]$, this contradicts (5.11), so the theorem holds.

Consequences of the theorem

Theorem 5.1 says that, if all that is known a priori about f is that $f \in C^2[a, b]$ and satisfies condition (5.1), then any algorithm, which is guaranteed to find $\hat{\mu}$ so that $f(\hat{\mu}) \leq \varphi_f + t$, must require at least N evaluations of f . This is so because, if an algorithm required only $v < N$ evaluations at points $x'_1 < x'_2 < \dots < x'_v$, say,

then it would be sure to fail for either f or for g , for f and g are indistinguishable on the basis of the v function evaluations, yet $\varphi_g + t < \varphi_f$. Of course, we are only considering algorithms which sequentially evaluate f at a finite number of points.

Conversely, Lemma 5.3 implies that $N+1$ function evaluations are sufficient (just evaluate f at μ_f and x_1, \dots, x_N), and possibly N are sufficient. (See Diagram 5.1.) Unfortunately, Lemma 5.3 does not give us an effective algorithm for approximating φ_f , for we do not know N or the points x_2, \dots, x_{N-1} in advance, and a large number of function evaluations is usually needed to approximate them.

Efficiency

Suppose that an algorithm requires N' function evaluations to find $\hat{\varphi} = f(\hat{\mu})$ such that $\hat{\varphi} \leq \varphi_f + t$ is guaranteed. We could define the efficiency E of the algorithm by

$$E = N/N'. \quad (5.13)$$

(Note that E depends on f , M , t , a and b , as well as on the algorithm.) We have shown that

$$E \leq 1 \quad (5.14)$$

for any correct (i.e., guaranteed) algorithm, so, if an algorithm has an efficiency close to 1, then we are justified in saying that the algorithm is nearly optimal (for that f , M , t etc.). In the next section we give numerical results which show that, for practical examples, the algorithm described in Section 3 is often nearly optimal.

6. Practical tests

The ALGOL procedure glomin given in Section 10 was tested using ALGOL W (Wirth and Hoare (1966), Bauer, Becker and Graham (1968)) on an IBM 360/91 computer with machine precision 16^{-13} . Some representative numerical results are summarized in Table 6.1. For all of these results the parameters ϵ and macheps were set at 10^{-14} and 16^{-13} respectively.

The table gives the upper bound M (parameter m of glomin) on f'' , and the total number of function evaluations required by procedure glomin: N'' with tolerance $t = 10^{-8}$, and N' with tolerance $t = 10^{-12}$. The lower bound N defined in Section 5 is also given for $t = 10^{-12}$. (Recall that no algorithm which is guaranteed to succeed can take less than N function evaluations.) N and the points x_1, \dots, x_N (see Section 5) were computed in the obvious way from Definition 5.2, using procedure zero of Chapter 4 to solve the nonlinear equation

$$P(x) = f(x), \quad (6.1)$$

where $P(x)$ is the parabola of Lemma 5.1. Finally, the efficiency $E = N/N'$ (equation (5.13)) is given.

For some more numerical results, see Section 8.

Table 6.1: Numerical results for procedure glomin

f	M	N''	N'	N	$E = N/N'$
f_1	0	2	2	2	1.00
	100	15	15	11	0.73
	10000	106	106	101	0.95
f_2	2	4	4	2	0.50
	2.1	8	11	8	0.73
	2.2	9	13	9	0.69
	8	25	34	29	0.85
	32	48	68	60	0.88
	128	95	141	120	0.85
f_3	14	38	51	37	0.73
	28	48	68	54	0.79
	56	67	98	76	0.78
f_4	72	222	246	126	0.51
f_5	72	456	542	437	0.81

The symbols are explained above. The functions are:

$$f_1(x) = 2 - x \text{ on } [7, 9] \text{ (in all cases } \hat{\mu} = 9, \hat{\phi} = 7),$$

$$f_2(x) = x^2 \text{ on } [-1, 2] \text{ (in all cases } \hat{\mu} = \hat{\phi} = 0),$$

$$f_3(x) = x^2 + x^3 \text{ on } [-\frac{1}{2}, 2] \text{ (for } t = 10^{-12}, |\hat{\mu}| < 3 \cdot 10^{-10}, |\hat{\phi}| < 6 \cdot 10^{-20}),$$

$$f_4(x) = (x + \sin(x)) \exp(-x^2) \text{ on } [-10, 10] \text{ } (\hat{\mu} = -0.6795786599525, \\ \hat{\phi} = -0.824239398476077), \text{ and}$$

$$f_5(x) = (x - \sin(x)) \exp(-x^2) \text{ on } [-10, 10]$$

$$(\hat{\mu} = -1.195136641665, \hat{\phi} = -0.0634905289364399).$$

Comments on Table 6.1

The results for the simple functions $f_1(x) = 2 - x$ and $f_2(x) = x^2$ verify the predictions made in Section 4. For example, the values $N = 11$ and $N = 101$ for f_1 are exactly as predicted: one more than the right side of equation (4.12). N , N' and N'' are roughly proportional to \sqrt{M} if $M \gg f''(\mu)$ (see also the results for f_3), but this rule breaks down if $M \approx f''(\mu)$, as expected from equation (4.23). (See the results for f_2 with $M = 2, 2.1, 2.2$.)

It appears that the number of function evaluations does not depend strongly on t : comparing N'' with N' , we see that the average number of function evaluations required is only about 20 percent more for $t = 10^{-12}$ than for $t = 10^{-8}$.

Finally, the efficiency E of the algorithm is fairly high, even for the difficult functions f_4 and f_5 . This means that no correct algorithm based entirely on function evaluations could do very much better than ours, at least on these examples. This is not too surprising, in view of the results of Section 5.

7. Some extensions and generalizations

So far we have assumed that $f \in C^2[a, b]$ and

$$f''(x) \leq M \quad (7.1)$$

for all $x \in [a, b]$, or at least that $f \in C^1[a, b]$ and

$$f'(x) - f'(y) \leq M(x - y) \quad (7.2)$$

for $a \leq y < x \leq b$. Condition (7.2) was necessary to prove the basic Theorem 2.1. For the application discussed in Section 8 (global minimization of a function of several variables), we need to find the global minimum of a function which is continuous, but not necessarily differentiable. We can justify using procedure glomin, even though f may not be differentiable, because of the following Theorems 7.1 to 7.3, which generalize Theorems 2.1 to 2.3. (If the reader is prepared to accept the fact that Theorems 2.1 to 2.3 can be generalized in the appropriate way, he may skip this section.)

Theorem 7.1

Let $f \in C[a, b]$, and suppose that there is a constant M such that, for all sufficiently small $h > 0$,

$$f(u+h) - 2f(u) + f(u-h) \leq Mh^2 \quad (7.3)$$

for all $u \in [a+h, b-h]$. Then, for all $x \in [a, b]$,

$$f(x) \geq \frac{(b-x)f(a) + (x-a)f(b)}{b-a} - \frac{1}{2}M(x-a)(b-x) \quad (7.4)$$

Proof

There is no loss of generality in assuming that

$$f(a) = f(b) = 0 \quad (7.5)$$

and

$$M = 0 \quad (7.6)$$

for we can consider $f(x) - P(x)$, where $P(x)$ is the right side of (7.4), instead of $f(x)$. Thus, we have to show that

$$\varphi_f \geq 0, \quad (7.7)$$

where φ_f is the least value of f on $[a, b]$. Suppose, by way of contradiction, that

$$\varphi_f < 0, \quad (7.8)$$

and let

$$u = \sup\{x \in [a, b] \mid f(x) = \varphi_f\}. \quad (7.9)$$

By the continuity of f , $f(u) = \varphi_f < 0$, so $u \neq a$ or b . Thus, for sufficiently small $h > 0$, $u \in [a+h, b-h]$, and, from the definition of u ,

$$f(u-h) \geq f(u) \quad (7.10)$$

and

$$f(u+h) > f(u). \quad (7.11)$$

Because of the assumption (7.6), this contradicts (7.3), so (7.8) is impossible, and the result follows. (Note the close connection with the maximum principle for elliptic difference operators.)

Theorem 7.2

Suppose that (7.3) holds, $M > 0$, $a \leq c_1 < c_2 \leq b$, and $f(a) \geq f(c_1) - f(c_2)$. Then

$$c_2 - a > \sqrt{\frac{f(a) - f(c_1)}{\frac{1}{2}M}}. \quad (7.12)$$

Proof

Apply Theorem 7.1 with x replaced by c_1 and b by c_2 . The

hypothesis that $f(c_1) = f(c_2)$ gives, after some simplification,

$$(c_1 - a)(c_2 - a) \geq \frac{f(a) - f(c_1)}{\frac{1}{2}M}, \quad (7.13)$$

and the result follows as $c_2 - a > c_1 - a \geq 0$.

Theorem 7.3

Suppose that (7.3) holds, $M > 0$, $a < c \leq b$, and the interval $I = [c, b] \cap [c, \frac{a+c}{2} - \frac{f(a) - f(c)}{M(a-c)}]$ has positive length. Then $f(x)$ is strictly monotonic decreasing on I .

Proof.

Suppose $x_1, x_2 \in I$ with $x_1 < x_2$. We have to show that

$$f(x_1) > f(x_2). \quad (7.14)$$

Apply Theorem 7.1, first with x replaced by c and b by x_1 , then with a replaced by c , x by x_1 and b by x_2 . The two resulting inequalities give, after some simplification,

$$\frac{f(x_1) - f(x_2)}{M(x_2 - x_1)} \geq \frac{a+c}{2} - \frac{f(a) - f(c)}{M(a-c)} - \frac{x_1 + x_2}{2}. \quad (7.15)$$

Since $\frac{x_1 + x_2}{2} < x_2$, the right side of (7.15) is positive, so (7.14) holds.

Remarks

Theorems 7.1 to 7.3 generalize Theorems 2.1 to 2.3 respectively.

Since the algorithm described in Section 3 is based entirely on Theorems 2.1 to 2.3, it is clear that condition (7.3) is sufficient for the algorithm to find a correct approximation to the global minimum of f . This is not surprising, for condition (7.3) is equivalent to (7.2) if $f \in C^1[a,b]$, and is equivalent to (7.1) if $f \in C^2[a,b]$. In the next section, we use this result to develop an algorithm for finding the global minimum of a function f of several variables. The conditions on f are much weaker than those required by Newman (1965), Sugie (1964), or Krolak and Cooper (1963). (See also Kaupe (1964) and Kiefer (1957).)

8. An algorithm for global minimization of a function of several variables

Suppose that $D = [a_x, b_x] \times [a_y, b_y]$ is a rectangle in R^2 , $f: D \rightarrow R$ has continuous second derivatives on D , and constants M_x and M_y are known such that

$$f_{xx}(x,y) \leq M_x \quad (8.1)$$

and

$$f_{yy}(x,y) \leq M_y, \quad (8.2)$$

for all $(x,y) \in D$. Let us define $\varphi: [a_y, b_y] \rightarrow R$ by

$$\varphi(y) = \min_{x \in [a_x, b_x]} f(x,y). \quad (8.3)$$

Clearly $\varphi(y)$ is continuous, and

$$\min_{(x,y) \in D} f(x,y) = \min_{y \in [a_y, b_y]} \varphi(y). \quad (8.4)$$

Thus, we have reduced the minimization of $f(x,y)$, a function of two variables, to the minimization of functions of one variable. Procedure glomin (see Sections 3 and 10) can be used to evaluate $\varphi(y)$ for a given y , using condition (8.1). If we could show that

$$\varphi''(y) \leq M_y, \quad (8.5)$$

then procedure glomin could be used again (recursively) to minimize $\varphi(y)$, and thus, from (8.4), $f(x,y)$. Unfortunately, examples show that $\varphi(y)$ need not be differentiable everywhere in $[a_y, b_y]$, so (8.5) may be meaningless (we shall see below that (8.5) holds when $\varphi''(y)$ exists). For example, consider

$$f(x,y) = xy \quad (8.6)$$

on $D = [-1,1] \times [-1,1]$. Then

$$\varphi(y) = \min(y, -y) = -|y|, \quad (8.7)$$

which is not differentiable at $y = 0$, and we can not expect to prove (8.5). The same problem may arise if the minimum in (8.3) occurs at an interior point of D : one example is

$$f(x,y) = (x^3 - 3x)\sin(y) \quad (8.8)$$

on $D = [-\sqrt{3}, \sqrt{3}] \times [-10, 10]$. ($f_x(x,y)$ vanishes for $x = \pm 1$, so $\varphi(y) = -2|\sin(y)|$, which is not differentiable at $0, \pm\pi$, etc.)

Fortunately, the following theorem shows that $\varphi(y)$ does satisfy a condition like (7.3), so the results of Section 7 show that procedure glomin can be used to find the global minimum of $\varphi(y)$, just as if (8.5) held.

Theorem 8.1

Let $f(x, y)$ and $\varphi(y)$ be as above. Then, for all $h > 0$ and $y \in [a_y + h, b_y - h]$,

$$\varphi(y+h) - 2\varphi(y) + \varphi(y-h) \leq M_y h^2. \quad (8.9)$$

Proof

From the definition (8.3) of $\varphi(y)$, there is a function $\mu(y)$ from $[a_y, b_y]$ into $[a_x, b_x]$ (not necessarily continuous), such that

$$\varphi(y) = f(\mu(y), y). \quad (8.10)$$

Thus

$$\varphi(y+h) \leq f(\mu(y), y+h), \quad (8.11)$$

so

$$\varphi(y+h) - 2\varphi(y) + \varphi(y-h) \leq f(\mu(y), y+h) - 2f(\mu(y), y) + f(\mu(y), y-h), \quad (8.12)$$

and the result follows from condition (8.2).

Corollary 8.1

For all $y \in [a_y, b_y]$ at which $\varphi''(y)$ exists,

$$\varphi''(y) \leq M_y. \quad (8.13)$$

Functions of n variables

Theorem 8.2 generalizes Theorem 8.1 to functions of any finite number of variables.

Theorem 8.2

Suppose that $n \geq 1$, I_1 is a nonempty compact set in \mathbb{R} for $i = 1, \dots, n+1$, $D = I_1 \times I_2 \times \dots \times I_{n+1} \subseteq \mathbb{R}^{n+1}$, $f: D \rightarrow \mathbb{R}$ is continuous,

and

$$f(\underline{x} + h\mathbf{e}_1) - 2f(\underline{x}) + f(\underline{x} - h\mathbf{e}_1) \leq M_1 h^2 \quad (8.14)$$

for all sufficiently small $h > 0$, all $\underline{x} \in \mathbb{R}^{n+1}$ such that $\underline{x}, \underline{x} \pm h\mathbf{e}_1 \in D$, and $i = 1, 2, \dots, n+1$. Let $D' = I_1 \times \dots \times I_n$, and define $\varphi: D' \rightarrow \mathbb{R}$ by

$$\varphi(\underline{y}) = \min_{x \in I_{n+1}} f(y_1, \dots, y_n, x). \quad (8.15)$$

Then φ is continuous on D' ,

$$\min_{\underline{x} \in D} f(\underline{x}) = \min_{\underline{y} \in D'} \varphi(\underline{y}), \quad (8.16)$$

and

$$\varphi(\underline{y} + h\mathbf{e}_j) - 2\varphi(\underline{y}) + \varphi(\underline{y} - h\mathbf{e}_j) \leq M_j h^2 \quad (8.17)$$

for all sufficiently small $h > 0$, $\underline{y} \in \mathbb{R}^n$ such that $\underline{y}, \underline{y} \pm h\mathbf{e}_j \in D'$, and $j = 1, 2, \dots, n$. (Here \mathbf{e}_1 is a unit vector in \mathbb{R}^{n+1} , and \mathbf{e}_j is a unit vector in \mathbb{R}^n .)

Proof

The proof is a straight-forward generalization of the proof of Theorem 8.1, so the details are omitted.

Theorem 8.2 shows that it is possible to use procedure glomin to find the global minimum of a function $f(x_1, \dots, x_n)$ of any finite number $n \geq 1$ of variables, provided upper bounds are known for the partial derivatives $f_{x_i x_i}(x)$ ($i = 1, \dots, n$). It is interesting that no bounds on the cross derivatives $f_{x_i x_j}(x)$ ($i \neq j$) are necessary.

If a one-dimensional minimization using procedure `glomin` requires about K function evaluations, then we would expect that about K^n function evaluations would be required for an n -dimensional minimization. Since K is likely to be in the range $10 \leq K \leq 100$ in practice (see Section 6), the computation involved is likely to be excessive for $n > 3$. Thus, for functions of more than three variables, we probably must be satisfied with methods which find local, but not necessarily global, minima (see Chapter 7). It should be noted, however, that the theorems of Section 5 do not extend to functions of more than one variable, so we do not know how far our procedure is from the best possible (given only upper bounds on $f_{x_i x_i}$ for $i = 1, \dots, n$). Thus, there is a chance that a much better method for finding the global minimum of a function of several variables exists. It is also possible that slightly stronger a priori conditions on f (e.g., both upper and lower bounds on certain derivatives) might enable us to find the global minimum much more efficiently.

Minimization of a function of two variables: procedure `glomin2d`

In Section 10 we give an ALGOL 60 procedure (`glomin2d`) for finding the global minimum of a function $f(x,y)$ of two variables, using the method suggested above. Note that `glomin2d` uses procedure `glomin` in a recursive manner, for `glomin` is required both to evaluate and to minimize ϕ . The error bounds given in the initial comment of procedure `glomin2d` are easily derived from the error bounds (3.36) and (3.37) for procedure `glomin`.

Procedure `glomin2d` was tested on an IBM 360/91 computer (using ALGOL W), and some numerical results are summarized in Table 8.1. In all cases shown in the table the parameters `macheps`, `e` and `t` were set at 16^{-13} , 10^{-14} and 10^{-10} respectively. (Thus $\phi_f - 10^{-14} \leq \hat{\phi} \leq \phi_f + 1.0002 \times 10^{-10}$ is guaranteed, where ϕ_f is the true minimum of f , and $\hat{\phi}$ is the value returned by the procedure.) In the table we give the upper bounds M_x and M_y (see equations (8.1) and (8.2)), the total number of function evaluations N , and the approximate global minimum $\hat{\phi}$ (always very close to the true global minimum ϕ_f).

Table 8.1: Numerical results for procedure glomin2d

f	M_x	M_y	N	$\hat{\phi}$
f_1	0	0	4	-1
	4	4	9	-1
f_2	2	4	51	0
	2	10	116	0
	10	4	446	3'-35
	10	10	956	4'-39
f_3	2210	200	13320	2'-18
f_4	200	2210	1815	0
f_5	4	4	1954	-0.396652961085471
f_6	4	4	100336	-0.396652961085468
	8	8	130496	-0.396652961085434

The symbols are explained above. The functions are:

$$f_1(x,y) = 133 + 99x - 35y \quad \text{on } [-1,1] \times [-1,1];$$

$$f_2(x,y) = x^2 + xy + 2y^2 \quad \text{on } [-1,3] \times [-2,4];$$

$$f_3(x,y) = 100(y-x^2)^2 + (1-x)^2 \quad \text{on } [-1.2,1.2] \times [-1.2,1.2];$$

$$f_4(x,y) = f_3(y,x) \quad \text{on the same domain};$$

$$f_5(x,y) = \sin(x)\cos(y)\exp(-(x^2+y^2)) \quad \text{on } [-1,2] \times [-1,2];$$

$$f_6(x,y) = f_5(x,y) \quad \text{on } [-2,4] \times [-2,4].$$

Comments on Table 8.1

The results for the simple functions f_1 and f_2 are not very surprising. As expected from the behaviour of procedure glomin on functions of one variable (see Sections 5 and 6), the number of function evaluations (N) increases with M_x and M_y .

$f_3(x,y) = 100(y-x^2)^2 + (1-x)^2$ is the well-known Rosenbrock function (Rosenbrock (1960)), and it has a steep curved valley along the parabola $y = x^2$. $f_4(x,y) = f_3(y,x)$ is just the Rosenbrock function in disguise, and it is interesting that only 1815 function evaluations were required to minimize f_4 , compared to 13320 for f_3 . Thus, it can make a large difference whether we minimize first over x (with y fixed) and then over y , or vice versa, but it is difficult to give a reliable rule as to which should be done first. Of course, even the lower figure of 1815 function evaluations is very high by comparison with 100 or less for methods which seek local minima (see Chapter 7), but perhaps this is the price which must be paid to guarantee that we do have the global minimum. (This is only a conjecture, for the results of Section 5 have not been extended to functions of several variables.)

The functions f_5 and f_6 are the same, but the domain of f_6 is four times as large as the domain of f_5 . For this function the size of the domain has much more influence on N than do the bounds M_x and M_y : increasing the size of the domain by a factor of four increased N by a factor of about 50, but doubling M_x and M_y only increased N by about 30 percent. With a different function, though, we could easily reach the opposite conclusion. (f_2 is one example.)

To summarize: if it is possible to give upper bounds M_x and M_y on the partial second derivatives f_{xx} and f_{yy} , then procedure `glomin2d` will find a guaranteed good approximation to the global minimum, but the number of function evaluations required may be considerable, especially if the domain of f is large or if the bounds M_x and M_y are weak. As for one-dimensional minimization, the size of the tolerance t has a fairly small influence on the total number of function evaluations required.

Finally, we should note that we have restricted ourselves to rectangular domains merely for the sake of simplicity: there is no real difficulty in dealing with nonrectangular domains.

9. Summary and conclusions

In Section 1 we saw that the problem of finding the global minimum $\phi_F = f(\mu_F)$ of a function f defined on a compact set is well-posed, whereas the problem of finding μ_F is not well-posed. To be sure to find the global minimum, some a priori conditions on f are necessary, and several possible conditions were discussed in Section 1. We concentrated our attention mainly on one such condition, a given upper bound on f'' , and small variations of this condition.

An efficient algorithm for one-dimensional global minimization, based on theorems in Sections 2 and 7, is described in Section 3. The effect of rounding errors, and the number of function evaluations required, are discussed in Sections 3 to 5, and numerical results are given in Section 6. Finally, in Section 8 the results for functions of

one variable are used to give an algorithm for finding the global minimum of a function of several variables (practically useful for two or three variables), and ALGOL procedures are given in Section 10. The ALGOL procedures are guaranteed to give correct results, provided the basic arithmetic operations are performed with a small relative error (see the remark following equation (3.30)).

For practical problems, the main difficulty in using the results of this chapter lies in finding the necessary bounds on second derivatives. One intriguing idea is that, if $f(x)$ were expressed in terms of elementary functions, then the second derivatives could be computed symbolically, and upper bounds could then be obtained from the symbolic second derivatives by using simple inequalities. Thus, the entire process of finding the global minimum could be automated. In some cases functions defined on infinite domains could also be dealt with automatically by using suitable elementary transformations.

10. ALGOL 60 procedures

The ALGOL procedures `glomin` (for global minimization of a function of one variable) and `glomin2d` (for global minimization of a function of two variables) are given below. The algorithms and some numerical results are described in Sections 3 to 6 and 8.

Procedure glomin

real procedure glomin (a, b, c, m, macheps, e, t, f, x);

value a, b, c, m, macheps, e, t;

real a, b, c, m, macheps, e, t, x; real procedure f;

begin comment:

Glomin returns the global minimum y at x of the function $f(x)$ defined on $[a, b]$. The procedure assumes that $f \in C^{(2)}[a, b]$ and $f''(x) \leq m$ for all $x \in [a, b]$ (weaker conditions are sufficient: see the text). e and t are positive tolerances: we assume that $f(x)$ is computed with an absolute error bounded by e ; i.e., that $|fl(f(x(1+macheps))) - f(x)| \leq e$, where macheps is the relative

machine precision. Then x and $y = glomin$ are returned so that

$\min(f) \leq f(x) \leq \min(f) + t + 2e$ and

$\min(f) - e \leq y = fl(f(x)) \leq \min(f) + t + e$.

c is an initial guess at x (a or b will do). The number of function evaluations required is usually close to the least possible, and considerably less than $(b-a)(m/8t)^{1/2}$, provided t is not unreasonably small (see Sections 3 to 5);

integer k; real a0, a2, a3, d0, d1, d2, b, m2, p, q, qs, r, s, y, y0, y1, y2, y3, yb, z0, z1, z2;

comment: Initialization;

$x := a0 := b; a2 := a;$

$yb := y0 := f(b); y := y2 := f(a);$

if $y0 < y$ then $y := y0$ else $x := a;$

if $m > 0 \wedge a < b$ then

begin comment: Nontrivial case ($m > 0, a < b$);

$m2 := 0.5 \times (1 + 16 \times macheps) \times m;$

if $c \leq a \vee c \geq b$ then $c := 0.5 \times (a+b);$

$y1 := f(c); k := 3; d0 := a2 - c; h := 9/11;$

if $y1 < y$ then

begin $x := c; y := y1$ end;

comment: Main loop

next: $d1 := a2 - a0; d2 := c - a0;$

$z2 := b - a2; z0 := y2 - y1; z1 := y2 - y0;$

$p := r := d1 \times d1 \times z0 - d0 \times d0 \times z1;$

$q := qs := 2 \times (d0 \times z1 - d1 \times z0);$

comment: Try to find a lower value of f using quadratic interpolation;

if $k > 100000 \wedge y < y2$ then go to skip;

retry: if $q \times (r \times (yb - y2) + z2 \times q \times ((y2 - y) + t))$

$< z2 \times m2 \times r \times (z2 \times q - r)$ then

begin $a3 := a2 + r/q; y3 := f(a3);$

if $y3 < y$ then

begin $x := a3; y := y3$

end

end;

comment: With probability about 0.1 do a random search for a lower value of f . Any reasonable random number generator can be used in place of the one here (it need not be very good);

skip: $k := 1611 \times k; k := k - 1048576 \times (k \div 1048576);$

$q := 1; r := (b-a) \times (k/100000);$

if $r < z2$ then go to retry;

```

comment:   Prepare to step as far as possible;
r := m2 x d0 x d1 x d2;  s := sqrt(((y2-y)+t)/m2);
h := 0.5 x (1+h);
p := h x (p+2 x r x s);  q := r+0.5 x qs;
r := -0.5 x (d0 + (z0 + 2.01 x e)/(d0 x m2));
r := a2 + (if r < s v d0 < 0 then s else r);
comment:   It is safe to step to r, but we may try to step further;
a3 := if p x q > 0 then a2 + p/q else r;
inner:  if a3 < r then a3 := r;
if a3 ≥ b then
  begin a3 := b;  y3 := yb end
else y3 := f(a3);
if y3 < y then
  begin x := a3;  y := y3 end;
d0 := a3 - a2;
if a3 > r then
  begin comment:   Inspect the parabolic lower bound on f in (a2,a3);
  p := 2 x (y2 - y3)/(m x d0);
  if abs(p) < (1 + 9 x macheps) x d0
  ^ 0.5 x m2 x (d0 x d0 + p x p) > (y2-y) + (y3-y) + 2 x t then
    begin comment:   Halve the step and try again;
    a3 := 0.5 x (a2 + a3);  h := 0.9 x h;  go to inner
  end
end;
if a3 < b then

```

```

  begin comment:   Prepare for the next step;
  a0 := c;  c := a2;  a2 := a3;
  y0 := y1;  y1 := y2;  y2 := y3;
  go to next
end
end;

glomin := y
end glomin;

Procedure glomin2d
real procedure glomin2d (ax, ay, bx, by, mx, my, macheps, e, t, f, x, y);
value ax, ay, bx, by, mx, my, macheps, e, t;
real ax, ay, bx, by, mx, my, macheps, e, t, x, y;
real procedure f;

  begin comment:

    Glomin2d returns the global minimum  $z = f(x,y)$  of the function
     $f(x,y)$  defined on the rectangle  $[ax,bx] \times [ay,by]$ .   $mx$  and  $my$ 
    are upper bounds on the second partial derivatives of  $f$ : we
    assume that  $f_{xx}(x,y) \leq mx$  and  $f_{yy}(x,y) \leq my$  in the rectangle.
     $e$  and  $t$  are positive tolerances:  $f$  must be evaluated to an
    accuracy of  $\pm e$ , and on return
     $\min(f) \leq f(x,y) \leq \min(f) + t + 3e$  and
     $\min(f) - e \leq z = f(f(x,y)) \leq \min(f) + t + 2e$ .

    macheps is the relative machine precision, and procedure glomin (for
    one-dimensional minimization) is assumed to be global;

```



```

real procedure phi (y); value y; real y;
  begin comment: Returns min f(x,y) over x (y fixed), and may
                  alter the global variables first, xs and zm;
  real procedure fx (x); value x; real x;
    begin fx := f(x,y) end fx;
  real ym;
  ym := glomin (ax, bx, xs, mx, macheps, e, tl, fx, xs);
  if first  $\vee$  ym < zm then
    begin first := false; zm := ym; x := xs end;
  phi := ym
end phi;
real tl, xs, zm; Boolean first;
first := true; zm := 0;
tl := 0.5 x t; xs := ax;
glomin2d := glomin (ay, by, ay, my, macheps, tl + e, tl, phi, y)
end glomin2d;

```

Chapter 7.

A New Algorithm for Minimizing a Function of Several Variables

Without Calculating Derivatives

1. Introduction and survey of the literature

In this chapter we consider the general unconstrained minimization problem: given a function $f: \mathbb{R}^n \rightarrow \mathbb{R}$, find an approximate local minimum of f . There is no need to emphasize the practical importance of this problem, and the recent literature on the subject is quite extensive. Here we give only a brief introduction, and no attempt is made to duplicate the survey articles by Box (1966), Fletcher (1965, 1969c), and Powell (1970a, e), or the books by Beale (1968), Box, Davies and Swann (1969), Jacoby, Kowalik and Pizzo (1971), Kowalik and Osborne (1968), Wilde (1964), and Wilde and Beightler (1967).

In practical problems the global minimum, not a mere local minimum, is usually of interest. Methods for finding global minima are discussed in Chapter 6, but for functions of a moderate or large number of variables the methods of Chapter 6 are impractical. Usually the best that we can do, in the absence of any special knowledge about f , is to use a good local minimizer and try several different combinations of starting positions, steplengths etc., in the hope that the best local minimum found is the global minimum.

Constrained problems

It often happens that we want to minimize $f(\underline{x})$ subject to the constraint that \underline{x} is in some subset D of \mathbb{R}^n . (Sometimes f is only defined on D .) Simple upper and/or lower bounds, of the form

$$a_i \leq x_i \leq b_i \quad (1.1)$$

on the components x_i of \underline{x} , are particularly common, and problems

with such constraints can be reduced to unconstrained problems by a transformation of variables (see Box (1966)).

More general constraints may be of the form

$$g_i(\underline{x}) = 0 \quad (\text{an equality constraint})$$

or

$$g_i(\underline{x}) \geq 0 \quad (\text{an inequality constraint}),$$

$$\left. \begin{array}{l} \\ \\ \end{array} \right\} (1.2)$$

where $g_i: D_i \subseteq \mathbb{R}^n \rightarrow \mathbb{R}$ is some given function, for $i = 1, \dots, m$.

$g_i(\underline{x})$ may be linear, say

$$g_i(\underline{x}) = \underline{a}_i^T \underline{x} + c_i \quad (1.3)$$

for some $\underline{a}_i \in \mathbb{R}^n$ and $c_i \in \mathbb{R}$, or $g_i(\underline{x})$ may be nonlinear, and perhaps quite difficult to compute. From the point of view of efficiency, it is probably best to deal with linear constraints directly, but this is difficult for nonlinear constraints. Direct methods for linear constraints are given in Fletcher (1968b), Goldfarb (1969a), and Rosen (1960). (See also Bartels (1968), Bartels and Golub (1969), Bartels, Golub and Saunders (1970), Gill and Murray (1970), Goldfarb and Lapidus (1968), Hanson (1970), and Shanno (1965, 1970b).)

Problems with nonlinear constraints can be reduced to a sequence of unconstrained problems by the use of penalty or barrier functions. (See Carroll (1961), Fiacco (1961, 1967, 1969), Fiacco and Jones (1969), Fiacco and McCormick (1968), Fletcher (1969b), Fletcher and McCormick (1969), Jones and McCormick (1969), Kowalik, Osborne and Ryan (1969), Lootsma (1968, 1970), Murray (1969a, b), Osborne and Ryan (1970, 1971), Pietrzykowski (1969), and Zangwill (1967b).) Attempts have also been made

to deal with nonlinear constraints directly. (See Allran and Johnsen (1970), Box (1965), Haarhoff and Buys (1970), Kalfon, Ribiere and Sogno (1968), Luenberger (1970), Mitchell and Kaplan (1968), Murtagh and Sargent (1969), Powell (1969d), Rosen (1961), and Zoutendijk (1960, 1970).)

Methods using derivatives

Many methods for the constrained or unconstrained minimization of $f: D \rightarrow \mathbb{R}$ explicitly use the partial derivatives $\partial f / \partial x_i$, for $i = 1, \dots, n$, and some methods also use the second partial derivatives of f . (Methods for constrained minimization may also use the partial derivatives of the constraint functions g_i .) For example, the classical method of steepest descent (Akaike (1959), Cauchy (1847), Curry (1944), Forsythe (1968), Goldstein (1962, 1965), and Ostrowski (1966, 1967a)) repeatedly minimizes f in the direction $-\underline{g}$, where

$$\underline{g} = \begin{pmatrix} \partial f / \partial x_1 \\ \vdots \\ \partial f / \partial x_n \end{pmatrix} \quad (1.5)$$

is the gradient of f . Perhaps the most successful methods using derivatives are the Davidon-Fletcher-Powell "variable metric" method (Davidon (1959), Fletcher and Powell (1963), Huang (1970), and McCormick (1969)), and the conjugate gradient method of Fletcher and Reeves (1964), which is slower but requires less storage than the variable metric method. (For other methods using derivatives, and related topics, see Bard (1968, 1970), Broyden (1970a, b), Cantrell (1969), Cragg

and Levy (1969), Davidon (1968, 1969), Davies (1968), Fletcher (1966, 1970), Goldfarb (1966, 1969b, 1970), Goldfeld, Quandt and Trotter (1968), Greenstadt (1967, 1970), Hestenes (1969), Kelley and Myers (1967), Luenberger (1969b), McCormick and Pearson (1969), Miele and Cantrell (1969, 1970), Myers (1968), Pearson (1969), Powell (1969b, c, 1970b, c, d), Ramsay (1970), Shanno (1969a, b), Shanno and Kettler (1959), Sorensen (1969), Takahashi (1965), Tokumaru, Adachi and Goto (1970), Vercoestre (1970), Goldstein and Price (1967), and Wells (1965).)

In many practical problems, it is difficult or impossible to find the partial derivatives of $f(\underline{x})$ directly. One possibility is to compute derivatives numerically, e.g., by finite differences, and then use one of the methods requiring derivatives. Stewart (1967) has successfully modified the variable metric method so that difference approximations to derivatives can be used. The difficulty is in balancing the influence of rounding errors and truncation errors when using finite differences to estimate derivatives. For a computer program, see Lill (1970).

Methods not using derivatives

Although Stewart's modification of the variable metric method appears to work well in most practical cases (see Stewart (1967), Powell (1970a), and Section 7), it is more natural to use a method which does not need derivatives, if derivatives can only be found numerically. Possibly such methods could be more efficient than methods which approximate derivatives numerically, although this is less clear in n dimensions than in one dimension (for which see Chapter 5).

Several methods which do not use derivatives have been compared in the survey papers of Box (1966), Fletcher (1965, 1969c), Powell (1970a, e), and Spang (1962). (See also Bell and Pike (1966), Berman (1969), Box (1957), Chazan and Miranker (1970), Hooke and Jeeves (1961), Kowalik and Osborne (1968), Nelder and Mead (1965), Smith (1962), Spendley (1969), Spendley, Hext and Himsworth (1962), Swann (1964), and Winfield (1967).) Excluding Stewart's method, the most successful method, especially for functions of more than three or four variables, appears to be that of Powell (1964) (see Section 5). The main object of this chapter is to present some modifications which improve the speed and reliability of Powell's method. The modifications are discussed in Sections 4 to 6, and some numerical results are given in Section 7.

Quadratic convergence

Suppose that $f(\underline{x})$ has continuous second derivatives

$$f_{ij} = \frac{\partial^2 f}{\partial x_i \partial x_j} \quad (1.6)$$

for $i, j = 1, \dots, n$, in a neighbourhood N of a local minimum $\underline{\mu}$. Since $\underline{\mu}$ is a minimum, the gradient of f vanishes at $\underline{\mu}$, and the Hessian matrix

$$A = (f_{ij}) \quad (1.7)$$

is positive definite or semi-definite. Near $\underline{\mu}$, the quadratic form

$$Q(\underline{x}) = f(\underline{\mu}) + \frac{1}{2} (\underline{x} - \underline{\mu})^T A (\underline{x} - \underline{\mu}) \quad (1.8)$$

is a good approximation to $f(\underline{x})$. Thus, any minimization method, having ultimate fast convergence for a general function $f(\underline{x})$ with continuous second derivatives, must have fast convergence for a positive definite quadratic form, and we might expect the converse to hold too. This observation has led to the investigation of methods which have quadratic convergence, i.e., which find the minimum of a positive definite quadratic form in a finite number of function and/or derivative evaluations, apart from the effect of rounding errors. Examples of methods with quadratic convergence are those of Davidon-Fletcher-Powell, Fletcher and Reeves, and Powell (1964) (this is not quite true: see Section 3). The method of steepest descent exhibits only linear convergence on a quadratic form, so it is not quadratically convergent.

A few methods are not quadratically convergent, for exact convergence requires an infinite number of steps, but they do exhibit superlinear convergence on quadratic forms. Examples are the methods of Rosenbrock, as modified by Davies, Swann and Campey (see Swann (1964)), of Goldstein and Price (1967), and of Greenstadt (1970). There is no apparent reason why such methods should fail to perform as well as quadratically convergent methods on general (nonquadratic) functions. Thus, quadratic convergence is a desirable property, but it is neither necessary nor sufficient for a good minimization method.

Stability: the descent property

In many methods for unconstrained minimization, $f(\underline{x})$ has been evaluated at \underline{x}_0 , the current best estimate of the position of the minimum of $f(\underline{x})$. A new estimate, \underline{x}_1^* , is made on the basis of the

values of f at \underline{x}_0 and a small number of other points (previous best estimates, or points close to \underline{x}_0). Additional information built up from previous iterations, e.g., an approximation to the Hessian matrix of f at \underline{x}_0 , may also be used. The prediction \underline{x}_1^* may be unreliable, and it may happen that

$$f(\underline{x}_1^*) > f(\underline{x}_0) \quad (1.9)$$

For example, this often occurs if \underline{x}_0 is not close to a local minimum, and an inadequate quadratic approximation to $f(\underline{x})$ is used.

To avoid the possibility of instability, most procedures do not accept \underline{x}_1^* as the next approximation to the minimum. Instead, they perform a "linear search" in the direction $\underline{x}_1^* - \underline{x}_0$, i.e., they take the point

$$\underline{x}_1 = \underline{x}_0 + \lambda_0(\underline{x}_1^* - \underline{x}_0) \quad (1.10)$$

as the next approximation, where λ_0 is chosen to minimize the function

$$\varphi(\lambda) = f(\underline{x}_0 + \lambda(\underline{x}_1^* - \underline{x}_0)) \quad (1.11)$$

of one variable. This ensures that

$$f(\underline{x}_1) \leq f(\underline{x}_0) \quad (1.12)$$

so the successive points generated must lie in the "level set"

$$S = \{\underline{x} \in \mathbb{R}^n \mid f(\underline{x}) \leq f(\underline{x}_0)\} \quad (1.13)$$

In practice, it is not worthwhile to try to minimize the function $\varphi(\lambda)$ very accurately. In fact, the minimum may not even exist: $\varphi(\lambda)$ may

be monotonic increasing or decreasing, or have a maximum but no minimum.

Box (1966) gives examples where an attempt to minimize $\varphi(\lambda)$ too accurately prevents a minimization procedure from finding the desired minimum. It is sometimes stated that the quadratic convergence property of certain methods depends on $\varphi(\lambda)$ being minimized exactly, but all that is really required for these methods is that the one-dimensional minimization procedure minimizes a quadratic function of λ exactly. Thus, for quadratic convergence, it is sufficient to fit a parabola $P(\lambda)$ to $\varphi(\lambda)$, and take $\lambda_0 = \lambda_0^*$, where λ_0^* minimizes $P(\lambda)$. Because of the danger of instability, this simple procedure is not acceptable, but it is reasonable to take $\lambda_0 = \lambda_0^*$ provided that

$$\varphi(\lambda_0^*) \leq \varphi(0) \quad (1.14)$$

which ensures that (1.12) holds. (Powell (1970e) gives some reasons for requiring rather more than (1.14).) See also Sections 6 and 7.

Sums of squares

A very common unconstrained minimization problem is to minimize a function $f(\underline{x})$ of the form

$$f(\underline{x}) = \sum_{i=1}^m \{f_i(\underline{x})\}^2 \quad (1.15)$$

for some (generally nonlinear) functions $f_i(\underline{x})$. For example, this problem arises when parameters x_1, \dots, x_n are fitted, by the method of least squares, using m observations. An important special case arises when the minimum value of $f(\underline{x})$ is zero: then we have a solution of the

system of equations

$$f_i(\underline{x}) = 0, \quad (1.16)$$

for $i = 1, \dots, m$.

Applying a general function minimizer to $f(\underline{x})$ may not be the most efficient way to minimize (1.15). Methods which make use of the individual residuals $f_i(\underline{x})$ are likely to be considerably more efficient than methods which merely try to minimize $f(\underline{x})$ without considering the individual residuals, at least if the minimum value of $f(\underline{x})$ is close to zero. Methods which make use of the residuals are described in Barnes (1965), Box (1966), Brown and Dennis (1968, 1970, 1971a, b), Broyden (1967, 1969), Dennis (1968, 1969a, b, c), Fletcher (1968a), Gauss (1809), Hartley (1961), Jones (1970), Levenberg (1944), Marquardt (1963), Matthews and Davies (1969), Morrison (1968), Ortega (1970), Ortega and Rheinboldt (1970), Peckham (1970), Powell (1965, 1968b, 1969a), Rabinowitz (1969), Rall (1966, 1969), Schubert (1970), Shanno (1970a), Späth (1967), Voigt (1969), Wolfe (1959a), and Zeleznik (1968). Good numerical methods for solving linear least squares problems are also relevant: see Björck (1967a, b, 1968), Businger and Golub (1965), Golub (1965, 1968), Golub and Reinsch (1970), Golub and Saunders (1969), Golub and Wilkinson (1966), Jordan (1968), Khabaza (1963), Maddison (1966), and Powell and Reid (1968).

Let us see why it may be worthwhile to use the residuals. Suppose that we have a good initial approximation to the minimum of $f(\underline{x})$, so the functions $f_i(\underline{x})$ can be closely represented by linear approximations in the region of interest. To find a linear approximation to $f_i(\underline{x})$, we

need to evaluate $f_i(\underline{x})$ at $n+1$ points, or evaluate $f_i(\underline{x})$ and the n components of its gradient at one point. Thus, after the same amount of work as is required for $n+1$ evaluations of $f(\underline{x})$, or one evaluation of $f(\underline{x})$ and its gradient, the solution of a linear least squares problem gives an approximation to the minimum. This approximation is usually good if the minimum value of $f(\underline{x})$ is small (see Powell (1965)), unless the linear problem is very ill-conditioned. On the other hand, if the special form (1.15) of $f(\underline{x})$ is disregarded, then it is necessary to evaluate $f(\underline{x})$ at $\frac{1}{2}(n+1)(n+2)$ points to find an approximating quadratic form. (Alternatively, f and its gradient must be evaluated at $\lceil \frac{1}{2}(n+2) \rceil$ or more points.) This suggests that methods which disregard the special form of $f(\underline{x})$ are likely to be much slower than methods which use the individual residuals, at least if n is large. Empirical evidence supports this conclusion (see particularly Table 3 of Box (1966) for $n = 20$), although some of the present methods which make use of the residuals appear to be rather unreliable.

Despite our conclusion, most of the numerical examples given in Section 7 are of the form (1.15). This is because a particularly simple way to construct test functions with bounded level sets is to use functions of the form (1.15), and most of the test functions given in the literature have this form.

Some additional references

The following general references on function minimization and related topics have not been mentioned above: Abadie (1970), Balakrishnan (1970), Bennett (1965), Bennett and Green (1966), Colville (1968), Davies (1969),

Davies and Swann (1969), Dold and Eckmann (1970a, b), Evans and Gould (1970), Fletcher (1969a), Hadley (1964), King (1966), Künzi, Tzschach and Zehnder (1968), Lavi and Vogl (1966), Leon (1966), Luenberger (1969a), Mangasarian (1969), Murtagh (1969), Murtagh and Sargent (1970), Powell (1966, 1969e), Ralston and Wilf (1960), Rice (1970), Rosen and Suzuki (1965), Shah, Buehler and Kempthorne (1964), Wolfe (1963, 1969), Zadeh (1969), Zangwill (1969a, b), and Zoutendijk (1966).

2. The effect of rounding errors

Rounding errors in the computation of $f(\underline{x})$ limit the accuracy attainable with any minimization method using only the computed values of $f(\underline{x})$. In this section, we generalize the results of Section 5.2, where the same problem is considered for functions of one variable. As in Section 5.2, the results of this section do not necessarily apply to methods which use the gradient of f , computed analytically. (They do apply if the gradient is computed by finite differences.)

Suppose that, in a neighbourhood N of a local minimum $\underline{\mu}$, the partial derivatives $f_{ij}(\underline{x})$ are Lipschitz continuous, i.e., for all $\underline{x}, \underline{y} \in N$,

$$|f_{ij}(\underline{x}) - f_{ij}(\underline{y})| \leq M_{ij} \|\underline{x} - \underline{y}\|, \quad (2.1)$$

where M_{ij} is a Lipschitz constant ($i, j = 1, \dots, n$), and any of the usual vector norms may be used. Since the gradient of $f(\underline{x})$ vanishes at $\underline{\mu}$, a simple extension of Lemma 2.3.1 shows that, for $\underline{x} \in N$,

$$f(\underline{x}) = f(\underline{\mu}) + \frac{1}{2} (\underline{x} - \underline{\mu})^T A (\underline{x} - \underline{\mu}) + R(\underline{x}), \quad (2.2)$$

where

$$A = (f_{ij}(\underline{\mu})) \quad (2.3)$$

is the Hessian matrix of $f(\underline{x})$ at $\underline{\mu}$, and

$$|R(\underline{x})| \leq M \|\underline{x} - \underline{\mu}\|^3, \quad (2.4)$$

for some constant M depending on n , the norm used, and the Lipschitz constants M_{ij} .

As in Section 5.2, the best that can be expected is that the computed value $fl(f(\underline{x}))$ of $f(\underline{x})$ satisfies the nearly attainable bound

$$fl(f(\underline{x})) = f(\underline{x}) \cdot (1 + \epsilon_{\underline{x}}) \quad (2.5)$$

where

$$|\epsilon_{\underline{x}}| \leq \epsilon, \quad (2.6)$$

and ϵ is the relative machine precision (see Section 4.2). If f is computed using single-precision arithmetic, the error bound will probably be considerably worse than this.

Let δ be the largest number such that, according to equations (2.2) to (2.6), it is possible that

$$fl(f(\underline{\mu} + \delta \underline{u})) \leq f(\underline{\mu}), \quad (2.7)$$

for some unit vector \underline{u} . Then it is unreasonable to expect any minimization procedure, based on single-precision evaluations of f , to return an approximation $\hat{\underline{\mu}}$ to $\underline{\mu}$ with a guaranteed upper bound for $\|\hat{\underline{\mu}} - \underline{\mu}\|$ less than δ .

Let the eigenvalues of A be $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$, with a set of corresponding normalized eigenvectors u_1, u_2, \dots, u_n . Since $\underline{\mu}$ is a local minimum of $f(\underline{x})$, certainly

$$\lambda_n \geq 0, \quad (2.8)$$

and we suppose that $\lambda_n > 0$. (The position of the minimum is worse determined if $\lambda_n = 0$.) If $\frac{M\delta}{\lambda_n}$ is small compared to unity, and we take $\underline{u} = u_n$, then (2.7) is possible for

$$\delta \sim \sqrt{\frac{2|f(\underline{\mu})|\varepsilon}{\lambda_n}}. \quad (2.9)$$

Thus, an upper bound on $\|\underline{\hat{\mu}} - \underline{\mu}\|$ can hardly be less than the right side of (2.9).

The condition number

With the assumptions above, and δ given by (2.9),

$$f(\underline{\mu} + \delta u_1) \simeq f(\underline{\mu}) + \kappa \varepsilon |f(\underline{\mu})|, \quad (2.10)$$

where

$$\kappa = \lambda_1 / \lambda_n \quad (2.11)$$

is the usual condition number of A . We shall say that κ is the condition number of the minimization problem (for the local minimum $\underline{\mu}$). The condition number determines the rate of convergence of some minimization methods (e.g., steepest descent), and it is also important because rounding errors make it difficult to solve problems with condition numbers of the order of ε^{-1} or greater (see below).

Scaling

A change of scale along the coordinate axes has the effect of replacing the Hessian matrix A by SAS , where S is a positive diagonal matrix. The problem of choosing S to minimize the condition number of SAS is difficult, even if A is known explicitly. (See Forsythe and Moler (1967) for the problem of minimizing the condition number of $S_1 A S_2$, where A is not necessarily symmetric.) A good general rule is that SAS should be roughly row (and hence column) equilibrated (see Wilkinson (1963, 1965a)). In practical minimization problems, one difficulty is that little is known about the Hessian matrix A until a reasonable approximation to the minimum has been found. This suggests that a general function minimizer which is scale-dependent could incorporate an automatic scaling procedure, using current information about A to determine the scaling. One way of doing this is described in Section 4.

3. Powell's algorithm

In this section we briefly describe Powell's algorithm for minimization without calculating derivatives. The algorithm is described more fully in Powell (1964), and a small error in this paper is pointed out by Zangwill (1967a). Numerical results are given in Fletcher (1965), Box (1966), and Kowalik and Osborne (1968). A modified algorithm, which is suitable for use on a parallel computer, and which converges for strictly convex C^2 functions with bounded level sets, is described by Chazan and Miranker (1970).

Powell's method is a modification of a quadratically convergent method proposed by Smith (1962). Both methods ensure convergence in a finite number of steps, for a positive definite quadratic form, by making use of some properties of conjugate directions.

Conjugate directions

If A is positive definite and symmetric, then minimizing the quadratic function

$$\underline{x}^T A \underline{x} - 2\underline{b}^T \underline{x} = (\underline{x} - A^{-1}\underline{b})^T A (\underline{x} - A^{-1}\underline{b}) - \underline{b}^T A^{-1} \underline{b} \quad (3.1)$$

is equivalent to solving the system of linear equations

$$A \underline{x} = \underline{b} \quad (3.2)$$

If the matrix A is known explicitly, then, instead of minimizing (3.1), we can solve (3.2) by any suitable method: for example, by forming the Cholesky decomposition of A . In the applications of interest here, A is the Hessian matrix of a certain function, and is not known explicitly, but the equivalence of the problems (3.1) and (3.2) is still useful.

Definition 3.1

Two vectors \underline{u} and \underline{v} are said to be conjugate with respect to the positive definite symmetric matrix A if

$$\underline{u}^T A \underline{v} = 0 \quad (3.3)$$

When there is no risk of confusion, we shall simply say that \underline{u} and \underline{v} are conjugate. By a set of conjugate directions, we mean a set of vectors which are pairwise conjugate.

Remark

If $\{\underline{u}_1, \dots, \underline{u}_m\}$ is any set of nonzero conjugate directions in R^n , then $\underline{u}_1, \dots, \underline{u}_m$ are linearly independent. Thus $m \leq n$, and $m = n$ iff $\underline{u}_1, \dots, \underline{u}_m$ span R^n .

Theorem 3.1

If A is positive definite symmetric, $A \underline{x} = \underline{b}$, and $\{\underline{u}_1, \dots, \underline{u}_m\}$ is a set of nonzero conjugate directions, then

$$\underline{x}' = \underline{x} - \sum_{i=1}^m \left(\frac{\underline{u}_i^T \underline{b}}{\underline{u}_i^T A \underline{u}_i} \right) \underline{u}_i \quad (3.4)$$

is conjugate to each of $\underline{u}_1, \dots, \underline{u}_m$.

Proof

If $1 \leq j \leq m$, then, from (3.4),

$$\underline{u}_j^T A \underline{x}' = \underline{u}_j^T (A \underline{x} - \underline{b}) = 0 \quad (3.5)$$

Corollary 3.1

If $m = n$ in Theorem 3.1, then $\underline{x}' = 0$, so

$$\underline{x} = \sum_{i=1}^n \left(\frac{\underline{u}_i^T \underline{b}}{\underline{u}_i^T A \underline{u}_i} \right) \underline{u}_i \quad (3.6)$$

Returning to the minimization problem, Theorem 3.1 and the equivalence of problems (3.1) and (3.2) give the following result.

Theorem 3.2

If A is positive definite symmetric,

$$f(\underline{x}) = \underline{x}^T A \underline{x} - 2\underline{b}^T \underline{x} + c \quad (3.7)$$

for some $\underline{b} \in \mathbb{R}^n$ and $c \in \mathbb{R}$, and $\underline{u}_1, \dots, \underline{u}_m$ is a set of nonzero conjugate directions, then the minimum of $f(\underline{x})$ in the space spanned by $\underline{u}_1, \dots, \underline{u}_m$ occurs at the point $\sum_{i=1}^m \beta_i \underline{u}_i$, where

$$\beta_i = \frac{\underline{u}_i^T \underline{b}}{\underline{u}_i^T A \underline{u}_i} \quad (3.8)$$

Proof

This follows from Theorem 3.1, or, alternatively, from the relation

$$f\left(\sum_{i=1}^m \alpha_i \underline{u}_i\right) = \sum_{i=1}^m (\alpha_i - \beta_i)^2 \frac{\underline{u}_i^T A \underline{u}_i}{\underline{u}_i^T A \underline{u}_i} + c - \sum_{i=1}^m \frac{(\underline{u}_i^T \underline{b})^2}{\underline{u}_i^T A \underline{u}_i} \quad (3.9)$$

(cross terms vanish because of the conjugacy of $\underline{u}_1, \dots, \underline{u}_m$).

The usefulness of Theorem 3.2 stems from the following result, which shows how we can calculate the β_i of (3.8) using function evaluations, even if A , \underline{b} and c are not known explicitly.

Theorem 3.3

With the notation of Theorem 3.2, a fixed j satisfying $1 \leq j \leq m$, and fixed $\alpha_1, \dots, \alpha_{j-1}, \alpha_{j+1}, \dots, \alpha_m$, the minimum of

$$\phi_j(\alpha_j) = f\left(\sum_{i=1}^m \alpha_i \underline{u}_i\right) \quad (3.10)$$

occurs at $\alpha_j = \beta_j$.

Proof

This follows immediately from equation (3.9).

From Theorems 3.2 and 3.3, we see that the minimum of the quadratic form $f(\underline{x})$ can be found by n one-dimensional minimizations along nonzero conjugate directions $\underline{u}_1, \dots, \underline{u}_n$, and the order of the one-dimensional minimizations is irrelevant. To use this result, we have to be able to generate sets of conjugate directions. Both Powell's method and Smith's method do this by using the following theorem, given in Powell (1964).

Theorem 3.4

If the minimum of $f(\underline{x})$ (given by (3.7)) in the direction \underline{u} from the point \underline{x}_i^* is at \underline{x}_i , for $i = 0, 1$, then $\underline{x}_1 - \underline{x}_0$ is conjugate to \underline{u} .

Proof.

For $i = 0$ and 1 ,

$$\frac{\partial}{\partial \lambda} f(\underline{x}_i + \lambda \underline{u}) = 0 \quad \text{at } \lambda = 0, \quad (3.11)$$

so, from (3.7),

$$\underline{u}^T (A \underline{x}_i - \underline{b}) = 0 \quad (3.12)$$

Subtracting equations (3.12) for $i = 0$ and 1 gives

$$\underline{u}^T A (\underline{x}_1 - \underline{x}_0) = 0, \quad (3.13)$$

which completes the proof.

7.3

Powell's basic procedure

We can now describe the basic idea of Powell's algorithm. Let \underline{x}_0 be the initial approximation to the minimum, and let $\underline{u}_1, \dots, \underline{u}_n$ be the columns of the identity matrix. One iteration of the basic procedure consists of the following steps:

1. For $i = 1, \dots, n$, compute β_i to minimize $f(\underline{x}_{i-1} + \beta_i \underline{u}_i)$, and define $\underline{x}_i = \underline{x}_{i-1} + \beta_i \underline{u}_i$.
2. For $i = 1, \dots, n-1$, replace \underline{u}_i by \underline{u}_{i+1} .
3. Replace \underline{u}_n by $\underline{x}_n - \underline{x}_0$.
4. Compute β to minimize $f(\underline{x}_0 + \beta \underline{u}_n)$, and replace \underline{x}_0 by $\underline{x}_0 + \beta \underline{u}_n$.

For a general (non-quadratic) function, we just repeat the iteration until some stopping criterion is satisfied. Suppose that $1 \leq k \leq n$, and consider the situation after the k -th iteration. If f is quadratic then we can show, by induction on k , that $\underline{u}_{n-k+1}, \dots, \underline{u}_n$ are conjugate. This follows from the choice of \underline{u}_n at step 3, and Theorem 3.4: see Powell (1964). After n iterations, we have minimized along n conjugate directions $\underline{u}_1, \dots, \underline{u}_n$, so, by Theorems 3.2 and 3.3, the minimum will have been reached if the \underline{u}_i are all nonzero. This is true if, at each iteration, $\beta_i \neq 0$, for then the directions $\underline{u}_1, \dots, \underline{u}_n$ can not become linearly dependent.

The problem of linear dependence

Unfortunately, as pointed out by Zangwill (1967a), even for a quadratic function f one of the iterations may have $\beta_1 = 0$, which

7.4

results in the directions $\underline{u}_1, \dots, \underline{u}_n$ becoming linearly dependent, and from then on the procedure can only find the minimum of $f(\underline{x})$ over a proper subspace of R^n . The same is, of course, true for non-quadratic functions, and even though it is unlikely that β_1 will vanish exactly, Powell discovered that the directions $\underline{u}_1, \dots, \underline{u}_n$ often become nearly linearly dependent. Thus, he suggests that the new direction $\underline{x}_n - \underline{x}_0$ should be used, and one of the old $\underline{u}_1, \dots, \underline{u}_n$ discarded, only if this does not decrease the value of $|\det(\underline{v}_1 \dots \underline{v}_n)|$, where

$$\underline{v}_i = (\underline{u}_i^T \underline{A} \underline{u}_i)^{-\frac{1}{2}} \underline{u}_i \quad (3.14)$$

for $i = 1, \dots, n$. With this modification the algorithm is quite successful (see Fletcher (1965) and Box (1966) for a comparison with other methods), but the desirable property of quadratic convergence is lost, for a complete set of conjugate directions may never be built up. In the next section, we describe a different way of avoiding the problem of linear dependence of the search directions. The numerical results given in Section 7 suggest that our method of ensuring linear independence may be preferable to Powell's.

4. The main modification

The simplest way to avoid linear dependence of the search directions with Powell's basic procedure, and retain quadratic convergence if $\beta_1 \neq 0$, is to reset the search directions $\underline{u}_1, \dots, \underline{u}_n$ to the columns of the identity matrix after, say, every n iterations. A similar "restarting"

device is suggested by Fletcher and Reeves (1964) for their conjugate gradient method. Unfortunately, restarting tends to slow down convergence for approximately quadratic functions, because any information built up about the function is periodically thrown away. (Perhaps this is why the Fletcher-Reeves algorithm is generally slower than the Davidon-Fletcher-Powell algorithm.)

Instead of resetting $U = [u_1, \dots, u_n]$ to the identity matrix, we could equally well reset U to any orthogonal matrix Q . To avoid discarding useful information about f , we could choose Q so that, if f is quadratic, u_1, \dots, u_n remain conjugate. This suggests that principal vectors q_1, \dots, q_n should be computed on the assumption that f is quadratic, and U should be reset to $Q = [q_1, \dots, q_n]$. The motivation for this procedure may be summarized thus:

1. If the quadratic approximation to f is good, then the new search directions should be conjugate with respect to a matrix which is close to the Hessian matrix of f at the minimum, and thus subsequent iterations should give fast convergence.
2. Regardless of the validity of the quadratic approximation, the new search directions are orthogonal, so the search for a minimum can never become restricted to a subspace.

The extra computation involved

We show below that finding principal axes does not require any extra function evaluations, but it does involve finding an orthogonal set of eigenvectors for a symmetric matrix H of order n . This requires

about $6n^3$ multiplications, and a similar number of additions, if done as suggested below. Since the principal axes are found only once for every n^2 linear minimizations, and a linear minimization requires about 2.25 function evaluations on the average (see Section 7), the extra computation is less than $3n$ multiplications per function evaluation. We can expect the evaluation of a nontrivial function of n variables to require considerably more than $3n$ multiplications, and possibly order n^2 , so the overhead caused by our modification is not excessive. Also, it may be worth paying a little for the principal axis reduction, for the extra information about f is often of interest. For example, it shows the sensitivity of $f(\underline{x})$ to slight changes in \underline{x} near the minimum. The principal axes and eigenvalues may be of interest in statistical problems when f is minus the log-likelihood, for then the inverse of the Hessian at the minimum is the sample variance-covariance matrix of the maximum likelihood estimates: see Nelder and Mead (1965).

Scaling

Powell's modification of his basic procedure has one feature which ours lacks: his determinantal criterion is independent of a linear transformation of the independent variable space (an important special case is a change of scale for the independent variables). This feature is certainly desirable, for when a function of, say, temperature and pressure is to be minimized, there is no natural way to scale the variables. We should note, though, that Powell's algorithm is not completely independent of linear transformations of the variable space, or even of

scale changes, for these influence both the initial choice of the vectors $\underline{u}_1, \dots, \underline{u}_n$, and the stopping criterion.

Finding the principal vectors

Suppose that

$$f(\underline{x}) = \underline{x}^T \underline{A} \underline{x} - 2\underline{b}^T \underline{x} + c \quad (4.1)$$

is a positive definite quadratic form, although \underline{A} , \underline{b} and c may not be known explicitly. If n iterations of Powell's basic procedure are performed as described above, and at each iteration $\beta_1 \neq 0$, then we obtain n nonzero conjugate directions $\underline{u}_1, \dots, \underline{u}_n$. Let $\underline{U} = [\underline{u}_1 \dots \underline{u}_n]$. By the conjugacy of $\underline{u}_1, \dots, \underline{u}_n$,

$$\underline{U}^T \underline{A} \underline{U} = \underline{D}, \quad (4.2)$$

where \underline{D} is a diagonal matrix with positive diagonal elements d_i .

During the last (i.e., n -th) iteration, we have performed one-dimensional minimizations in the directions $\underline{u}_1, \dots, \underline{u}_n$. Consider a minimization from the point \underline{x}_{i-1} , in the direction \underline{u}_i , for $1 \leq i \leq n$. We minimize the function

$$\varphi_i(\alpha) = f(\underline{x}_{i-1} + \alpha \underline{u}_i) \quad (4.3)$$

$$= \alpha^2 \underline{u}_i^T \underline{A} \underline{u}_i + 2\alpha (\underline{u}_i^T \underline{A} \underline{x}_{i-1} - \underline{u}_i^T \underline{b}) + (\underline{x}_{i-1}^T \underline{A} \underline{x}_{i-1} - 2\underline{x}_{i-1}^T \underline{b} + c). \quad (4.4)$$

To minimize $\varphi_i(\alpha)$ we fit a parabola, which necessitates computing the second difference $\varphi_i[\alpha_0, \alpha_1, \alpha_2]$ for three distinct points α_0 , α_1 , and α_2 . From equation (4.4),

$$\varphi_i[\alpha_0, \alpha_1, \alpha_2] = \underline{u}_i^T \underline{A} \underline{u}_i = d_i, \quad (4.5)$$

so the diagonal elements d_i of \underline{D} are known without any extra computation. (If the quadratic approximation to $\varphi_i(\alpha)$ is bad we may have $\varphi_i[\alpha_0, \alpha_1, \alpha_2] \leq 0$, and then we arbitrarily set d_i to a small positive number.)

$$\text{Let } \underline{V} = \underline{U} \underline{D}^{-\frac{1}{2}} \quad (4.6)$$

be the matrix with columns $\underline{v}_1, \dots, \underline{v}_n$ given by (3.14), and let

$$\underline{H} = \underline{A}^{-1}. \quad (4.7)$$

Since \underline{U} is nonsingular, equation (4.2) gives

$$\underline{H} = \underline{U} \underline{D}^{-1} \underline{U}^T = \underline{V} \underline{V}^T. \quad (4.8)$$

The matrix \underline{V} is easily computed from \underline{U} in n^2 multiplications and n square roots, but the computation of $\underline{V} \underline{V}^T$ is more expensive, and can be avoided: see below.

Our aim is to find the principal axes of the quadratic form f , i.e., to find an orthogonal matrix \underline{Q} such that

$$\underline{Q}^T \underline{A} \underline{Q} = \underline{\Lambda}, \quad (4.9)$$

where $\underline{\Lambda} = \text{diag}(\lambda_i)$ is diagonal. Thus, the columns \underline{q}_i of \underline{Q} are just the eigenvectors of \underline{A} , with corresponding eigenvalues $\lambda_1, \dots, \lambda_n$, and we can assume that $\lambda_1 \geq \dots \geq \lambda_n$. The obvious way to find \underline{Q} and $\underline{\Lambda}$ is to compute $\underline{H} = \underline{V} \underline{V}^T$ explicitly, and then find \underline{Q} and $\underline{\Lambda}$ such that

$$\underline{Q}^T \underline{H} \underline{Q} = \underline{\Lambda}^{-1}, \quad (4.10)$$

by finding the eigensystem of \underline{H} .

Use of the singular value decomposition to find Q and A

If the condition number $\kappa = \lambda_1/\lambda_n$ is of order ϵ^{-1} , where ϵ is the relative machine precision (see Section 4.2), then rounding errors may lead to disastrous errors in the computed small eigenvalues $\lambda_1^{-1}, \lambda_2^{-1}, \dots$ of H , and in the corresponding eigenvectors q_1, q_2, \dots , even if they are well-determined by V . Thus, it may be necessary to compute H , and find its eigensystem, using double precision arithmetic. This difficulty can be avoided if, instead of forming $H = VV^T$, we work directly with V . Suppose that we find the singular value decomposition of V , i.e., find orthogonal matrices Q and Q' such that

$$Q^T V Q' = \Sigma, \quad (4.11)$$

where $\Sigma = \text{diag}(\sigma_i)$ is a diagonal matrix. (See Golub and Kahan (1965), and Kogbetliantz (1955).) Then

$$A^{-1} = Q^T H Q = (Q^T V Q') (Q^T V Q')^T = \Sigma^2, \quad (4.12)$$

so Q is the desired matrix of eigenvectors of A , and the eigenvalues λ_i are given by

$$\lambda_i = \sigma_i^{-2}. \quad (4.13)$$

Note that the matrix Q' is not required, and it is not necessary to compute VV^T .

Since it is desirable that the computed matrix Q should be close to an orthogonal matrix, we suggest that Q and Σ should be found by the method of Golub and Reinsch (1970). This involves reducing V to bidiagonal form by Householder transformations, and then computing the

singular value decomposition of the bidiagonal matrix by a variant of the QR algorithm.

Let us compare the amount of computational work involved in computing Q and A via

1. The singular value decomposition (SVD) of V as described above, and
2. Finding the matrix H and its eigensystem, using Householder's reduction to tridiagonal form and then the QR algorithm. (See Bowdler, Martin, Reinsch and Wilkinson (1968), Francis (1962), Householder (1964), Kublanovskaya (1961), Martin, Reinsch and Wilkinson (1968), and Wilkinson (1965a, b, 1968).)

For purposes of comparison, we count only multiplications, and ignore terms of order n^2 , so our conclusions may not be valid for very small n . Suppose that, in each case, the QR process requires ρn iterations, for some modest number ρ .

For method 1, the Householder reduction requires $4n^3/3$ multiplications, accumulation of the (left-hand) transformations requires another $4n^3/3$ multiplications, and the QR process with accumulation of the transformations requires $2\rho n^3$ multiplications, if no splitting occurs. Thus, method 1 requires $(8+6\rho)n^3/3$ multiplications in all.

For method 2, the Householder reduction requires $2n^3/3$ multiplications (only half as much as for method 1 because of symmetry), accumulation of the transformations requires $2n^3/3$ multiplications, and the QR process requires $2\rho n^3$, giving $(4+6\rho)n^3/3$ altogether. This could be reduced to $4n^3/3$, still ignoring terms of order n^2 , if inverse iteration were used to compute the eigenvectors of the tridiagonal matrix, but then it

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would be difficult to guarantee orthogonality of eigenvectors corresponding to close or multiple eigenvalues. Another $\frac{1}{2}n^3$ multiplications are needed to compute $H = VV^T$ by the usual method (but taking advantage of symmetry), making $(11+12\rho)n^3/6$ multiplications in all.

The ratio of the work involved for methods 1 and 2 is thus

$$r = \frac{16 + 12\rho}{11 + 12\rho} < \frac{16}{11}, \quad (4.14)$$

and for a typical value of $\rho = 1.6$ we have $r = 1.17$. Thus, method 1 can be expected to be only about 20 percent slower than the numerically inferior method 2. Both methods can be done in place, and require temporary storage for only a few n -vectors, apart from the n by n matrix V which is overwritten by Q .

Scaling

We mentioned in Section 1 that a general minimization procedure might incorporate automatic scaling of the independent variables, in an attempt to reduce the condition number of the problem. Scaling has the effect of replacing the matrix V above by $S^{-1}V$, where S is a positive diagonal matrix (as in Section 1). The ALGOL procedure "praxis" given in Section 9 chooses S automatically to try to reduce the condition number of $S^{-1}V$. S is chosen so that $S^{-1}V$ is row-equilibrated, with the constraint that

$$1 \leq s_{ii} \leq \text{scbd}, \quad (4.15)$$

where scbd is a bound which may be set to 1 if no scaling is desired. Numerical experiments on the examples described in Section 7 suggest that

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scbd should be fairly small (say about 10) unless the axes are very badly scaled initially. The automatic scaling is worthwhile, but its effect is not dramatic, and it is rather unreliable, which is the reason for introducing scbd . Thus, it is still worthwhile for the user to try to scale his problem as well as possible.

Another modification

For Powell's basic procedure to minimize a positive definite quadratic form in n iterations, steps 1 to 3 of the first iteration are unnecessary. Thus, our algorithm omits steps 1 to 3 on the first iteration, and, subsequently, after each singular value decomposition (i.e., at the $(n+1)$ -st, $(2n+1)$ -st, ... , iterations). For this reason, there are exactly

$$1 + (n-1)(n+1) = n^2 \quad (4.16)$$

linear minimizations, instead of $n(n+1)$, between each singular value decomposition. This modification is not important for large n , but numerical results suggest that it is worthwhile for small n .

5. The "resolution ridge" problem

Suppose temporarily that we are trying to maximize a function $f(x_1, x_2)$ of two variables by an ascent method. Wilde (1964) points out that rounding errors in the computation of f may lead to premature termination because of the "resolution ridge" problem illustrated in Diagram 5.1.

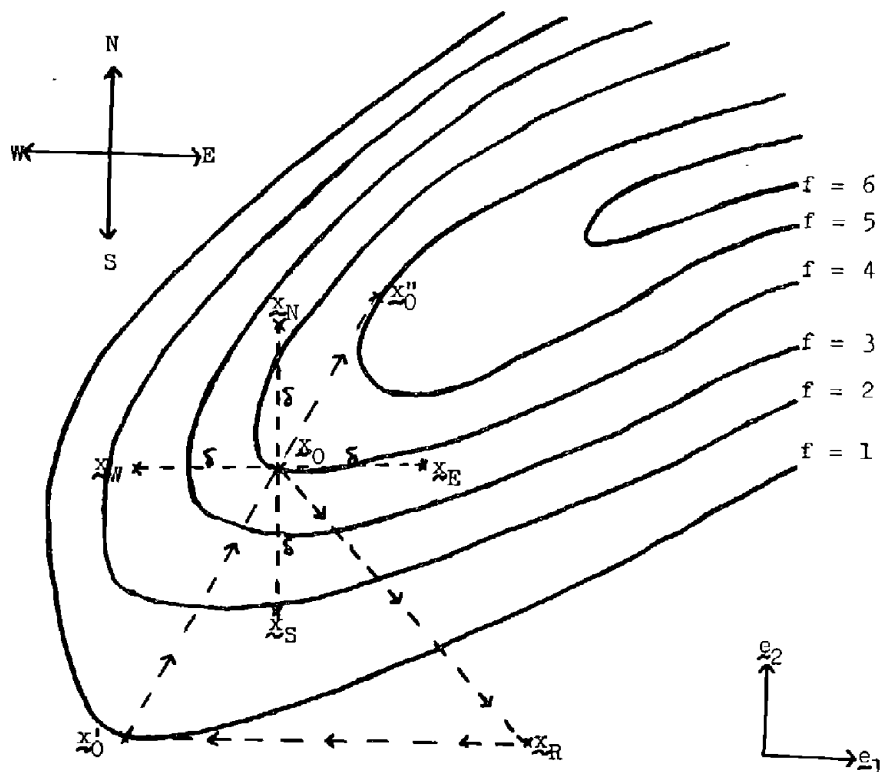


Diagram 5.1: A resolution ridge

Regarding the surface defined by $f(x_1, x_2)$ as a hill, we may reach a point x_0 , situated on a narrow ridge, and then try to proceed to a higher point by performing linear searches in certain directions. Suppose, for example, that we attempt linear searches in the EW and NS directions. The point x_0 may not be at the true minimum of f in both these directions but, because of the effect of rounding errors in evaluating f , our one-dimensional search procedure will only attempt to locate the position of maxima to within some positive tolerance δ (see

Section 2). Let $x_E = x_0 + \delta e_1$, $x_W = x_0 - \delta e_1$, $x_N = x_0 + \delta e_2$, and $x_S = x_0 - \delta e_2$. As shown in the diagram, it may happen that $f(x_0)$ is greater than each of $f(x_N)$, $f(x_S)$, $f(x_E)$ and $f(x_W)$, so x_0 is within the tolerance δ of local maxima in both of the search directions, even though x_0 may be a long way from the true maximum, which could be reached by climbing up the ridge. The same problem can arise with functions of more than two variables, or when we are looking for a minimum rather than a maximum (then we might speak of a "resolution valley" problem).

It is clear from the diagram that, if we know another point x'_0 on the ridge, then a linear search in the direction $x_0 - x'_0$ will give a point x''_0 with $f(x''_0) > f(x_0)$, unless the ridge is sharply curved. This is the motivation for the method suggested by Rosenbrock (1960), and improved by Davies, Swann and Campey. (See Swann (1964), and also Andrews (1959), Baer (1962), Fletcher (1965, 1969c, d), Osborne (1969), Palmer (1969), Powell (1968a), Rice (1966), and Section 7.)

Finding another point on the ridge

If linear searches from the point x_0 fail to give a higher point, and a resolution ridge is suspected, then the following strategy may be successful: take a step of length, say 10δ , in a random direction from x_0 , reaching the point x_R . Then perform one or more linear searches, starting at x_R , and reaching the point x'_0 . As the diagram shows, the point x'_0 is likely to be on the ridge, so a linear search in the direction $x_0 - x'_0$ may be successful.

Although he does not refer to the resolution ridge problem, Powell (1964) incorporates such a strategy in his stopping criterion. We propose to use this strategy during the regular iterations as well.

Incorporating a random step into Powell's basic procedure

Suppose that we are commencing iteration k of Powell's basic procedure, counting either from the start or from the last singular value decomposition, and $2 \leq k \leq n$. To ensure quadratic convergence, we must search along the directions u_{n-k+2}, \dots, u_n in step 1 of iteration k , but the searches along directions u_1, \dots, u_{n-k+1} are not necessary for quadratic convergence. (They are desirable for other reasons: see Fletcher (1965) for a comparison of Powell's method and Smith's method.) The quadratic convergence property still holds if, at step 1, we move to any point

$$x_{n-k+1} = x_0 + \sum_{i=1}^n \beta'_i u_i \quad (5.1)$$

with $\beta'_1 \neq 0$, before performing linear searches in the directions u_{n-k+2}, \dots, u_n . Thus, before performing linear searches in directions u_1, \dots, u_n at step 1 of iteration k , we may try the random step strategy as described above. Procedure praxis does this if the problem appears to be ill-conditioned, or if the procedure is about to terminate (i.e., if previous linear searches have failed to find a better approximation to the minimum).

This modification is not necessary for well-conditioned problems, but numerical results show that it is essential in order to ensure that a

good approximation to the minimum is found for very ill-conditioned problems. For example, consider minimizing

$$f(x) = x^T A x, \quad (5.2)$$

where A is a 10 by 10 Hilbert matrix (i.e., $a_{ij} = 1/(i+j-1)$ for $1 \leq i, j \leq 10$), with a condition number of 1.6×10^{13} . Using long real on an IBM 360 computer (machine precision 16^{-13}), and starting from $(1, 1, \dots, 1)^T$, our algorithm successfully found the position of the minimum of $f(x)$ to within the specified tolerance of 10^{-5} , but it failed without the random step strategy. (For further details, see Section 7.)

Extrapolation along the ridge

If the function minimizer has been climbing a ridge for several complete cycles, so the quadratic approximation to f is obviously inadequate (or the maximum would already have been found), then it may be worthwhile to try an extrapolation along the ridge. Suppose that immediately before three successive singular value decompositions, the best approximations to the maximum are x' , x'' , and x''' , with $d_0 = \|x' - x''\|_2 > 0$ and $d_1 = \|x'' - x'''\|_2 > 0$. Numerical tests indicate that curved ridges are often approximated fairly well by the space-curve given parametrically by

$$x(\lambda) = \frac{\lambda(\lambda-d_1)}{d_0(d_0+d_1)} x' - \frac{(\lambda+d_0)(\lambda-d_1)}{d_0 d_1} x'' + \frac{\lambda(\lambda+d_0)}{d_1(d_0+d_1)} x''' \quad (5.3)$$

which is chosen because $x(-d_0) = x'$, $x(0) = x''$, and $x(d_1) = x'''$. Hence, before the 3rd, 5th ... singular value decompositions,

procedure praxis (see Section 9) moves to the point $\underline{x}(\lambda_0)$, where λ_0 is chosen to approximately minimize $f(\underline{x}(\lambda))$. λ_0 is computed by the same procedure that performs linear searches.

6. Some further details

In this section we give some more details of the ALGOL procedure given in Section 9. The criterion for discarding search directions, the linear search procedure, and the stopping criterion are described briefly. (For the sake of clarity, some unimportant details are omitted.)

The discarding criterion

Suppose for the moment that $f(\underline{x})$ is the quadratic form given by equation (3.7). In steps 2 and 3 of Powell's basic procedure (see Section 3), we effectively discard the search direction \underline{u}_1 , and replace it by $\underline{x}_n - \underline{x}_0$. The algorithm suggested by Powell does not necessarily discard \underline{u}_1 : instead, as mentioned in Section 3, it discards one of $\underline{u}_1, \dots, \underline{u}_n$, $\underline{u}_{n+1} = \underline{x}_n - \underline{x}_0$, so as to maximize

$$|\det(\underline{v}_1 \dots \underline{v}_n)|, \quad (6.1)$$

where \underline{v}_i is given by equation (3.14), after renumbering the remaining n directions. We wish to retain convergence for a quadratic form in n iterations, so we are not free to discard any one of $\underline{u}_1, \dots, \underline{u}_{n+1}$. At the k -th iteration, for $2 \leq k \leq n$, we can discard any one of $\underline{u}_1, \dots, \underline{u}_{n-k+1}$ without losing quadratic convergence (see Section 5). For

lack of a better criterion, we choose to discard the direction, from $\underline{u}_1, \dots, \underline{u}_{n-k+1}$, to maximize the resulting determinant (6.1).

Suppose that the new direction $\underline{x}_n - \underline{x}_0 = \underline{u}_{n+1}$ satisfies

$$\frac{\underline{u}_{n+1}}{(\underline{u}_{n+1}^T \underline{A} \underline{u}_{n+1})^{1/2}} = \sum_{i=1}^n \alpha_i \frac{\underline{u}_i}{(\underline{u}_i^T \underline{A} \underline{u}_i)^{1/2}}. \quad (6.2)$$

Then, the effect of discarding \underline{u}_i and replacing it by \underline{u}_{n+1} (and then renumbering the directions) is to multiply the determinant (6.1) by $|\alpha_i|$, so our criterion is to choose i , with $1 \leq i \leq n-k+1$, so that $|\alpha_i|$ is at its maximum. If β_1, \dots, β_n are as in the description of Powell's basic procedure (see Section 3), and the linear minimization with step $\beta_i \underline{u}_i$ decreases $f(\underline{x})$ by an amount Δ_i , then, from (3.7),

$$\Delta_i = \beta_i^2 \frac{\underline{u}_i^T \underline{A} \underline{u}_i}{\underline{u}_i^T \underline{u}_i}, \quad (6.3)$$

so $\sqrt{\Delta_i} / |\beta_i|$ may be used as an estimate of $(\underline{u}_i^T \underline{A} \underline{u}_i)^{1/2}$. (If $\beta_i = 0$ then we use the result of a previous iteration.)

Suppose that the random step procedure described in Section 5 moves from \underline{x}_0 to

$$\underline{x}'_0 = \underline{x}_0 + \sum_{i=1}^n \gamma_i \underline{u}_i, \quad (6.4)$$

before the linear searches in the directions $\underline{u}_1, \dots, \underline{u}_n$ are performed. Then

$$\underline{u}_{n+1} = \underline{x}_n - \underline{x}_0 = \sum_{i=1}^n (\beta_i + \gamma_i) \underline{u}_i, \quad (6.5)$$

and the β'_i of equation (5.1) are given by

$$\beta'_i = \begin{cases} \beta_i + \gamma_i & \text{if } 1 \leq i \leq n-k+1, \\ \gamma_i & \text{if } n-k+2 \leq i \leq n. \end{cases} \quad (6.6)$$

From (6.2), (6.3) and (6.5),

$$(u_{n+1}^T A u_{n+1})^{1/2} \alpha_i = (\beta_i + \gamma_i) \sqrt{\Delta_i} / |\beta_i|, \quad (6.7)$$

so we must discard direction u_i , $1 \leq i \leq n-k+1$, to maximize the modulus of the right side of (6.7). Since this does not explicitly depend on the matrix A , the same criterion is used even if f is not necessarily a quadratic form. Note that our criterion reduces to Powell's, apart from our restriction that $i \leq n-k+1$, if there are no random steps, i.e., if $\gamma_i = 0$ for $i = 1, \dots, n$. Quadratic convergence is guaranteed (apart from the effect of rounding errors) unless, for some $k = 2, \dots, n$,

$$\beta'_1 = \beta'_2 = \dots = \beta'_{n-k+1} = 0 \quad (6.8)$$

at iteration k .

The linear search

Our linear search procedure is similar to that suggested by Powell (1964). We wish to find a value of λ which approximately minimizes

$$\varphi(\lambda) = f(x_0 + \lambda u), \quad (6.9)$$

where the initial point x_0 and direction $u \neq 0$ are given, and $\varphi(0) = f(x_0)$ is already known. If a linear search in the direction u has already been performed, or if u resulted from a singular value decomposition, then an estimate of $\varphi''(0)$ is available. A parabola $P(\lambda)$ is fitted to $\varphi(\lambda)$, using $\varphi(0)$, the estimate of $\varphi''(0)$ if

available, and the computed value of $\varphi(\lambda)$ at another point, or at two points if there is no estimate of $\varphi''(\lambda)$. If $P(\lambda)$ has a minimum at $\lambda = \lambda^*$, and $\varphi(\lambda^*) < \varphi(0)$, then λ^* is accepted as a value of λ to approximately minimize (6.9). Otherwise λ^* is replaced by $\lambda^*/2$, $\varphi(\lambda^*)$ is re-evaluated, and the test is repeated. (After a number of unsuccessful tries, the procedure returns with $\lambda = 0$.)

The stopping criterion

The user of procedure praxis provides two parameters: t (a positive absolute tolerance), and ϵ (i.e., macheps, the machine precision); and the procedure attempts to return x satisfying

$$\|x - \mu\|_2 \leq \epsilon^{1/2} \|x\|_2 + t, \quad (6.10)$$

where μ is the position of the true local minimum near x . The exact form of the right side of (6.10) is not important, and could easily be changed if desired. It was chosen because of the analogy with the one-dimensional case (see Chapter 5).

It is impossible to guarantee that (6.10) will hold for all functions f , or even for f which are C^2 near μ . Our stopping criterion is, however, rather cautious, and (6.10) is satisfied for all numerical examples discussed in Section 7, with the sole exception of the extremely ill-conditioned problem

$$f(x) = x^T A x, \quad (6.11)$$

where A is a 12 by 12 Hilbert matrix, with a condition number $\kappa \simeq 1.7 \times 10^{16} > \epsilon^{-1} \simeq 4 \times 10^{15}$. In most cases the stopping criterion is over-cautious, and some unnecessary function evaluations are performed.

Let us remark, as does Powell (1964), that the stopping criterion is not an essential part of our algorithm, so an improved criterion could easily be incorporated.

Let \underline{x}' be the current best approximation to the minimum before an iteration of the basic procedure, and let \underline{x}'' be the best approximation after the iteration, i.e., n linear searches later. We test if

$$2\|\underline{x}' - \underline{x}''\|_p \leq \varepsilon^{1/2}\|\underline{x}''\|_p + t. \quad (6.12)$$

The stopping criterion is simply to stop, and return the approximation \underline{x}'' , if (6.12) is satisfied for a prescribed number of consecutive iterations. The number of consecutive iterations depends on how cautious we wish to be: 2 is reasonable, and was used for the examples described in Section 7. Because of the random step strategy described in Section 5, and always adopted if (6.12) was satisfied on the previous iteration, there is no need for a more complicated criterion, such as the one used by Powell (1964).

7. Numerical results and comparison with other methods

The ALGOL W procedure "praxis", given in Section 9, has been tested on IBM 360/67 and 360/91 computers with machine precision 16^{-13} . In this section we summarize the results of the numerical tests, and compare them with results for other methods reported in the literature. Our procedure has also been translated into SAIL (an extension of ALGOL: see Swinchart and Sproull (1970)) and used to solve least-squares parameter-fitting problems with up to 16 variables on a PDP 10 computer

(machine precision 2^{-26}). The parameter-fitting problem is described in Sobel (1970).

Table 7.1 summarizes the performance of procedure praxis on the test functions described below. In all cases the tolerance $t = 10^{-5}$ and macheps = 16^{-13} . The table gives the number of variables, n ; the initial step-size (a rough estimate of the distance to the minimum), h ; and the starting point, \underline{x}_0 . So that the results can be compared with those of methods with a different stopping criterion, we give the number n_f of function evaluations, and the number n_l of linear searches (including any parabolic extrapolations), required to reduce $f(\underline{x}) - f(\underline{\mu})$ below 10^{-10} , where $f(\underline{\mu})$ is the true minimum of f . As $f(\underline{x})$ was only printed out after each iteration of the basic procedure, i.e., after every n linear minimizations, the number of function evaluations required to reduce $f(\underline{x}) - f(\underline{\mu})$ to 10^{-10} is often slightly less than n_f , so we also give the actual value of $f(\underline{x}) - f(\underline{\mu})$ after n_f function evaluations. Finally, the table gives κ , the estimated condition number of the problem. Except for the few cases where it is easily found analytically, κ is estimated from the computed singular values, and may be rather inaccurate.

For those examples marked with an asterisk, the random step strategy was used from the start. (In the initialization phase of procedure praxis, the variable "illc" was set to true.) For the other examples the procedure was used as given in Section 9 (with "illc" set to false initially). Although the automatic scaling feature (see Section 4) reduces n_f by about 25 percent for some of the badly scaled problems, this feature was switched off for the examples given in the table. (The bound "scbd" of equation (4.15) was set to 1.)

Definitions of the test functions, and comments on the results summarized in Table 7.1, are given after the table.

A cautionary note

When comparing different minimization methods, such as ours, Powell's and Stewart's, the reader should not forget that the numerical results reported for the methods may have been obtained on different computers (with different word-lengths), and with different linear search procedures. The effect of different word-lengths should only be significant in the final stages of the search, when rounding errors determine the limiting accuracy attainable, except for ill-conditioned problems (say $\kappa > 10^4$). This is another reason why we prefer to consider the number of function evaluations required to reduce $f(\underline{x}) - f(\underline{\mu})$ to a reasonable threshold (say 10^{-10}), rather than the number required for convergence.

Because apparently minor differences in the linear search procedures can be quite important, Fletcher (1965) prefers to consider the number of linear searches, n_1 , instead of the number of function evaluations, n_f . This approach discriminates against methods, such as Powell's, which use most of the search directions several times, and can thus use second derivative estimates to reduce the number of function evaluations required for the second and later searches in each direction. Note that, for the examples given in Table 7.1, n_f/n_1 lies between 2.1 and 2.7, but it would be at least 3.0 for methods which do not use second derivative information, if the linear search involves fitting a parabola and evaluating f at the minimum of the parabola. Also, there are promising methods which do not use linear searches at all (see Broyden (1967)),

Davidon (1968, 1969), Goldstein and Price (1967), and Powell (1970e)), and these methods could presumably be adapted to accept difference approximations to derivatives. Thus, we prefer to compare methods on the basis of the number of function evaluations required, and regard the linear search procedure, if any, as an integral part of each method.

Table 7.1: Results for various test functions

Function	n	h	\underline{x}_0^T	n_f	n_1	$f(\underline{x}) - f(\underline{\mu})$	κ
Rosenbrock	2	1	(-1.2, 1)	120	47	6.61'-18	2508
Rosenbrock	2	3	(3, 3)	110	42	8.53'-17	2508
Rosenbrock	2	12	(8, 8)	181	67	9.71'-18	2508
Cube	2	1	(-1.2, -1)	177	68	7.18'-18	10018
Beale	2	1	(0.1, 0.1)	54	22	2.00'-15	162
Helix	3	1	(-1, 0, 0)	155	67	1.75'-11	500
Powell	3	1	(0, 1, 2)	55	23	1.99'-11	28
Box*	3	20	(0, 10, 20)	100	37	2.37'-13	8300
Singular*	4	1	(3, -1, 0, 1)	234	106	9.76'-11	∞
Wood*	4	10	-(3, 1, 3, 1)	452	191	6.06'-14	1400
Chebysquad	2	0.1	$x_i = i/(n+1)$	31	12	7.89'-20	1.3
Chebysquad	4	0.1	$x_i = i/(n+1)$	74	32	7.89'-11	7
Chebysquad	6	0.1	$x_i = i/(n+1)$	223	101	7.00'-13	50
Chebysquad	8	0.1	$x_i = i/(n+1)$	326	147	6.32'-11	200?
Watson*	6	1	$\vec{0}^T$	316	145	2.83'-12	86000
Watson*	9	1	$\vec{0}^T$	1184	541	3.18'-11	1.7'9

* For these results we set `ilic := true` in the initialization phase of procedure `praxis`, and the random number generator was initialized by calling `raninit(2)` in procedure `test`.

Table 7.1 continued

Function	n	h	x_0^T	n_f	n_1	$f(\underline{x}) - f(\underline{\mu})$	n
Tridiag	4	8	0^T	27	11	0	29.3
Tridiag	6	12	0^T	51	22	0	64.9
Tridiag	8	16	0^T	126	55	0	113
Tridiag	10	20	0^T	201	89	1.56'-15	175
Tridiag	12	24	0^T	259	118	2.23'-15	250
Tridiag	16	32	0^T	488	222	1.26'-13	438
Tridiag	20	40	0^T	805	379	0	677
Hilbert	2	10	(1,...,1)	11	4	3.98'-15	19
Hilbert	4	10	(1,...,1)	50	22	6.11'-15	1.5'4
Hilbert	6	10	(1,...,1)	133	58	1.50'-11	1.5'7
Hilbert	8	10	(1,...,1)	262	119	8.14'-11	1.5'10
Hilbert ⁺	10	10	(1,...,1)	592	267	7.84'-11	1.6'13
Hilbert ⁺	12	10	(1,...,1)	731	328	1.98'-11	1.7'16

+ For these results the stopping criterion was more conservative:
we set $ktm := 4$ in the initialization phase of procedure praxis.

Definitions of the test functions and comments on Table 7.1

Rosenbrock (Rosenbrock (1960)):

$$f(\underline{x}) = 100(x_2 - x_1^2)^2 + (1 - x_1)^2. \quad (7.1)$$

This is a well-known function with a parabolic valley. Descent methods tend to fall into the valley, and then follow it around to the minimum at (1,1). Details of the progress of the algorithm, for the starting point (-1.2, 1), are given in Table 7.2. In Diagram 7.1 we compare these results with those reported for Stewart's method (Stewart (1967)), Powell's method, and the method of Davies, Swann and Campey (as reported by Fletcher (1965)). The graph shows that our method compares favourably with the other methods. Although the function (7.1) is rather artificial, similar curved valleys often arise when penalty function methods are used to reduce constrained problems to unconstrained problems: consider minimizing $(1 - x_1)^2$, with the constraint that $x_2 = x_1^2$, by a simple-minded penalty function method.

Cube (Leon (1966)):

$$f(\underline{x}) = 100(x_2 - x_1^3)^2 + (1 - x_1)^2. \quad (7.2)$$

This function is similar to Rosenbrock's, and much the same remarks apply. Here the valley follows the curve $x_2 = x_1^3$.

Beale (Beale (1958)):

$$f(\underline{x}) = \sum_{i=1}^3 (c_i - x_1(1 - x_2^i))^2, \quad (7.3)$$

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where $c_1 = 1.5$, $c_2 = 2.25$, $c_3 = 2.625$. This function has a valley approaching the line $x_2 = 1$, and has a minimum of 0 at $(3, \frac{1}{2})^T$. Kowalik and Osborne (1968) report that the Davidon-Fletcher-Powell algorithm reduced f to 2.18×10^{-11} in 20 function and gradient evaluations (equivalent to 60 function evaluations if the usual $(n+1)$ weighting factor is used), and Powell's method required 86 function evaluations to reduce f to 2.94×10^{-8} . Thus, our method compares favourably on this example.

Helix (Fletcher and Powell (1963)):

$$f(\underline{x}) = 100((x_3 - 10\theta)^2 + (r - 1)^2) + x_3^2, \quad (7.4)$$

where

$$r = (x_1^2 + x_2^2)^{1/2} \quad (7.5)$$

and

$$2\pi\theta = \begin{cases} \arctan(x_2/x_1) & \text{if } x_1 > 0, \\ \pi + \arctan(x_2/x_1) & \text{if } x_1 < 0. \end{cases} \quad (7.6)$$

This function of three variables has a helical valley, and a minimum at $(1, 0, 0)^T$. The results are given in more detail in Table 7.3 and Diagram 7.2. For this example our method is faster than Powell's method, but slightly slower than Stewart's.

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Powell (Powell (1964)):

$$f(\underline{x}) = 3 - \left(\frac{1}{1 + (x_1 - x_2)^2} \right) - \sin\left(\frac{\pi}{2} x_2 x_3\right) - \exp\left\{ \left[- \left(\frac{x_1 + x_2}{x_2} \right) - 2 \right]^2 \right\}. \quad (7.7)$$

For a description of this function, see Powell (1964). Perhaps by good luck, our procedure had no difficulty with this function: it found the true minimum quickly and did not stop prematurely.

Box (Box (1966)):

$$f(\underline{x}) = \sum_{i=1}^{10} \left[\frac{(\exp(-ix_1/10) - \exp(-ix_2/10))^2}{-x_3(\exp(-i/10) - \exp(-i))} \right]^2. \quad (7.8)$$

This function has minima of 0 at $(1, 10, 1)^T$, and also along the line $\{(\lambda, \lambda, 0)^T\}$. (Our procedure found the first minimum.) Kowalik and Osborne (1968) report that Powell's method took 205 function evaluations to reduce f to 3.09×10^{-9} , so our method is about twice as fast. Our method took 79 function evaluations to reduce f to 2.29×10^{-7} , so it is faster, in this example, than any of the methods compared by Box (1966), with the exception of Powell's method for sums of squares (Powell (1965)). See the comment in Section 1 about special methods for minimizing sums of squares!

Singular (Powell (1962)):

$$f(\underline{x}) = (x_1 + 10x_2)^2 + 5(x_3 - x_1)^2 + (x_2 - 2x_3)^4 + 10(x_1 - x_4)^4. \quad (7.9)$$

This function is difficult to minimize, and provides a severe test of the stopping criterion, because the Hessian matrix at the minimum ($\underline{x} = \underline{0}$) is doubly singular. The function varies very slowly near $\underline{0}$ in the two-dimensional subspace $\{(10\lambda_1, -\lambda_1, \lambda_2, \lambda_2)^T\}$. Table 7.4 and Diagram 7.3 suggest that the algorithm converges only linearly, as does Powell's algorithm. It is interesting to note that the output from our procedure would strongly suggest the singularity, if we did not know it in advance: after 219 function evaluations, with $f(\underline{x}) = 7.67 \times 10^{-9}$, the computed eigenvalues were 101.0, 9.999, 0.003790, and 0.001014. (The exact eigenvalues at $\underline{0}$ are 101, 10, 0, and 0.) After 384 function evaluations, with $f(\underline{x})$ reduced to 1.02×10^{-17} , the two smallest eigenvalues were 1.56×10^{-7} and 5.98×10^{-8} . Thus, our procedure should enable singularity of the Hessian matrix to be detected, in the unlikely event that it occurred in a practical problem. (For one example, see Freudenstein and Roth (1963).)

Wood (see Colville (1968)):

$$f(\underline{x}) = 100(x_2 - x_1^2)^2 + (1 - x_1)^2 + 90(x_4 - x_3^2)^2 + (1 - x_3)^2 + 10.1[(x_2 - 1)^2 + (x_4 - 1)^2] + 19.8(x_2 - 1)(x_4 - 1) \quad (7.10)$$

This function is rather like Rosenbrock's, but with four variables instead of two. Procedures with an inadequate stopping criterion may terminate prematurely on this function (see McCormick and Pearson (1969)), but our procedure did find the minimum at $\underline{\mu} = (1, 1, 1, 1)^T$.

Chebysquad (Fletcher (1965)):

$f(\underline{x})$ is defined by the ALGOL procedure given by Fletcher (1965). As the minimization problem is still valid, we have not corrected a small error in this procedure. (The procedure does not compute exactly what Fletcher intended.) In contrast to most of our other test functions, which are designed to be difficult to minimize, this function is fairly easy to minimize. For $n = 1(1)7$ and 9 the minimum is 0, for other n it is nonzero. (For $n = 8$ it is approximately 0.003516873/2568.) The results given in Table 7.5, and illustrated in Diagrams 7.4 to 7.7, show that our method is faster than those of Powell or of Davies, Swann and Campey, but a little slower than Stewart's.

Watson (see Kowalik and Osborne (1968)):

$$f(\underline{x}) = x_1^2 + (x_2 - x_1^2 - 1)^2 +$$

$$\sum_{i=2}^{30} \left[\sum_{j=2}^n (j-1)x_j \left(\frac{i-1}{29}\right)^{j-2} - \left(\sum_{j=1}^n x_j \left(\frac{i-1}{29}\right)^{j-1} \right)^2 - 1 \right]^2 \quad (7.11)$$

Here a polynomial

$$p(t) = x_1 + x_2 t + \dots + x_n t^{n-1} \quad (7.12)$$

is fitted, by least squares, to approximate a solution of the differential equation

$$dz/dt = 1 + z^2, \quad (7.13)$$

with $z(0) = 0$, for $t \in [0, 1]$. (The exact solution is $z = \tan(t)$.)

Because of a bad choice of basis functions $\{1, t, \dots, t^{n-1}\}$, the

minimization problem is ill-conditioned, and rather difficult to solve.

For $n = 6$, the minimum is $f(\underline{\mu}) \simeq 2.28767005355 \times 10^{-3}$, at

$$\underline{\mu} \simeq (-0.015725, 1.012435, -0.232992, 1.260430, -1.513729, 0.992996)^T.$$

For $n = 9$, $f(\underline{\mu}) \simeq 1.399760138 \times 10^{-6}$, and $\underline{\mu} \simeq (-0.000015, 0.999790, 0.014764, 0.146342, 1.000821, -2.617731, 4.104403, -3.143612, 1.052627)^T$.

(We do not claim that all the figures given are significant.)

Kowalik and Osborne (1968) report that, after 700 function evaluations, Powell's method had only reduced f to 2.434×10^{-3} (for $n = 6$), so our method is at least twice as fast here. The Watson problem for $n = 9$ is very ill-conditioned, and seems to be a good test for a minimization procedure.

Tridiag (see Gregory and Karney (1969), pp. 41 and 74):

$$f(\underline{x}) = \underline{x}^T A \underline{x} - 2x_1, \quad (7.14)$$

where

$$A = \begin{bmatrix} 1 & -1 & & & & & & & \\ -1 & 2 & -1 & & & & & & \\ & -1 & 2 & -1 & & & & & \\ & & -1 & 2 & -1 & & & & \\ & & & -1 & 2 & -1 & & & \\ & & & & \ddots & \ddots & \ddots & \ddots & \\ & & & & & -1 & 2 & & \end{bmatrix} \quad (7.15)$$

This function is useful for testing the quadratic convergence property.

The minimum $f(\underline{\mu}) = -n$ occurs when $\underline{\mu}$ is the first column of A^{-1} , i.e.,

$$\underline{\mu} = (n, n-1, n-2, \dots, 2, 1)^T. \quad (7.16)$$

The results given in Table 7.1 show that, as expected, the minimum is found in n^2 or less linear minimizations. The eigenvalues of A are

$$\text{just } \lambda_j = 4 \cos^2\left(\frac{j\pi}{2n+1}\right) \quad \text{for } j = 1, \dots, n.$$

Hilbert

$$f(\underline{x}) = \underline{x}^T A \underline{x}, \quad (7.17)$$

where A is an n by n Hilbert matrix, i.e.,

$$a_{ij} = 1/(i+j-1) \quad (7.18)$$

for $1 \leq i, j \leq n$. $f(\underline{x})$ can be computed directly without storing the matrix A . Like (7.14), (7.17) is a positive definite quadratic form, but the condition number increases rapidly with n . Because of the effect of rounding errors, more than n^2 linear minimizations were required to reduce f to 10^{-10} , except for $n = 2$. The procedure successfully found the minimum $\underline{\mu} = \underline{0}$, to within the prescribed tolerance, for $n \leq 10$. For $n = 12$, some components of the computed minimum were greater than 0.1, even though f was reduced to 2.76×10^{-15} . This illustrates how ill-conditioned the problem is!

Some more detailed results

Tables 7.2 to 7.5 give more details of the progress of our procedure (B) on the Rosenbrock, Helix, Singular, and Chebyquad functions. In Diagrams 7.1 to 7.7, we plot

$$\Delta = \log_{10}(f(\underline{x}) - f(\underline{\mu})) \quad (7.19)$$

against n_f , the number of function evaluations. Using the results given by Fletcher (1965) and Stewart (1967), the corresponding graphs for the methods of Davies, Swann and Campey (D), Powell (P), and Stewart (S), are also given, for purposes of comparison.

Table 7.2: Rosenbrock

n_f	n_1	$f(\underline{x})$	x_1	x_2
1	0	2.42'1	-1.200000	1.000000
11	4	4.14'0	-1.034611	1.071270
21	8	3.42'0	-0.811598	0.621199
31	12	2.59'0	-0.549031	0.258076
45	17	1.67'0	-0.268211	0.046503
58	22	1.07'0	-0.028125	-0.010783
72	27	3.71'-1	0.482692	0.200894
84	32	2.79'-3	0.947231	0.897130
98	37	5.89'-4	0.996384	0.990382
109	42	6.69'-9	0.999991	0.999974
120	47	6.61'-18	1.000000	1.000000
132	52	1.13'-23	1.000000	1.000000
155	57	4.47'-24	1.000000	1.000000

Table 7.3: Helix

n_f	n_1	$f(\underline{x})$	x_1	x_2	x_3
1	0	2.50'3	-1.000000	0.000000	0.000000
14	5	1.62'2	1.000000	2.000000	2.000000
23	9	1.18'2	0.563832	1.952025	1.759493
36	14	5.22'0	0.311857	1.000020	2.096124
44	18	4.04'0	0.305534	0.967190	1.987145
57	23	3.78'0	0.347506	0.907981	1.922708
65	27	3.01'0	0.847973	0.734103	1.074593
82	33	9.46'-1	0.816717	0.566910	0.969820
91	37	3.66'-1	0.965734	0.342023	0.548844
105	43	2.46'-1	1.004624	0.239418	0.364506
113	47	2.84'-2	0.993843	0.091699	0.153178
126	53	6.35'-3	1.002319	0.045726	0.072132
134	57	8.01'-4	1.002726	0.002303	0.002966
147	63	8.66'-6	0.999996	0.001853	0.002942
155	67	1.75'-11	1.000000	8.49'-9	2.47'-7
169	73	1.12'-20	1.000000	-6.45'-11	-9.92'-11
178	77	1.99'-24	1.000000	-1.69'-13	-2.47'-13
200	83	1.94'-24	1.000000	-1.60'-13	-2.53'-13

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Table 7.4: Singular*

n_f	n_1	$f(x)$	n_f	n_1	$f(x)$
1	0	2.15'-2	234	106	9.76'-11
19	6	1.18'-1	244	111	2.03'-12
31	11	7.96'-0	254	116	4.11'-13
42	16	7.75'-0	269	123	2.61'-14
58	22	2.94'-0	279	128	6.43'-15
68	27	9.86'-1	289	133	8.88'-16
78	32	1.34'-1	308	140	7.35'-16
94	38	6.92'-3	319	145	3.87'-16
104	43	1.18'-3	330	150	9.92'-17
114	48	5.25'-5	358	157	9.92'-17
129	55	8.25'-6	373	162	1.65'-17
139	60	2.13'-6	384	167	1.02'-17
149	65	2.70'-7	404	174	9.95'-18
164	72	7.91'-8	421	179	6.02'-23
174	77	3.95'-8	436	184	5.89'-23
184	82	3.90'-8	464	191	5.89'-23
199	89	3.90'-8	486	196	5.89'-23
209	94	3.89'-8			
219	99	7.67'-9			

$\hat{\mu}^T \approx (-9.73 \times 10^{-7}, 9.73 \times 10^{-8}, 5.31 \times 10^{-7}, 5.31 \times 10^{-7})$, lying approximately in the subspace $\{(10\lambda_1, -\lambda_1, \lambda_2, \lambda_2)\}$, as expected.

* See the comment under Table 7.1.

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Table 7.5: Chebyquad

$n = 2$

n_f	n_1	$f(x)$
1	0	1.98'-1
12	4	4.53'-3
22	8	1.89'-8
31	12	7.89'-20
45	17	4.89'-24
73	22	4.89'-24

$$\hat{\mu}^T = (0.2113249, 0.7886751)$$

$n = 6$

n_f	n_1	$f(x)$
1	0	4.64'-2
23	8	2.35'-2
37	15	1.80'-2
51	22	1.21'-2
66	29	5.69'-3
81	36	2.07'-3
103	44	9.89'-5
117	51	3.47'-5

$$\hat{\mu}^T = (0.066877, 0.288741, 0.366682, 0.633318, 0.711259, 0.933123)$$

$n = 4$

n_f	n_1	$f(x)$
1	0	7.12'-2
17	6	1.43'-2
27	11	1.59'-3
38	16	1.00'-4
54	22	4.22'-7
64	27	1.86'-8
74	32	7.89'-11
87	38	7.75'-14
98	43	1.88'-16

$$\hat{\mu}^T = (0.1026728, 0.4062037, 0.5937963, 0.8973272)$$

$n = 6$ (continued)

n_f	n_1	$f(x)$
131	58	2.14'-5
145	65	1.14'-5
159	72	2.71'-6
181	80	1.13'-7
195	87	6.59'-10
209	94	1.38'-10
223	101	7.00'-13
238	108	3.77'-15

Table 7.5 continued

n = 8					
n_f	n_1	$f(\underline{x})$	n_f	n_1	$f(\underline{x})$
1	0	0.0386176982859	208	92	0.0035269968747
29	10	0.0171124413073	226	101	0.0035191392494
47	19	0.0109131815974	244	110	0.0035180637576
65	28	0.0102860269896	262	119	0.0035176364629
83	37	0.0093337335931	280	128	0.0035171964541
102	46	0.0071908595069	308	138	0.0035168743745
125	55	0.0049952481593	326	147	0.0035168737890
144	64	0.0044432513463	345	156	0.0035168737290
172	74	0.0037940416125	364	165	0.0035168737288
190	83	0.0035390722159			

$\hat{1}^T = (0.043153, 0.193091, 0.266329, 0.500000, 0.500000, 0.733671,$
 $0.806910, 0.956847)$

Diagram 7.1: Rosenbrock

Key: B: Our method,
D: The method of Davies, Swann and Campey,
as given by Fletcher (1965),
P: Powell's (1964) method, as given by Fletcher (1965),
S: Stewart's method, as given by Stewart (1967).

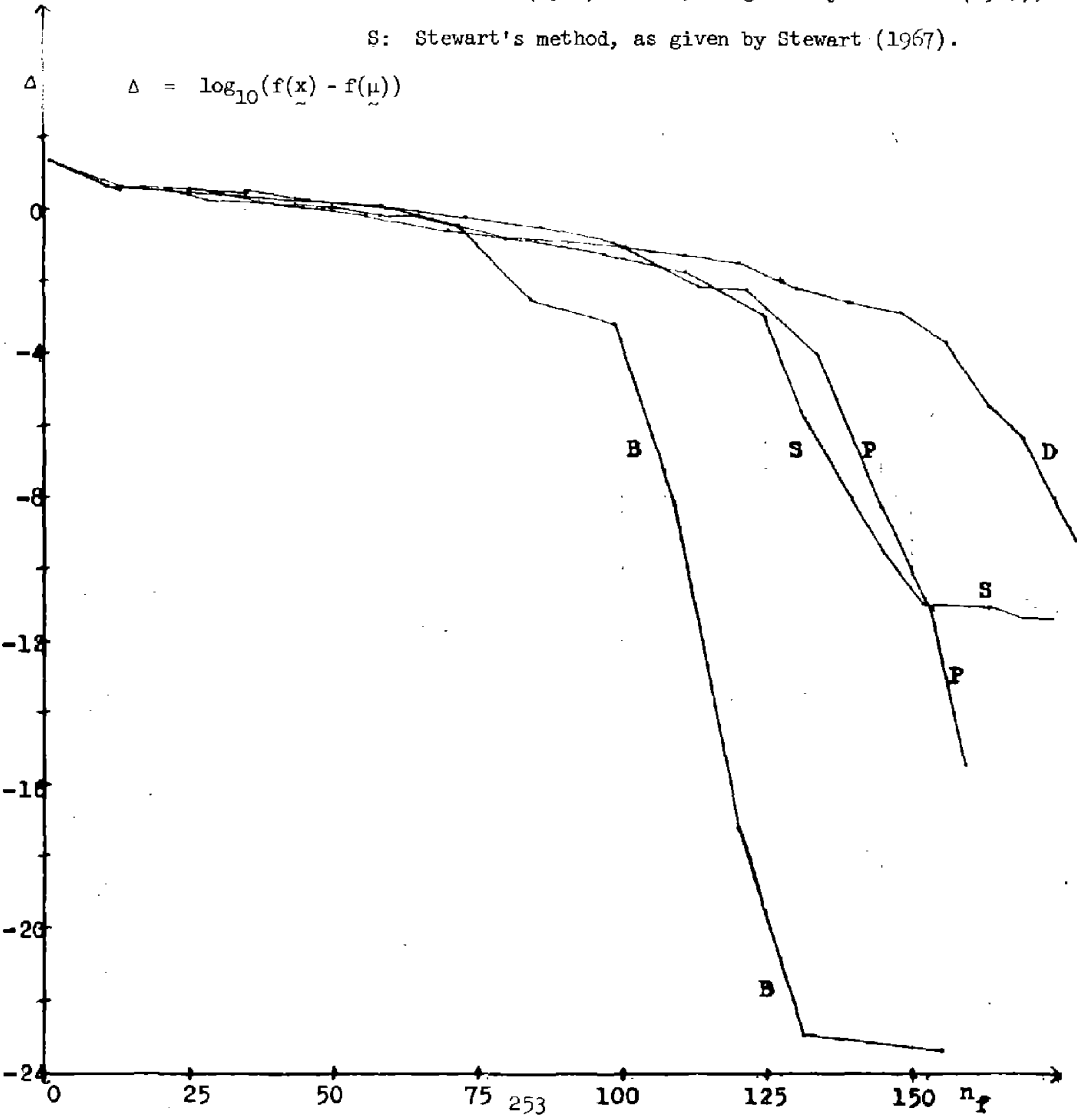
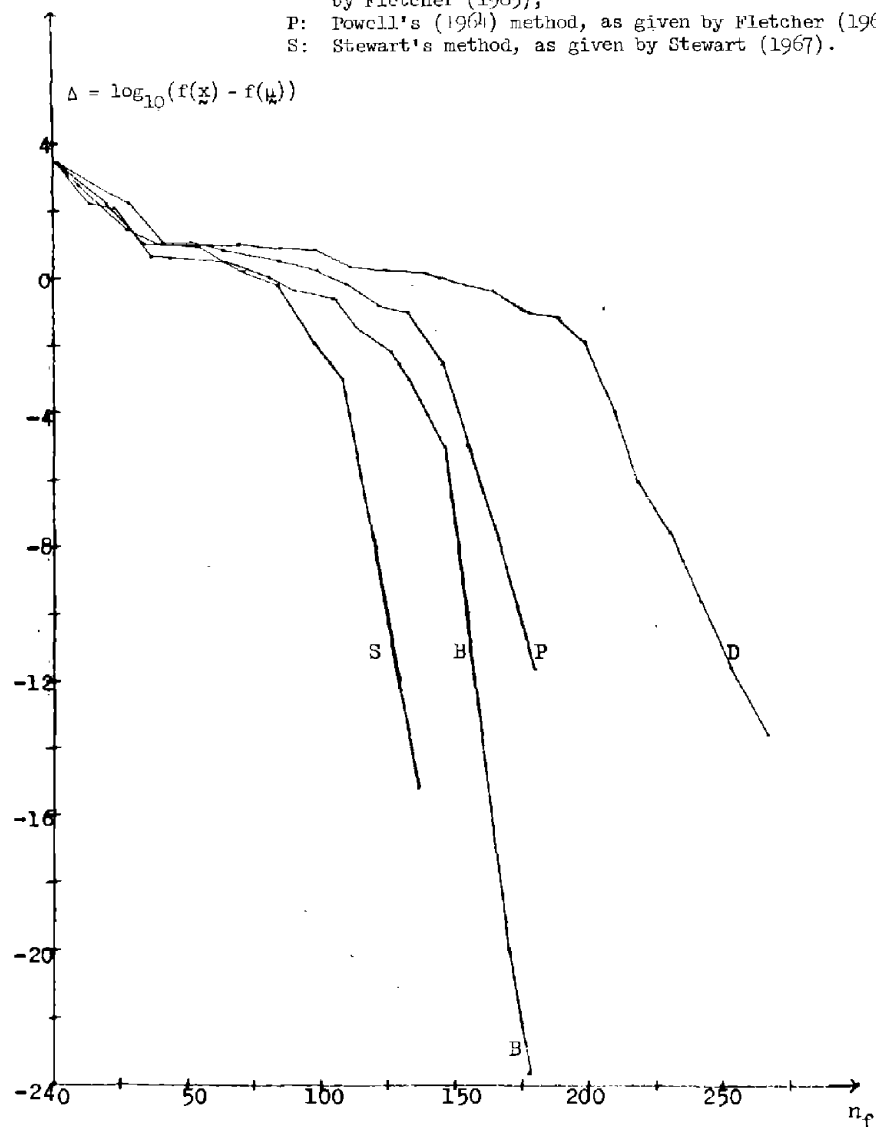


Diagram 7.2: Helix

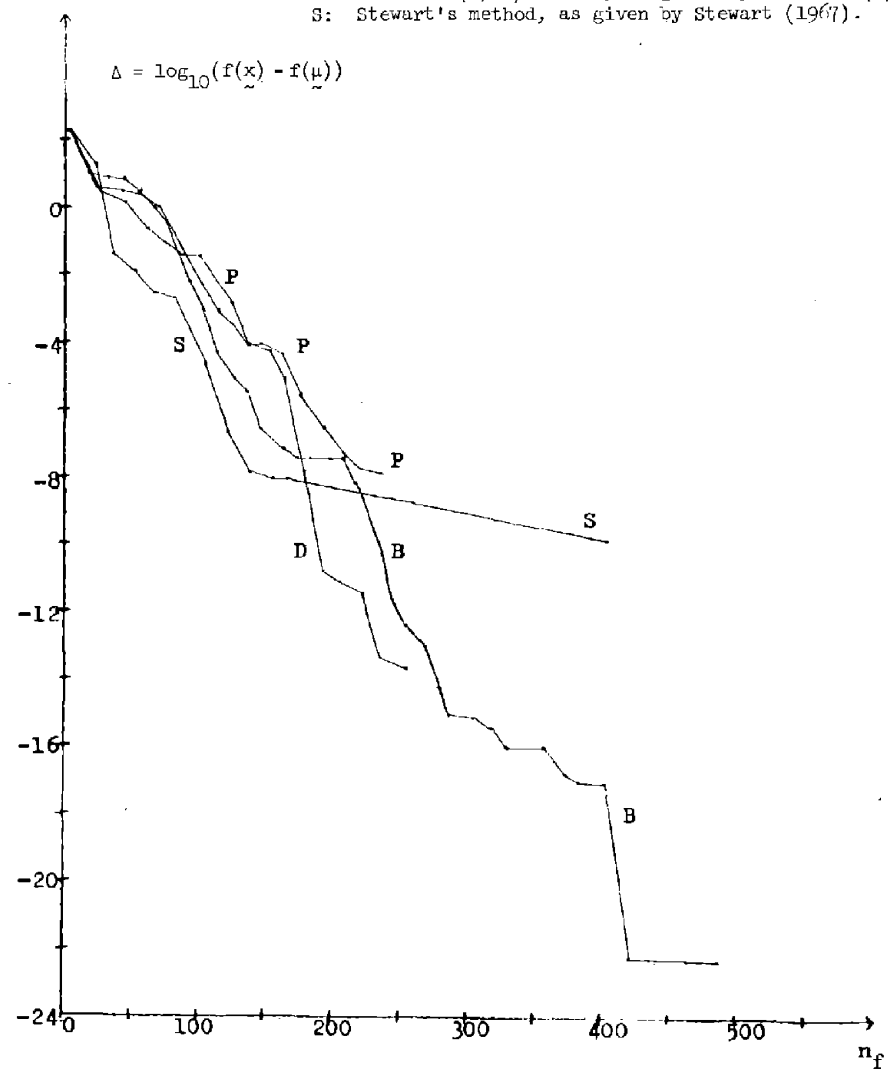
Key: B: Our method,
 D: The method of Davies, Swann and Campey, as given
 by Fletcher (1965),
 P: Powell's (1964) method, as given by Fletcher (1965),
 S: Stewart's method, as given by Stewart (1967).



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Diagram 7.3: Singular (Powell's function of four variables)

Key: B: Our method,
 D: The method of Davies, Swann and Campey, as
 given by Fletcher (1965),
 P: Powell's (1964) method, as given by Fletcher (1965),
 S: Stewart's method, as given by Stewart (1967).

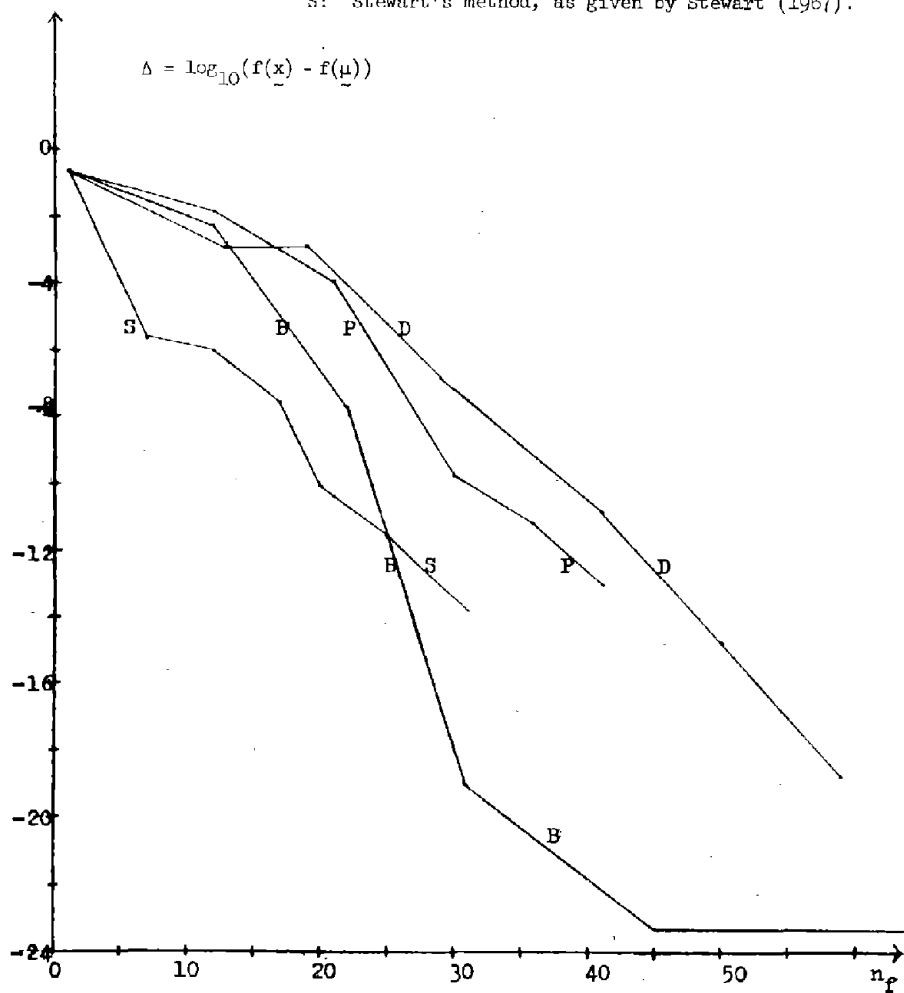


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Diagram 7.4: Chebyquad, $n = 2$

Key: B: Our method,
 D: The method of Davies, Swann and Campey, as given by Fletcher (1965),
 P: Powell's (1964) method, as given by Fletcher (1965),
 S: Stewart's method, as given by Stewart (1967).

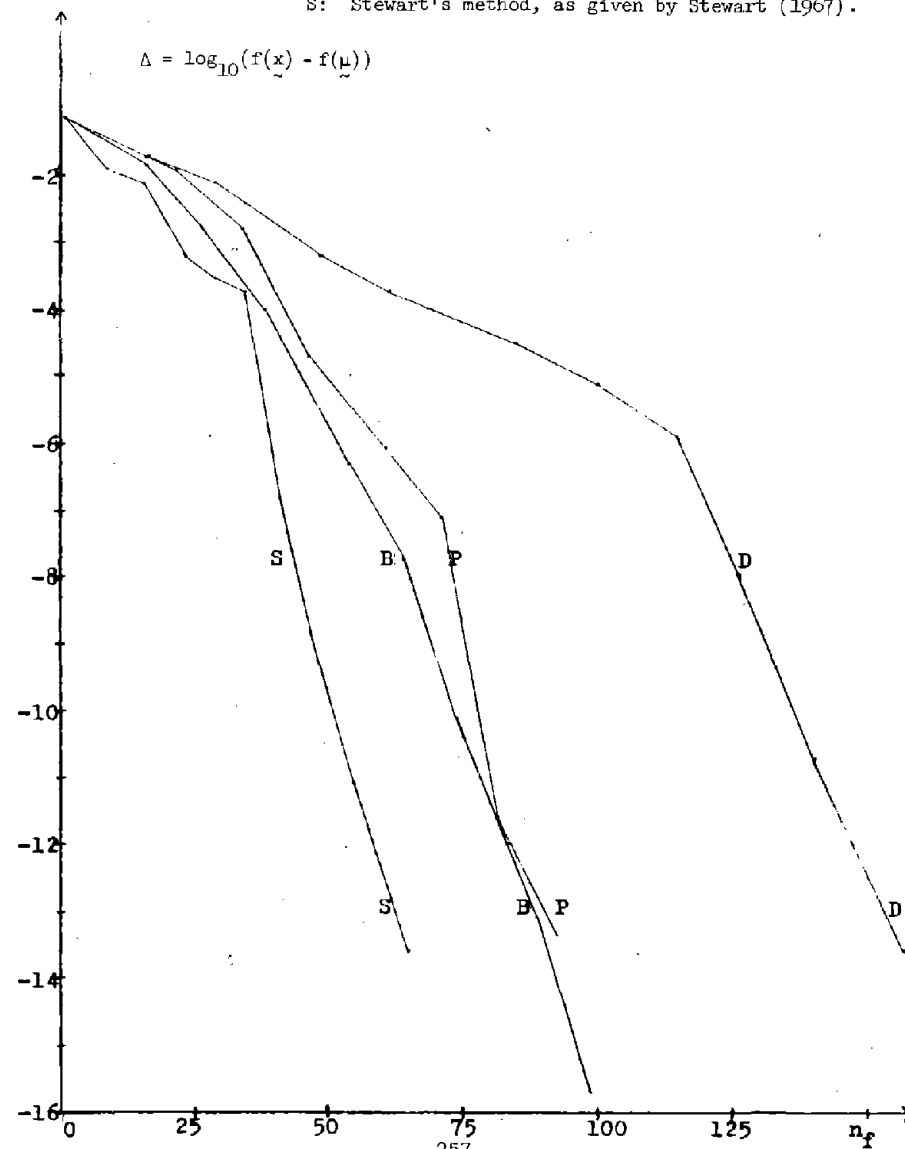


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Diagram 7.5: Chebyquad, $n = 4$

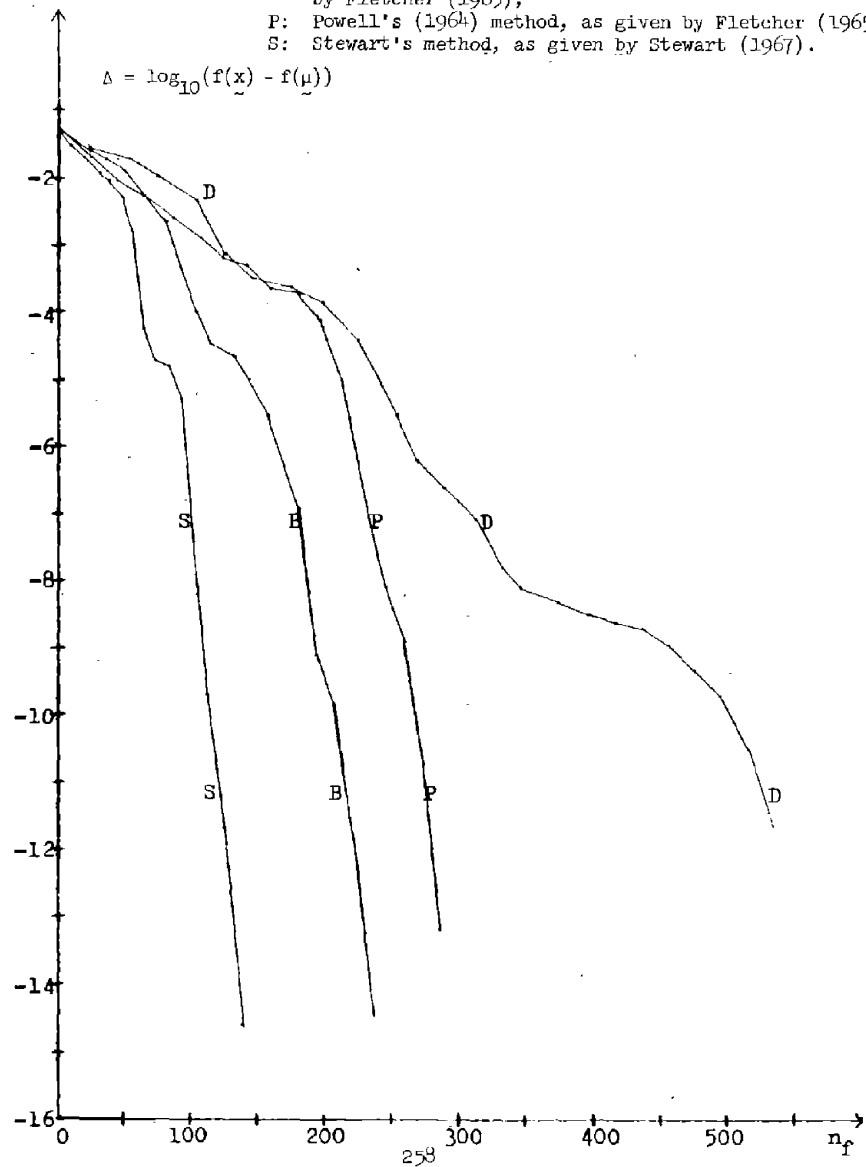
Key: B: Our method,
 D: The method of Davies, Swann and Campey, as given by Fletcher (1965),
 P: Powell's (1964) method, as given by Fletcher (1965),
 S: Stewart's method, as given by Stewart (1967).



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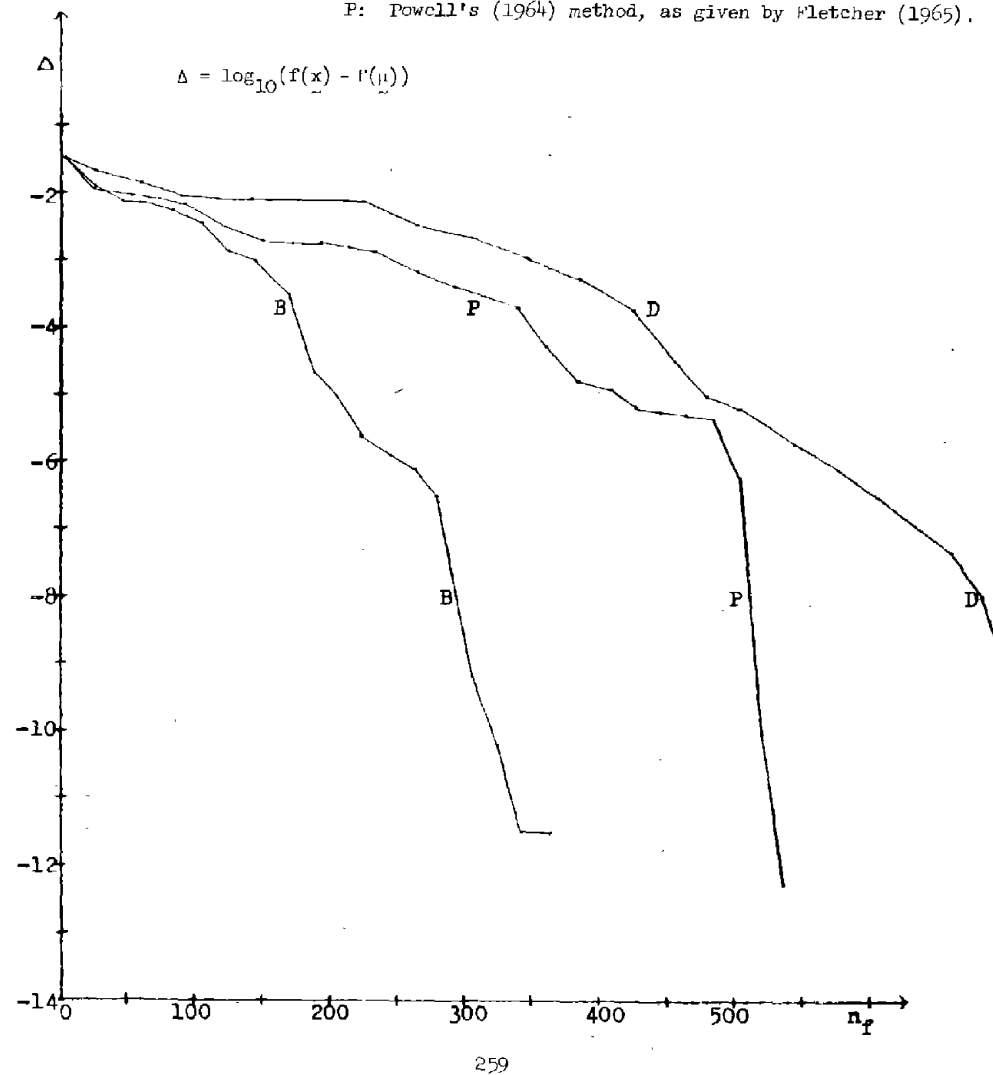
Diagram 7.6: Chebyquad, $n = 6$

Key: B: Our method,
 D: The method of Davies, Swann and Campey, as given
 by Fletcher (1965),
 P: Powell's (1964) method, as given by Fletcher (1965),
 S: Stewart's method, as given by Stewart (1967).

Diagram 7.7: Chebyquad, $n = 8$

(Results for Stewart's method not available.)

Key: B: Our method,
 D: The method of Davies, Swann and Campey, as given
 by Fletcher (1965),
 P: Powell's (1964) method, as given by Fletcher (1965).



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8. Conclusion

Powell (1964) observes that, with his determinantal criterion for accepting new search directions (see Section 3), there is a tendency for the new directions to be accepted less often as the number of variables increases, and the quadratic convergence property of his basic procedure is lost. Our aim was to avoid this difficulty, keep the quadratic convergence property, and ensure that the search directions continue to span the whole space, while using basically the same method as Powell (and Smith (1962)) to generate conjugate directions.

The numerical results given in Section 7 suggest that our algorithm is faster than Powell's, and comparable to Stewart's, if the criterion is the number of function evaluations required to reduce $f(x)$ to a certain threshold. Also, our algorithm seems to be reliable even for very ill-conditioned problems like Watson ($n = 9$) and Hilbert ($n = 10$), while Stewart's method breaks down because of numerical difficulties on some functions, e.g., the Rosenbrock and Singular functions (see Stewart (1967)). However, we should not try to conclude too much from the numerical results: see the warning in Section 7.

Theoretical convergence results

Suppose that all arithmetic is exact (i.e., there are no rounding errors), and consider our algorithm with the stopping criterion removed. Since the algorithm keeps on performing linear searches along n orthogonal directions, the same conditions that ensure convergence of the method of coordinate search to a local minimum will ensure convergence of our algorithm. In particular, the algorithm will converge to the

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(unique) minimum for all functions f which are C^2 , strictly convex, and satisfy

$$\lim_{\lambda \rightarrow \infty} f(\lambda e) = +\infty \quad (8.1)$$

for all nonzero vectors e . Of course, this result is of little practical interest, for in practice rounding errors may be very important: see Section 5.

It is plausible that, if the Hessian matrix of f is strictly positive definite at the minimum, then our algorithm will converge superlinearly. McCormick (1969) shows that this is true for the reset Davidon-Fletcher-Powell algorithm, provided a Lipschitz condition is satisfied. Figures 7.1, 7.2, and 7.4 to 7.7 certainly suggest that convergence is superlinear until rounding errors become important. We do not have a proof of this conjecture though: perhaps additional conditions on f , or a slight modification of the algorithm, are necessary.

9. An ALGOL W procedure and test program

The procedure praxis, plus a driver program and test functions, is given below. The language is ALGOL W (Wirth and Hoare (1966), Bauer, Becker and Graham (1968)), but none of the special features of ALGOL W have been used, so translation into another dialect of ALGOL should be straightforward.

BEGIN COMMENT:

TEST PROGRAM FOR PROCEDURE PRAXIS.
*****;

LONG REAL PROCEDURE PRAXIS (LONG REAL VALUE T, MACHEPS, H;
INTEGER VALUE N, PRIN;
LONG REAL ARRAY X(*); LONG REAL PROCEDURE F, RANDOM);
BEGIN COMMENT:

THIS PROCEDURE MINIMIZES THE FUNCTION $F(X, N)$ OF N VARIABLES $X(1), \dots, X(N)$, USING THE PRINCIPAL AXIS METHOD. ON ENTRY X HOLDS A GUESS, ON RETURN IT HOLDS THE ESTIMATED POINT OF MINIMUM, WITH (HOPEFULLY) $|ERROR| < \sqrt{T(MACHEPS)} \cdot |X| + T$, WHERE $MACHEPS$ IS THE MACHINE PRECISION, THE SMALLEST NUMBER SUCH THAT $1 + MACHEPS > 1$, T IS A TOLERANCE, AND 1.1 IS THE 2-NORM. H IS THE MAXIMUM STEP SIZE: SET TO ABOUT THE MAXIMUM EXPECTED DISTANCE FROM THE GUESS TO THE MINIMUM (IF H IS SET TOO SMALL OR TOO LARGE THEN THE INITIAL RATE OF CONVERGENCE WILL BE SLOW). THE USER SHOULD OBSERVE THE COMMENT ON HEURISTIC NUMBERS AFTER PROCEDURE QUAD.

PRIN CONTROLS THE PRINTING OF INTERMEDIATE RESULTS.

IF PRIN = 0, NO RESULTS ARE PRINTED.

IF PRIN = 1, F IS PRINTED AFTER EVERY $N+1$ OR $N+2$ LINEAR MINIMIZATIONS, AND FINAL X IS PRINTED, BUT INTERMEDIATE X ONLY IF $N \leq 4$.

IF PRIN = 2, EIGENVALUES OF A AND SCALE FACTORS ARE ALSO PRINTED.

IF PRIN = 3, F AND X ARE PRINTED AFTER EVERY FEW LINEAR MINIMIZATIONS.

IF PRIN = 4, EIGENVECTORS ARE ALSO PRINTED.

FMIN IS A GLOBAL VARIABLE: SEE PROCEDURE PRINT.

RANDOM IS A PARAMETERLESS LONG REAL PROCEDURE WHICH RETURNS A RANDOM NUMBER UNIFORMLY DISTRIBUTED IN $(0, 1)$. ANY INITIALIZATION MUST BE DONE BEFORE THE CALL TO PRAXIS.

THE PROCEDURE IS MACHINE-INDEPENDENT, APART FROM THE OUTPUT STATEMENTS AND THE SPECIFICATION OF MACHEPS. WE ASSUME THAT $MACHEPS^{**(-4)}$ DOES NOT OVERFLOW (IF IT DOES THEN MACHEPS MUST BE INCREASED), AND THAT ON FLOATING-POINT UNDERFLOW THE RESULT IS SET TO ZERO;

PROCEDURE MINFIT (INTEGER VALUE N; LONG REAL VALUE EPS, TOL;
LONG REAL ARRAY AB(*,*); LONG REAL ARRAY Q(*));
BEGIN COMMENT: AN IMPROVED VERSION OF MINFIT, SEE GOLUB & REINSCH (1969), RESTRICTED TO $M = N$, $P = 0$. THE SINGULAR VALUES OF THE ARRAY AB ARE RETURNED IN Q , AND AB IS OVERWRITTEN WITH THE ORTHOGONAL MATRIX V SUCH THAT $U \cdot \text{DIAG}(Q) = AB \cdot V$, WHERE U IS ANOTHER ORTHOGONAL MATRIX;

INTEGER L, KT;

LONG REAL C, F, G, H, S, X, Y, Z;

LONG REAL ARRAY E(1::N);

COMMENT: HOUSEHOLDER'S REDUCTION TO BIDIAGONAL FORM;

G := X := 0;

FOR I := 1 UNTIL N DO

BEGIN

E(I) := G; S := 0; L := I+1;

FOR J := I UNTIL N DO S := S + AB(J, I)**2;

IF S < TOL THEN G := 0 ELSE

BEGIN

F := AB(I, I); G := IF F < 0 THEN LONGSQRT(S)
ELSE -LONGSQRT(S);

H := F*G-S; AB(I, I) := F-G;

FOR J := L UNTIL N DO

BEGIN F := 0;

FOR K := I UNTIL N DO F := F + AB(K, I)*AB(K, J);

F := F/H;

FOR K := I UNTIL N DO AB(K, J) := AB(K, J) + F*AB(K, I)

END J

END S;

Q(I) := G; S := 0;

IF I <= N THEN FOR J := L UNTIL N DO

S := S + AB(I, J)**2;

IF S < TOL THEN G := 0 ELSE

BEGIN

F := AB(I, I+1); G := IF F < 0 THEN LONGSQRT(S)
ELSE -LONGSQRT(S);

H := F*G-S; AB(I, I+1) := F-G;

FOR J := L UNTIL N DO E(J) := AB(I, J)/H;

FOR J := L UNTIL N DO

BEGIN S := 0;

FOR K := L UNTIL N DO S := S + AB(J, K)*AB(I, K);

FOR K := L UNTIL N DO AB(J, K) := AB(J, K) + S*E(K)

END J

END S;

Y := ABS(Q(I)) + ABS(E(I)); IF Y > X THEN X := Y

END I;

COMMENT: ACCUMULATION OF RIGHT-HAND TRANSFORMATIONS;

FOR I := N STEP -1 UNTIL 1 DO

BEGIN

IF G**=0 THEN

BEGIN

H := AB(I, I+1)*G;

FOR J := L UNTIL N DO AB(J, I) := AB(J, I)/H;

FOR J := L UNTIL N DO

BEGIN S := 0;

FOR K := L UNTIL N DO S := S + AB(I, K)*AB(K, J);

FOR K := L UNTIL N DO AB(K, J) := AB(K, J) + S*AB(K, I)

END J

END G;

```

FOR J := L UNTIL N DO AB(I,J) := AB(J,I) := 0;
AB(I,I) := 1; G := E(I); L := I
END I;

COMMENT: DIAGONALIZATION OF THE BIDIAGONAL FORM;
EPS := EPS*X;
FOR K := N STEP -1 UNTIL 1 DO
  BEGIN KT := 0;
  TESTFSPLITTING:
  KT := KT + 1; IF KT > 30 THEN
    BEGIN E(K) := 0L;
    WRITE ("QR FAILED")
    END;
  FOR L2 := K STEP -1 UNTIL 1 DO
    BEGIN
      L := L2;
      IF ABS(E(L)) <= EPS THEN GOTO TESTFCONVERGENCE;
      IF ABS(Q(L-1)) <= EPS THEN GOTO CANCELLATION
    END L2;

    COMMENT: CANCELLATION OF E(L) IF L>1;
    CANCELLATION:
    C := 0; S := 1;
    FOR I := L UNTIL K DO
      BEGIN
        F := S*E(I); E(I) := C*E(I);
        IF ABS(F) <= EPS THEN GOTO TESTFCONVERGENCE;
        G := Q(I); Q(I) := H := IF ABS(F) < ABS(G) THEN
          ABS(G)*LONGSQRT(1 + (F/G)**2) ELSE IF F = 0 THEN
          ABS(F)*LONGSQRT(1 + (G/F)**2) ELSE 0;
        IF H = 0 THEN G := H := 1;
        COMMENT: THE ABOVE REPLACES Q(I):=H:=LONGSQRT(G*G+F*F)
          WHICH MAY GIVE INCORRECT RESULTS IF THE
          SQUARES UNDERFLOW OR IF F = G = 0;
        C := G/H; S := -F/H
      END I;

    TESTFCONVERGENCE:
    Z := Q(K); IF L=K THEN GOTO CONVERGENCE;

    COMMENT: SHIFT FROM BOTTOM 2*2 MINOR;
    X := Q(L); Y := Q(K-1); G := E(K-1); H := E(K);
    F := ((Y-Z)*(Y+Z) + (G-H)*(G+H))/(2*H*Y);
    G := LONGSQRT(F*F+1);
    F := ((X-Z)*(X+Z)+H*(Y/(IF F<0 THEN F-G ELSE F+G)-H))/X;

    COMMENT: NEXT QR TRANSFORMATION;
    C := S := 1;
    FOR I := L+1 UNTIL K DO
      BEGIN
        G := E(I); Y := Q(I); H := S*G; G := G+C;

```

```

E(I-1) := Z := IF ABS(F) < ABS(H) THEN
  ABS(H)*LONGSQRT(1 + (F/H)**2) ELSE IF F = 0 THEN
  ABS(F)*LONGSQRT(1 + (H/F)**2) ELSE 0;
  IF Z = 0 THEN Z := F := 1;
  C := F/Z; S := H/Z;
  F := X*C + G*S; G := -X*S + G*C; H := Y*S;
  Y := Y*C;
  FOR J := 1 UNTIL N DO
    BEGIN
      X := AB(J,I-1); Z := AB(J,I);
      AB(J,I-1) := X*C + Z*S; AB(J,I) := -X*S + Z*C
    END J;
    Q(I-1) := Z := IF ABS(F) < ABS(H) THEN ABS(H)*
      LONGSQRT(1 + (F/H)**2) ELSE IF F = 0 THEN
      ABS(F)*LONGSQRT(1 + (H/F)**2) ELSE 0;
    IF Z = 0 THEN Z := F := 1;
    C := F/Z; S := H/Z;
    F := C*G + S*Y; X := -S*G + C*Y
  END I;
  E(L) := 0; E(K) := F; Q(K) := X;
  GO TO TESTFSPLITTING;

  CONVERGENCE:
  IF Z<0 THEN
    BEGIN COMMENT: Q(K) IS MADE NON-NEG;
      Q(K) := -Z;
      FOR J := 1 UNTIL N DO AB(J,K) := -AB(J,K)
    END Z
  END K
END MINFIT;

PROCEDURE SORT;
  BEGIN COMMENT: SORTS THE ELEMENTS OF D AND CORRESPONDING
    COLUMNS OF V INTO DESCENDING ORDER;

  INTEGER K;
  LONG REAL S;
  FOR I := 1 UNTIL N - 1 DO
    BEGIN K := I; S := D(I); FOR J := I + 1 UNTIL N DO
      IF D(J) > S THEN
        BEGIN K := J; S := D(J) END;
      IF K > I THEN
        BEGIN D(K) := D(I); D(I) := S; FOR J := 1 UNTIL N DO
          BEGIN S := V(J,I); V(J,I) := V(J,K); V(J,K) := S
        END
      END
    END
  END SORT;

PROCEDURE PRINT;
  COMMENT: THE VARIABLE FMIN IS GLOBAL, AND ESTIMATES THE
    VALUE OF F AT THE MINIMUM: USED ONLY FOR

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        PRINTING LOG(FX - FMIN);
IF PRIN > 0 THEN
BEGIN INTEGER SVINT; SVINT := INTFIELDSize;
INTFIELDSize := 10;
WRITE (NL, NF, FX);
COMMENT: IF THE NEXT TWO LINES ARE OMITTED THEN FMIN IS
        NOT REQUIRED;
IF FX <= FMIN THEN WRITEON ("      UNDEFINED ") ELSE
WRITEON (ROUNDTOREAL (LONGLOG (FX - FMIN)));
COMMENT: "IOCONTROL(2)" MOVES TO THE NEXT LINE;
IF N > 4 THEN IOCONTROL(2);
IF (N <= 4) OR (PRIN > 2) THEN
FOR I := 1 UNTIL N DO WRITEON(ROUNDTOREAL(X(I)));
IOCONTROL(2); INTFIELDSize := SVINT
END PRINT;

PROCEDURE MATPRINT (STRING(80) VALUE S; LONG REAL ARRAY
V(*,*); INTEGER VALUE M, N);
BEGIN COMMENT: PRINTS M X N MATRIX V COLUMN BY COLUMN;
WRITE (S);
FOR K := 1 UNTIL (N + 7) DIV 8 DO
BEGIN FOR I := 1 UNTIL M DO
BEGIN IOCONTROL(2);
FOR J := 8*K - 7 UNTIL (IF N < (8*K) THEN N ELSE 8*K)
DO WRITEON (ROUNDTOREAL (V (I,J)))
END;
WRITE (" "); IOCONTROL(2)
END
END MATPRINT;

PROCEDURE VECPRINT (STRING(32) VALUE S; LONG REAL ARRAY V(*);
INTEGER VALUE N);
BEGIN COMMENT: PRINTS THE HEADING S AND N-VECTOR V;
WRITE(S);
FOR I := 1 UNTIL N DO WRITEON(ROUNDTOREAL(V(I)))
END VECPRINT;

PROCEDURE MIN (INTEGER VALUE J, NITS; LONG REAL VALUE
RESULT D2, X1; LONG REAL VALUE F1; BOOLEAN VALUE FK);
BEGIN COMMENT:
        MINIMIZES F FROM X IN THE DIRECTION V(*,J)
        UNLESS J<1, WHEN A QUADRATIC SEARCH IS DONE
        IN THE PLANE DEFINED BY Q0, Q1 AND X.
        D2 AN APPROXIMATION TO HALF F'' (OR ZERO),
        X1 AN ESTIMATE OF DISTANCE TO MINIMUM,
        RETURNED AS THE DISTANCE FOUND.
        IF FK = TRUE THEN F1 IS FLIN(X1), OTHERWISE
        X1 AND F1 ARE IGNORED ON ENTRY UNLESS FINAL
        FX > F1. NITS CONTROLS THE NUMBER OF TIMES
        AN ATTEMPT IS MADE TO HALVE THE INTERVAL.

SIDE EFFECTS: USES AND ALTERS X, FX, NF, NL.

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        IF J < 1 USES VARIABLES Q...
        USES H, N, T, M2, M4, LDT, DMIN, MACHEPS;

LONG REAL PROCEDURE FLIN (LONG REAL VALUE L);
COMMENT: THE FUNCTION OF ONE VARIABLE L WHICH IS
        MINIMIZED BY PROCEDURE MIN;
BEGIN LONG REAL ARRAY T(1:N);
IF J > 0 THEN
BEGIN COMMENT: LINEAR SEARCH;
FOR I := 1 UNTIL N DO T(I) := X(I) + L*V(I,J)
END
ELSE
BEGIN COMMENT: SEARCH ALONG A PARABOLIC SPACE-CURVE;
QA := L*(L - QD1)/(QD0*(QD0 + QD1));
QB := (L + QD0)*(QD1 - L)/(QD0*QD1);
QC := L*(L + QD0)/(QD1*(QD0 + QD1));
FOR I := 1 UNTIL N DO T(I) := QA*Q0(I)+QB*X(I)+QC*Q1(I)
END;
COMMENT: INCREMENT FUNCTION EVALUATION COUNTER;
NF := NF + 1;
F(T, N)
END FLIN;

INTEGER K; BOOLEAN DZ;
LONG REAL X2, XM, F0, F2, FM, D1, T2, S, SF1, SX1;
SF1 := F1; SX1 := X1;
K := 0; XM := 0; F0 := FM := FX; DZ := (D2 < MACHEPS);
COMMENT: FIND STEP SIZE;
S := 0; FOR I := 1 UNTIL N DO S := S + X(I)**2;
S := LONGSQRT(S);
T2 := M4*LONGSQRT(ABS(FX)/(IF DZ THEN DMIN ELSE D2)
        + S*LDT) + M2*LDT;
S := M4*S + T;
IF DZ AND (T2 > S) THEN T2 := S;
IF T2 < SMALL THEN T2 := SMALL;
IF T2 > (0.01*H) THEN T2 := 0.01*H;
IF FK AND (F1 <= FM) THEN BEGIN XM := X1; FM := F1 END;
IF ~FK OR (ABS(X1) < T2) THEN
BEGIN X1 := IF X1 >= 0L THEN T2 ELSE -T2;
F1 := FLIN(X1)
END;
IF F1 <= FM THEN BEGIN XM := X1; FM := F1 END;
L0: IF DZ THEN
BEGIN COMMENT: EVALUATE FLIN AT ANOTHER POINT AND
        ESTIMATE THE SECOND DERIVATIVE;
X2 := IF F0 < F1 THEN -X1 ELSE 2*X1; F2 := FLIN(X2);
IF F2 <= FM THEN BEGIN XM := X2; FM := F2 END;
D2 := (X2*(F1 - F0) - X1*(F2 - F0))/(X1*X2*(X1 - X2))
END;
COMMENT: ESTIMATE FIRST DERIVATIVE AT 0;
D1 := (F1 - F0)/X1 - X1*D2; DZ := TRUE;

```

```

COMMENT: PREDICT MINIMUM;
X2 := IF D2 <= SMALL THEN (IF D1 < 0 THEN H ELSE -H) ELSE
      -0.5L*D1/D2;
IF ABS(X2) > H THEN X2 := IF X2 > 0 THEN H ELSE -H;
COMMENT: EVALUATE F AT THE PREDICTED MINIMUM;
L1: F2 := FLIN(X2);
IF (K < NITS) AND (F2 > F0) THEN
  BEGIN COMMENT: NO SUCCESS SO TRY AGAIN; K := K + 1;
    IF (F0 < F1) AND ((X1*X2) > 0) THEN GO TO L0;
    X2 := 0.5L*X2; GO TO L1
  END;
COMMENT: INCREMENT ONE-DIMENSIONAL SEARCH COUNTER;
NL := NL + 1;
IF F2 > FM THEN X2 := XM ELSE FM := F2;
COMMENT: GET NEW ESTIMATE OF SECOND DERIVATIVE;
D2 := IF ABS(X2*(X2 - X1)) > SMALL THEN
      (X2*(F1 - F0) - X1*(FM - F0))/(X1*X2*(X1 - X2))
      ELSE IF K > 0 THEN 0 ELSE D2;
IF D2 <= SMALL THEN D2 := SMALL;
X1 := X2; FX := FM;
IF SF1 < FX THEN BEGIN FX := SF1; X1 := SX1 END;
COMMENT: UPDATE X FOR LINEAR SEARCH BUT NOT FOR PARABOLIC
      PARABOLIC SEARCH;
IF J > 0 THEN FOR I := 1 UNTIL N DO X(I) := X(I) + X1*V(I,J)
END MIN;

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PROCEDURE QUAD;
  BEGIN COMMENT: LOOKS FOR THE MINIMUM ALONG A CURVE
    DEFINED BY Q0, Q1 AND X;
    LONG REAL L, S;
    S := FX; FX := QF1; QF1 := S; QD1 := 0;
    FOR I := 1 UNTIL N DO
      BEGIN S := X(I); X(I) := L := Q1(I); Q1(I) := S;
        QD1 := QD1 + (S - L)**2
      END;
    L := QD1 := LONGSQR(TQD1); S := 0;
    IF (QD0 > 0) AND (QD1 > 0) AND (NL >= (3*N*N)) THEN
      BEGIN MIN (0, 2, S, L, QF1, TRUE);
        QA := L*(L - QD1)/(QD0*(QD0 + QD1));
        QB := (L + QD0)*(QD1 - L)/(QD0*QD1);
        QC := L*(L + QD0)/(QD1*(QD0 + QD1))
      END
    ELSE BEGIN FX := QF1; QA := QB := 0; QC := 1 END;
    QD0 := QD1; FOR I := 1 UNTIL N DO
      BEGIN S := QD(I); QD(I) := X(I);
        X(I) := QA*S + QB*X(I) + QC*Q1(I)
      END
    END QUAD;

```

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BOOLEAN ILLC;
INTEGER NL, NF, KL, KT, KTM;

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```

LONG REAL S, SL, DN, DMIN, FX, F1, LDS, LDT, SF, DF,
QF1, QD0, QD1, QA, QB, QC,
M2, M4, SMALL, VSMALL, LARGE, VLARGE, SCBD, LDFAC, T2;
LONG REAL ARRAY D, Y, Z, Q0, Q1 (1::N);
LONG REAL ARRAY V (1::N, 1::N);

```

```

COMMENT: INITIALIZATION;
COMMENT: MACHINE DEPENDENT NUMBERS;
SMALL := MACHEPS**2; VSMALL := SMALL**2;
LARGE := 1L/SMALL; VLARGE := 1L/VSMALL;
M2 := LONGSQR(TMACHEPS); M4 := LONGSQR(TM2);

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COMMENT: HEURISTIC NUMBERS
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  IF AXES MAY BE BADLY SCALED (WHICH IS TO BE AVOIDED IF
  POSSIBLE) THEN SET SCBD := 10, OTHERWISE 1.
  IF THE PROBLEM IS KNOWN TO BE ILLCONDITIONED SET
  ILLC := TRUE, OTHERWISE FALSE.
  KTM+1 IS THE NUMBER OF ITERATIONS WITHOUT IMPROVEMENT BEFORE
  THE ALGORITHM TERMINATES (SEE SECTION 6). KTM = 4 IS VERY
  CAUTIOUS: USUALLY KTM = 1 IS SATISFACTORY;

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SCBD := 1; ILLC := FALSE; KTM := 1;

LDFAC := IF ILLC THEN 0.1 ELSE 0.01;
KT := NL := 0; NF := 1; QF1 := FX := F(X,N);
T := T2 := SMALL + ABS(T); DMIN := SMALL;
IF H < (100*T) THEN H := 100*T; LDT := H;
FOR I := 1 UNTIL N DO FOR J := 1 UNTIL N DO
  V(I,J) := IF I = J THEN 1L ELSE 0L;
D(1) := QD0 := 0; FOR I := 1 UNTIL N DO Q1(I) := X(I);
PRINT;

COMMENT: MAIN LOOP;
L0: SF := D(1); D(1) := S := 0;
COMMENT: MINIMIZE ALONG FIRST DIRECTION;
MIN (1, 2, D(1), S, FX, FALSE);
IF S <= 0 THEN FOR I := 1 UNTIL N DO V(I,1) := -V(I,1);
IF (SF <= (0.9*D(1))) OR ((0.9*SF) >= D(1)) THEN
  FOR I := 2 UNTIL N DO D(I) := 0;
  FOR K := 2 UNTIL N DO
    BEGIN FOR I := 1 UNTIL N DO Y(I) := X(I); SF := FX;
      ILLC := ILLC OR (KT > 0);
      L1: KL := K; DF := 0; IF ILLC THEN
        BEGIN COMMENT: RANDOM STEP TO GET OFF RESOLUTION VALLEY;
          FOR I := 1 UNTIL N DO
            BEGIN S := Z(I) := (0.1*LDT + T2*10**KT)*(RANDOM-0.5L);
              COMMENT: PRAXIS ASSUMES THAT RANDOM RETURNS A RANDOM
                NUMBER UNIFORMLY DISTRIBUTED IN (0, 1) AND
                THAT ANY INITIALIZATION OF THE RANDOM NUMBER

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        GENERATOR HAS ALREADY BEEN DONE;
    FOR J := 1 UNTIL N DO X(J) := X(J) + S*V(J,I)
    END;
    FX := F(X, N); NF := NF + 1
    END;
    FOR K2 := K UNTIL N DO
        BEGIN SL := FX; S := 0;
        COMMENT: MINIMIZE ALONG "NON-CONJUGATE" DIRECTIONS;
        MIN (K2, 2, D(K2), S, FX, FALSE);
        S := IF ILLC THEN D(K2)*(S + Z(K2))*2 ELSE SL - FX;
        IF DF < S THEN
            BEGIN DF := S; KL := K2
            END
        END;
    IF ~ILLC AND (DF < ABS(100*MACHEPS*FX)) THEN
        BEGIN COMMENT: NO SUCCESS ILLC = FALSE SO TRY ONCE
            WITH ILLC = TRUE;
            ILLC := TRUE; GO TO L1
        END;
    IF (K = 2) AND (PRIN > 1) THEN VECPRINT ("NEW D", D, N);
    FOR K2 := 1 UNTIL K - 1 DO
        BEGIN COMMENT: MINIMIZE ALONG "CONJUGATE" DIRECTIONS;
        S := 0; MIN (K2, 2, D(K2), S, FX, FALSE)
        END;
    F1 := FX; FX := SF; LDS := 0;
    FOR I := 1 UNTIL N DO
        BEGIN SL := X(I); X(I) := Y(I); SL := Y(I) := SL - Y(I);
        LDS := LDS + SL*SL
        END;
    LDS := LONGSQRT(LDS); IF LDS > SMALL THEN
        BEGIN COMMENT: THROW AWAY DIRECTION KL AND MINIMIZE
            ALONG THE NEW "CONJUGATE" DIRECTION;
        FOR I := KL - 1 STEP -1 UNTIL K DO
            BEGIN FOR J := 1 UNTIL N DO V(J,I + 1) := V(J,I);
                D(I + 1) := D(I)
            END;
        D(K) := 0; FOR I := 1 UNTIL N DO V(I,K) := Y(I)/LDS;
        MIN (K, 4, D(K), LDS, F1, TRUE);
        IF LDS <= 0 THEN
            BEGIN LDS := -LDS;
            FOR I := 1 UNTIL N DO V(I,K) := -V(I,K)
            END
        END;
    LDT := LDFAC*LDT; IF LDT < LDS THEN LDT := LDS;
    PRINT;
    T2 := 0; FOR I := 1 UNTIL N DO T2 := T2 + X(I)**2;
    T2 := M2*LONGSQRT(T2) + T;
    COMMENT: SEE IF STEP LENGTH EXCEEDS HALF THE TOLERANCE;
    KT := IF LDT > (0.5*T2) THEN 0 ELSE KT + 1;
    IF KT > KTM THEN GO TO L2
    END;

```

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    COMMENT: TRY QUADRATIC EXTRAPOLATION IN CASE WE ARE STUCK
        IN A CURVED VALLEY;
    QUAD;
    DN := 0; FOR I := 1 UNTIL N DO
        BEGIN D(I) := 1/LONGSQRT(D(I));
        IF DN < D(I) THEN DN := D(I)
        END;
    IF PRIN > 3 THEN MATPRINT ("NEW DIRECTIONS", V, N, N);
    FOR J := 1 UNTIL N DO
        BEGIN S := D(J)/DN;
        FOR I := 1 UNTIL N DO V(I,J) := S*V(I,J)
        END;
    IF SCBD > 1 THEN
        BEGIN COMMENT: SCALE AXES TO TRY TO REDUCE CONDITION
            NUMBER;
        S := VLARGE; FOR I := 1 UNTIL N DO
            BEGIN SL := 0; FOR J := 1 UNTIL N DO SL := SL + V(I,J)**2;
                Z(I) := LONGSQRT(SL);
                IF Z(I) < M4 THEN Z(I) := M4; IF S > Z(I) THEN S := Z(I)
            END;
        FOR I := 1 UNTIL N DO
            BEGIN SL := S/Z(I); Z(I) := 1/SL; IF Z(I) > SCBD THEN
                BEGIN SL := 1/SCBD; Z(I) := SCBD
            END;
        FOR J := 1 UNTIL N DO V(I,J) := SL*V(I,J)
        END
    END;
    COMMENT: TRANSPOSE V FOR MINFIT;
    FOR I := 2 UNTIL N DO FOR J := 1 UNTIL I - 1 DO
        BEGIN S := V(I,J); V(I,J) := V(J,I); V(J,I) := S END;
    COMMENT: FIND THE SINGULAR VALUE DECOMPOSITION OF V. THIS
        GIVES THE EIGENVALUES AND PRINCIPAL AXES OF THE
        APPROXIMATING QUADRATIC FORM WITHOUT SQUARING THE
        CONDITION NUMBER;
    MINFIT (N, MACHEPS, VSMALL, V, D);
    IF SCBD > 1 THEN
        BEGIN COMMENT: UNSCALING; FOR I := 1 UNTIL N DO
            BEGIN S := Z(I);
            FOR J := 1 UNTIL N DO V(I,J) := S*V(I,J)
            END;
        FOR I := 1 UNTIL N DO
            BEGIN S := 0; FOR J := 1 UNTIL N DO S := S + V(J,I)**2;
                S := LONGSQRT(S); D(I) := S*D(I); S := 1/S;
                FOR J := 1 UNTIL N DO V(J,I) := S*V(J,I)
            END
        END;
    FOR I := 1 UNTIL N DO
        BEGIN D(I) := IF (DN*D(I)) > LARGE THEN VSMALL ELSE
            IF (DN*D(I)) < SMALL THEN VLARGE ELSE (DN*D(I))**(-2)
        END;
    COMMENT: SORT NEW EIGENVALUES AND EIGENVECTORS;

```

```

SORT;
DMIN := D(N); IF DMIN < SMALL THEN DMIN := SMALL;
ILLC := (M2*D(1)) > DMIN;
IF (PRIN > 1) AND (SCBD > 1) THEN
  VECPRINT ("SCALE FACTORS", Z, N);
IF PRIN > 1 THEN VECPRINT ("EIGENVALUES OF A", D, N);
IF PRIN > 3 THEN MATPRINT ("EIGENVECTORS OF A", V, N, N);
COMMENT: GO BACK TO MAIN LOOP;
GO TO L0;
L2: IF PRIN > 0 THEN VECPRINT ("X IS", X, N);
FX
END PRAXIS;

COMMENT:          RANDOM NUMBER GENERATOR
*****

PROCEDURE RANDOM RETURNS A LONG REAL RANDOM NUMBER UNIFORMLY
DISTRIBUTED IN (0,1) (INCLUDING 0 BUT NOT 1).
  RANINIT(R) WITH R ANY INTEGER MUST BE CALLED FOR
  INITIALIZATION BEFORE THE FIRST CALL TO RANDOM, AND THE
  DECLARATIONS OF RAN1, RAN2 AND RAN3 MUST BE GLOBAL.
  THE ALGORITHM RETURNS  $X(N)/2^{56}$ , WHERE
 $X(N) = X(N-1) + X(N-127) \pmod{2^{56}}$ .
  SINCE  $1 + X + X^{127}$  IS PRIMITIVE  $\pmod{2}$ , THE PERIOD IS AT
  LEAST  $2^{127} - 1 > .10^{38}$ . SEE KNUTH (1969), PP. 26, 34, 464.
  X(N) IS STORED IN A LONG REAL WORD AS
 $RAN3 = X(N)/2^{56} - 1/2$ , AND ALL FLOATING POINT ARITHMETIC
  IS EXACT;

LONG REAL RAN1; INTEGER RAN2; LONG REAL ARRAY RAN3 (0:126);

PROCEDURE RANINIT (INTEGER VALUE R);
  BEGIN R := ABS(R) REM 8190 + 1;
  RAN2 := 127; WHILE RAN2 > 0 DO
    BEGIN RAN2 := RAN2 - 1; RAN1 := -2L**55;
    FOR I := 1 UNTIL 7 DO
      BEGIN R := (1756*R) REM 8191;
      RAN1 := (RAN1 + (R DIV 32))*(1/256);
      END;
    RAN3 (RAN2) := RAN1
  END
END RANINIT;

LONG REAL PROCEDURE RANDOM;
  BEGIN RAN2 := IF RAN2 = 0 THEN 126 ELSE RAN2 - 1;
  RAN1 := RAN1 + RAN3 (RAN2);
  RAN3 (RAN2) := RAN1 := IF RAN1 < 0L THEN RAN1 + 0.5L
    ELSE RAN1 - 0.5L;
  RAN1 + 0.5L
END RANDOM;

```

```

COMMENT: TEST FUNCTIONS
*****

LONG REAL PROCEDURE ROS (LONG REAL ARRAY X(*); INTEGER VALUE N);
  COMMENT: SEE ROSENBROCK (1960);
  100L*((X(2) - X(1)**2)**2) + (1L - X(1))**2;

LONG REAL PROCEDURE SING(LONG REAL ARRAY X(*); INTEGER VALUE N);
  COMMENT: SEE POWELL (1962);
  (X(1) + 10L*X(2))**2 + 5L*(X(3)-X(4))**2 + (X(2)-2L*X(3))**4
  + 10L*(X(1) - X(4))**4;

LONG REAL PROCEDURE HELIX(LONG REAL ARRAY X(*); INTEGER VALUE N);
  COMMENT: SEE FLETCHER & POWELL (1963);
  BEGIN LONG REAL R, T;
  R := LONGSQRT (X(1)**2 + X(2)**2);
  T := IF X(1) = 0 THEN 0.25L ELSE LONGARCTAN (X(2)/X(1))/(2L*
    3.14159265358979L);
  IF X(1) < 0 THEN T := T + 0.5L;
  100L*((X(3) - 10L*T)**2 + (R - 1L)**2) + X(3)**2
  END HELIX;

LONG REAL PROCEDURE CUBE(LONG REAL ARRAY X(*); INTEGER VALUE N);
  COMMENT: SEE LEON (1966);
  100L*(X(2) - X(1)**3)**2 + (1L - X(1))**2;

LONG REAL PROCEDURE BEALE(LONG REAL ARRAY X(*); INTEGER VALUE N);
  COMMENT: SEE BEALE (1958);
  (1.5L - X(1)*(1L - X(2)))**2 +
  (2.25L - X(1)*(1L - X(2)**2))**2 +
  (2.625L - X(1)*(1L - X(2)**3))**2;

LONG REAL PROCEDURE WATSON (LONG REAL ARRAY X(*);
  INTEGER VALUE N);
  COMMENT: SEE KOWALIK & OSBORNE (1968);
  BEGIN LONG REAL S, T, U, Y;
  S := X(1)**2 + (X(2) - X(1)**2 - 1L)**2;
  FOR I := 2 UNTIL 30 DO
    BEGIN Y := (1 - 1)/29; T := X(N);
    FOR J := N - 1 STEP -1 UNTIL 1 DO T := X(J) + Y*T;
    U := (N - 1)*X(N);
    FOR J := N - 1 STEP -1 UNTIL 2 DO U := (J - 1)*X(J) + Y*U;
    S := S + (U - T*T - 1L)**2
    END;
  S
  END WATSON;

LONG REAL PROCEDURE CHEBYQUAD (LONG REAL ARRAY X(*);
  INTEGER VALUE N);
  COMMENT: SEE FLETCHER (1965);
  BEGIN

```

```

LONG REAL F, DELTA, TPLUS;
BOOLEAN EVEN;
LONG REAL ARRAY Y, TI, TMINUS (1::N);

DELTA := 0L;
FOR J := 1 UNTIL N DO
  BEGIN Y(J) := 2L*X(J) - 1L;
  DELTA := DELTA + Y(J);
  TI(J) := Y(J); TMINUS(J) := 1L
END;
F := DELTA**2; EVEN := FALSE;
FOR I := 2 UNTIL N DO
  BEGIN EVEN := NOT EVEN; DELTA := 0L;
  FOR J := 1 UNTIL N DO
    BEGIN TPLUS := 2L*Y(J)*TI(J) - TMINUS(J);
    DELTA := DELTA + TPLUS;
    TMINUS(J) := TI(J);
    TI(J) := TPLUS
  END;
  DELTA := DELTA/N - (IF EVEN THEN 1/(1 - I*I) ELSE 0);
  F := F + DELTA**2
END;
F
END CHEBYQUAD;

LONG REAL PROCEDURE POWELL (LONG REAL ARRAY X(*);
  INTEGER VALUE N);
  COMMENT: SEE POWELL (1964);
  3L - 1L/(1L + (X(1) - X(2))**2) -
  LONGSIN(0.5L*3.14159265358979L*X(2)*X(3))-(IF X(2) = 0 THEN
  0L ELSE LONGEXP(-(X(1)+X(3))/X(2) - 2L)**2));

LONG REAL PROCEDURE WOOD (LONG REAL ARRAY X(*); INTEGER VALUE N);
  COMMENT: SEE MCCORMICK & PEARSON (1969) OR COLVILLE (1968);
  100L*(X(2) - X(1)**2)**2 + (1L - X(1))**2 + 90L*(X(4) -
  X(3)**2)**2 + (1L - X(3))**2 + 10.1L*((X(2) - 1L)**2 + (X(4)
  - 1L)**2) + 19.8L*(X(2) - 1L)*(X(4) - 1L);

LONG REAL PROCEDURE HILBERT (LONG REAL ARRAY X(*);
  INTEGER VALUE N);
  COMMENT: COMPUTES XT.A.X, WHERE A IS THE N BY N HILBERT
  MATRIX, SEE GREGORY & KARNEY (1969), PP. 33, 66;
  BEGIN LONG REAL S, T;
  S := 0L; FOR I := 1 UNTIL N DO
    BEGIN T := 0L; FOR J := 1 UNTIL N DO
      T := T + X(J)/(1 + J - 1);
      S := S + T*X(I)
    END;
  S
END HILBERT;

```

```

LONG REAL PROCEDURE TRIDIAG (LONG REAL ARRAY X(*);
  INTEGER VALUE N);
  COMMENT: COMPUTES XT.A.X - 2E1T.X, WHERE N > 1,

```

$$A = \begin{pmatrix} 1 & -1 & 0 & 0 & \dots & 0 \\ -1 & 2 & -1 & 0 & \dots & 0 \\ 0 & -1 & 2 & -1 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & \dots & -1 & 2 & -1 \\ 0 & \dots & 0 & -1 & 2 \end{pmatrix},$$

AND E1T = (1, 0, ..., 0).

```

  SEE GREGORY & KARNEY (1969), PP. 41, 74;
  BEGIN LONG REAL S;
  S := X(1)*(X(1) - X(2));
  FOR I := 2 UNTIL N - 1 DO
    S := S + X(I)*((X(I) - X(I - 1)) + (X(I) - X(I + 1)));
  S + X(N)*(2*X(N) - X(N - 1)) - 2*X(1)
  END TRIDIAG;

LONG REAL PROCEDURE BOX (LONG REAL ARRAY X(*); INTEGER VALUE N);
  COMMENT: SEE BOX (1966) OR BROWN & DENNIS (1970);
  BEGIN LONG REAL P, S;
  S := 0; FOR I := 1 UNTIL 10 DO
    BEGIN P := -1/10;
    S := S + ((LONGEXP(P*X(1)) - (IF (P*X(2)) < (-40) THEN 0
    ELSE LONGEXP(P*X(2)))) -
    X(3)*(LONGEXP(P) - LONGEXP(10*P))**2
    END;
  S
  END BOX;

COMMENT: GENERAL TESTING PROCEDURE
*****;

PROCEDURE TEST (STRING (80) VALUE S; LONG REAL VALUE H;
  LONG REAL PROCEDURE F; INTEGER VALUE N);
  BEGIN LONG REAL FMIN; INTEGER TIM;
  WRITE(" "); WRITE(" "); WRITE(S);
  WRITE("N =", N, " H =", H, " ROUNDTOREAL(H)); WRITE(" ");
  COMMENT: INITIALIZE RANDOM NUMBER GENERATOR; RANINIT(4);
  COMMENT: TIME(2) RETURNS CLOCK TIME IN UNITS OF 26 MICROSEC;
  TIM := TIME(2);
  FMIN := PRAXIS (1'-5, 16**(-13), H, N, 1, X, F, RANDOM);
  WRITE ("TIME (MILLISEC) =", ROUND((TIME(2) - TIM)/38.4));
  WRITE(" ")
  END TEST;

COMMENT: TESTING PROGRAM
*****;

```

```

LONG REAL FMIN, LAM;
COMMENT: INCREASE DIMENSIONS FOR N > 20;
LONG REAL ARRAY X(1::20);
COMMENT: INTFIELD SIZE CONTROLS THE OUTPUT FORMAT OF INTEGERS;
INTFIELD SIZE := 7;

```

```

X(1) := -1.2L; X(2) := 1L; FMIN := 0;
TEST ("ROSENBROCK'S FUNCTION WITH A PARABOLIC VALLEY", 1, ROS, 2);

```

```

X(1) := X(2) := 3;
TEST ("ROSENBROCK'S FUNCTION ", 3, ROS, 2);

```

```

X(1) := X(2) := 8;
TEST ("ROSENBROCK'S FUNCTION", 12, ROS, 2);

```

```

X(1) := -1; X(2) := X(3) := 0;
TEST ("HELIX", 1, HELIX, 3);

```

```

X(1) := -1.2L; X(2) := -1;
TEST ("CUBE", 1, CUBE, 2);

```

```

X(1) := X(2) := 0.1L;
TEST ("BEALE", 1, BEALE, 2);

```

```

X(1) := 0; X(2) := 1; X(3) := 2;
TEST ("POWELL", 1, POWELL, 3);

```

```

FMIN := 0; X(1) := 0; X(2) := 10; X(3) := 20;
TEST ("BOX", 20, BOX, 3);

```

```

X(1) := 3L; X(2) := -1L; X(3) := 0L; X(4) := 1L;
TEST ("POWELL'S FUNCTION WITH A SINGULAR JACOBIAN", 1, SING, 4);

```

```

FMIN := 0; X(1) := X(3) := -3; X(2) := X(4) := -1;
TEST ("WOOD", 10, WOOD, 4);

```

```

FOR N := 2 STEP 2 UNTIL 8 DO
  BEGIN FOR I := 1 UNTIL N DO X(I) := 1/(N + 1);
    FMIN := IF N < 8 THEN 0L ELSE 0.0035168737256779L;
    TEST ("CHEBYQUAD", 0.1, CHEBYQUAD, N)
  END;

```

```

FOR N := 6 STEP 3 UNTIL 9 DO
  BEGIN FOR I := 1 UNTIL N DO X(I) := 0;
    FMIN := IF N = 6 THEN 0.00228767005355L ELSE
      IF N = 9 THEN 1.399760138098'-6L ELSE 0L;
    TEST ("WATSON", 1, WATSON, N)
  END;

```

```

FOR N := 4, 6, 8, 10, 12, 16, 20 DO

```

```

  BEGIN FOR I := 1 UNTIL N DO X(I) := 0L; FMIN := -N;
    TEST ("TRIDIAG", 2*N, TRIDIAG, N)
  END;

```

```

  FMIN := 0; FOR N := 2 STEP 2 UNTIL 12 DO
    BEGIN FOR I := 1 UNTIL N DO X(I) := 1;
      TEST ("HILBERT", 10, HILBERT, N)
    END
  END.

```


Bibliography

This bibliography contains references relevant to the minimization of nonlinear functions, and other references referred to in the text. There is no attempt at completeness, but a large number of recent (up to late 1970) references on unconstrained minimization have been included. There are also some references dealing with constrained problems, with methods for converting constrained problems to unconstrained problems, and with methods for solving nonlinear equations. For a brief survey, see Section 7.1. References on linear and quadratic programming have generally been excluded, and we have not attempted to duplicate the large bibliographies in Jacoby, Kowalik and Pizzo (1971), Kunzi and Oettli (1970), Lawson (1968), and Ortega and Rheinboldt (1970).

In lieu of annotations, the chapter and section numbers of references to each entry are given in parentheses after the entry.

References which are not known to have appeared have been assigned the year 1971. (Some may have appeared late in 1970.)

- Abadie, J. (ed.), 1970, "Nonlinear and integer programming", North-Holland, Amsterdam. (7.1, 8)
- Adachi, N., see Tokumaru, Adachi & Goto (1970).
- Akaike, H., 1959, "On a successive transformation of probability distribution and its application to the analysis of the optimum gradient method", Ann. Inst. Statist. Math. of Tokyo 11, 1-16. (7.1)
- Akilov, G. P., see Kantorovich & Akilov (1959).
- Allran, R. R. & Johnsen, S. E. J., 1970, "An algorithm for solving nonlinear programming problems subject to nonlinear inequality constraints", Comp. J. 13, 2, 171-177. (7.1)
- Andrews, A. M., 1969, "The calculation of orthogonal vectors", Comp. J. 12, 411. (7.5)
- Armijo, L., 1966, "Minimization of functions having Lipschitz-continuous first partial derivatives", Pacific J. Math. 16, 1-3. (1.2)
- Avriel, M. & Wilde, D. J., 1966, "Optimal search for a maximum with sequences of simultaneous function evaluations", Management Sci. 12, 722-731. (5.7)
- Baer, R. M., 1962, "Note on an extremum locating algorithm", Comp. J. 5, 193. (7.5)
- Baker, C. T. H., 1970, "The error in polynomial interpolation", Numer. Math. 15, 315-319. (2.4)
- Balakrishnan, A. V. (ed.), 1970, "Symposium on optimization (Nice, June 1969)", Springer-Verlag, Berlin. (7.1, 8)
- Bard, Y., 1968, "On a numerical instability of Davidon-like

methods", Math. Comp. 22, 665-666. (7.1)

Bard, Y., 1970, "Comparison of gradient methods for the solution of nonlinear parameter estimation problems", SIAM J. Numer. Anal. 7, 1, 157-186. (7.1)

Bard, Y., see Greenstadt (1970).

Barnes, J. P. G., 1965, "An algorithm for solving nonlinear equations based on the secant method", Comp. J. 8, 66-72. (7.1)

Bartels, R. H., 1968, "A numerical investigation of the simplex method", Tech. Report CS 104, Computer Sci. Dept., Stanford Uni. (7.1)

Bartels, R. H. & Golub, G. H., 1969, "The simplex method of linear programming using LU decomposition", Comm. ACM 12, 5, 266-268. (7.1)

Bartels, R. H., Golub, G. H. & Saunders, M. A., 1970, "Numerical techniques in mathematical programming", Tech. Report CS 162, Stanford Uni. (7.1)

Bauer, H., Becker, S. & Graham, S., 1968, "ALGOL W language description", Tech. Report CS 89 (revised as CS 110 with E. Satterthwaite, 1969), Stanford Uni. (4.4, 5.6, 6.6, 7.9)

Beale, E. M. L., 1958, "On an iterative method for finding a local minimum of a function of more than one variable", Tech. Report No. 25, Statistical Techniques Research Group, Princeton Uni. (7.7, 7.9)

Beale, E. M. L., 1968, "Mathematical programming in practice", Wiley, New York. (7.1)

Becker, S., see Bauer, Becker & Graham (1968).

Beckman, F. S., 1960, "The solution of linear equations by the conjugate gradient method", in Ralston & Wilf (1960). (7.3)

Beightler, C. S., see Wilde & Beightler (1967).

Bell, M. & Pike, M. C., 1966, "Remark on algorithm 178(E4), DIRECT SEARCH", Comm. ACM 9, 684. (7.1)

Bellman, R. E., 1957, "Dynamic programming", Princeton Uni. Press, Princeton, New Jersey. (1.2)

Bellman, R. E. & Dreyfus, S. E., 1962, "Applied dynamic programming", Princeton Uni. Press, Princeton, New Jersey. (1.2, 4.1)

Bennett, J. M., 1965, "Triangular factors of modified matrices", Numer. Math. 7, 217-221. (7.1)

Bennett, J. M. & Green, D. R., 1966, "Updating the inverse or the triangular factors of a modified matrix", Tech. Report 42, Basser Computing Dept., Uni. of Sydney. (7.1)

Berman, G., 1969, "Lattice approximations to the minima of functions of several variables", J. ACM 16, 286-294. (7.1)

Björck, A., 1967a, "Solving linear least squares problems by Gram-Schmidt orthogonalization", BIT 7, 1-21. (7.1)

Björck, A., 1967b, "Iterative refinement of linear least squares solutions I", BIT 7, 257-278. (7.1)

Björck, A., 1968, "Iterative refinement of linear least squares solutions II", BIT 8, 8-30. (7.1)

Boothroyd, J., 1965a, "Algorithm 7, MINIX", Comp. Bulletin 9, 104. (5.3)

Boothroyd, J., 1965b, "Certification of Algorithm 2, FIBONACCI SEARCH", Comp. Bulletin 9, 105. (5.3)

Bowdler, H., Martin, R. S., Reinsch, C. & Wilkinson, J. H., 1968, "The QR and QL algorithms for symmetric matrices", Numer. Math. 11, 293-306. (7.4)

Box, G. E. P., 1957, "Evolutionary operations: a method for increasing industrial productivity", Appl. Stat. 6, 3-23. (7.1)

Box, M. J., 1965, "A new method for constrained optimization and a comparison with other methods", Comp. J. 8, 42-52. (7.1)

Box, M. J., 1966, "A comparison of several current optimization methods, and the use of transformations in constrained problems", Comp. J. 9, 67-77. (7.1, 7.3, 7.7, 7.9)

Box, M. J., Davies, D. & Swann, W. H., 1969, "Non-linear optimization techniques", ICI Monograph No. 5, Oliver and Boyd, London. (5.4, 5.5, 7.1)

Brown, K. M. & Dennis, J. E., 1968, "On Newton-like iteration functions: general convergence theorems and a specific algorithm", Numer. Math. 12, 186-191. (7.1)

Brown, K. M. & Dennis, J. E., 1970, "A new algorithm for nonlinear least squares curve fitting", Tech. Report 70-57, Dept. of Computer Science, Cornell Uni. (7.1; 7.9)

Brown, K. M. & Dennis, J. E., 1971a, "A quadratically convergent finite difference analog of the

Levenberg-Marquardt algorithm for nonlinear least squares curve fitting", to appear. (7.1)

Brown, K. M. & Dennis, J. E., 1971b, "Derivative free analogues of the Levenberg-Marquardt and Gauss algorithms for nonlinear least squares approximation", to appear. (7.1)

Broyden, C. G., 1967, "Quasi-Newton methods and their application to function minimization", Math. Comp. 21, 368-381. (7.1, 7.7)

Broyden, C. G., 1969, "A new method of solving nonlinear simultaneous equations", Comp. J. 12, 1, 94-99. (7.1)

Broyden, C. G., 1970a, "The convergence of a class of double-rank minimization algorithms, Parts I and II", J. Inst. Maths. Apps. 6, 76-90 & 222-231. (7.1)

Broyden, C. G., 1970b, "The convergence of single-rank quasi-Newton methods", Math. Comp. 24, 365-382. (7.1)

Buehler, R. J., see Shah, Buehler & Kempthorne (1964).

Businger, P. & Golub, G. H., 1965, "Linear least squares solutions by Householder transformations", Numer. Math. 7, 269-276. (7.1)

Buys, J. D., see Haarhoff & Buys (1970).

Cantrell, J. W., 1969, "Relation between the memory gradient method and the Fletcher-Powell method", J. Optzn. Thry. & Apps. 4, 67-71. (7.1)

Cantrell, J. W., see Miele & Cantrell (1969, 1970).

Carroll, C. W., 1961, "The created response surface technique

for optimizing nonlinear restrained systems", *Operations Res.* 9, 169-184. (7.1)

Cauchy, A., 1840, "Sur les fonctions interpolaires", *C. R. Acad. Sci. Paris* 11, 775 (or see *Oeuvres complètes*, Gauthier-Villars, Paris, 1897, Vol. 5, 409-424). (2.2)

Cauchy, A., 1847, "Méthode générale pour la résolution des systèmes d'équations simultanées", *C. R. Acad. Sci. Paris* 25, 536-538 (or see *Oeuvres complètes*, Gauthier-Villars, Paris, 1897, Vol. 10, 399-402). (7.1)

Chazan, D. & Miranker, W. L., 1970, "A non-gradient and parallel algorithm for unconstrained minimization", *SIAM J. Control* 8, 2, 207-217. (7.1, 7.3)

Chernousko, F. L., 1970, "On optimal algorithms for search", in Dold & Eckmann (1970a). (4.1)

Clark, N. A., Cody, W. J., Hillstrom, K. E. & Thieleker, E. A., 1967, "Performance statistics of the FORTRAN IV (H) library for the IBM System/360", Argonne Nat. Lab. Report ANL-7321. (6.3)

Cody, W. J., see Clark, Cody, Hillstrom & Thieleker (1967).

Collatz, L., 1964, "Functional analysis and numerical mathematics", Springer-Verlag, Berlin (translation by H. Oser, Academic Press, New York, 1966, Chs. 17-20). (3.1)

Colville, A. R., 1968, "A comparative study of nonlinear programming codes", IBM New York Scientific Center Tech. Report 320-2949. (7.1, 7.7, 7.9)

Cooper, L., see Krolak & Cooper (1963).

Cox, M. S., 1970, "A bracketing technique for computing a zero of a function", *Comp. J.* 13, 1, 101-102. (4.2, 4.5)

Cragg, E. E. & Levy, A. V., 1969, "Study of a supermemory gradient method for the minimization of functions", *J. Optzn. Thry. & Apps.* 4, 191. (7.1)

Curry, H., 1944, "The method of steepest descent for nonlinear minimization problems", *Quart. Appl. Math.* 2, 258-261. (7.1)

Daniel, J. W., 1967a, "The conjugate gradient method for linear and nonlinear operator equations", *SIAM J. Numer. Anal.* 4, 10-26. (7.3)

Daniel, J. W., 1967b, "Convergence of the conjugate gradient method with computationally convenient modifications", *Numer. Math.* 10, 125-131. (7.3)

Daniel, J. W., 1970, "A correction concerning the convergence rate for the conjugate gradient method", *SIAM J. Numer. Anal.* 7, 277-280. (7.3)

Davidon, W. C., 1959, "Variable metric method for minimization", Argonne Nat. Lab. Report ANL-5990 (Rev. TID 4500). (5.7, 7.1)

Davidon, W. C., 1968, "Variance algorithm for minimization", *Comp. J.* 10, 406-410. (7.1, 7.7)

Davidon, W. C., 1969, "Variance algorithms for minimization", in Fletcher (1969a). (7.1, 7.7)

Davies, D., 1968, "The use of Davidon's method in nonlinear programming", ICI Management Services Report MSDH/68/110. (7.1)

Davies, D., 1969, "Some practical methods of optimization", ICI Management Services Report MSDH/69/90. (7.1)

Davies, D., see Box, Davies & Swann (1969), Matthews & Davies (1969), Swann (1964).

Davies, D. & Swann, W. H., 1969, "Review of constrained optimization", in Fletcher (1969a). (7.1)

Davis, P. J., 1965, "Interpolation and approximation", 2nd ed., Blaisdell, New York & London. (6.2)

Dejon, B. & Henrici, P. (eds.), 1969, "Constructive aspects of the fundamental theorem of algebra", Interscience, New York. (8)

Dekker, T. J., 1969, "Finding a zero by means of successive linear interpolation", in Dejon & Henrici (1969). (1.2, 4.1, 4.2, 4.3, 4.4)

Dekker, T. J., see van Wijngaarden, Zonneveld & Dijkstra (1963).

Dennis, J. E., 1968, "On Newton-like methods", Numer. Math. 11, 324-330. (7.1)

Dennis, J. E., 1969a, "On the convergence of Newton-like methods", in Rabinowitz (1969). (7.1)

Dennis, J. E., 1969b, "On the local convergence of Broyden's method for nonlinear systems of equations", Tech. Report 69-46, Dept. of Computer Science, Cornell Uni. (7.1)

Dennis, J. E., 1969c, "On the convergence of Broyden's method for nonlinear systems of equations", Tech. Report 69-48, Dept. of Computer Science, Cornell Uni. (7.1)

Dennis, J. E., see Brown & Dennis (1968, 1970, 1971a, b).

Dijkstra, E. W., see van Wijngaarden, Zonneveld & Dijkstra (1963).

Dold, A. & Eckmann, B. (eds.), 1970a, "Colloquium on methods of optimization (Novosibirsk, June 1968)", Springer-Verlag, Berlin. (7.1, 8)

Dold, A. & Eckmann, B. (eds.), 1970b, "Symposium on optimization (Nice, June 1969)", Springer-Verlag, Berlin & New York. (7.1)

Dreyfus, S. E., see Bellman & Dreyfus (1962).

Eckmann, B., see Dold & Eckmann (1970a, 1970b).

Ehrlich, L. W., 1971, "Eigenvalues of symmetric five-diagonal matrices", to appear. (4.4)

Evans, J. P. & Gould, F. J., 1970, "Stability in nonlinear programming", Oper. Res. 18, 107-118. (7.1)

Fiacco, A. V., 1961, "Comments on the paper of C. W. Carroll", Oper. Res. 9, 184. (7.1)

Fiacco, A. V., 1967, "Sequential unconstrained minimization methods for nonlinear programming", Ph. D. Thesis, Northwestern Uni. (7.1)

Fiacco, A. V., 1969, "A general regularized sequential unconstrained minimization technique", SIAM J. Appl. Math. 17, 6, 1239-1245. (7.1)

Fiacco, A. V. & Jones, A. P., 1969, "Generalized penalty methods in topological spaces", SIAM J. Apps. Math. 17, 5, 996-1000. (7.1)

Fiacco, A. V. & McCormick, G. P., 1968, "Nonlinear programming: sequential unconstrained minimization techniques", Wiley, New York. (7.1)

Flanagan, P. D., Vitale, P. A. & Mendelsohn, J., 1969, "A numerical investigation of several one-dimensional search procedures in nonlinear regression problems", *Technometrics* 11, 265-284. (5.4)

Fletcher, R., 1965, "Function minimization without evaluating derivatives - a review", *Comp. J.* 8, 33-41. (1.2, 7.1, 7.3, 7.5, 7.7, 7.9)

Fletcher, R., 1966, "Certification of Algorithm 251", *Comm. ACM* 9, 686. (7.1)

Fletcher, R., 1968a, "Generalized inverse methods for the best least squares solution of systems of non-linear equations", *Comp. J.* 10, 392-399. (7.1)

Fletcher, R., 1968b, "Programming under linear equality and inequality constraints", ICI Management Services Report MSDH/68/19. (7.1)

Fletcher, R. (ed.), 1969a, "Optimization", Academic Press, New York. (7.1, 8)

Fletcher, R., 1969b, "A class of methods for nonlinear programming with termination and convergence properties", Report TP 386, AERE, Harwell, England. (7.1)

Fletcher, R., 1969c, "A review of methods for unconstrained optimization", in Fletcher (1969a). (7.1, 7.5)

Fletcher, R., 1969d, "A technique for orthogonalization",

J. Inst. Maths. Apps. 5, 162-166. (7.5)

Fletcher, R., 1970, "A new approach to variable metric algorithms", *Comp. J.* 13, 3, 317-322. (7.1)

Fletcher, R. & McCann, A. P., 1969, "Acceleration techniques for nonlinear programming", in Fletcher (1969a). (7.1)

Fletcher, R. & Powell, M. J. D., 1963, "A rapidly convergent 'descent' method for minimization", *Comp. J.* 6, 163-168. (7.1, 7.7, 7.9)

Fletcher, R. & Reeves, C. M., 1964, "Function minimization by conjugate gradients", *Comp. J.* 7, 149-154. (5.4, 7.1, 7.4)

Forsythe, G. E., 1968, "On the asymptotic directions of the s-dimensional optimum gradient method", *Numer. Math.* 11, 57-76. (7.1)

Forsythe, G. E., 1969, "Remarks on the paper by Dekker", in Dejon & Henrici (1969). (4.1)

Forsythe, G. E. & Moler, C. B., 1967, "Computer solution of linear algebraic systems", Prentice-Hall, New Jersey. (7.2)

Fox, L., Henrici, P. & Moler, C. B., 1967, "Approximations and bounds for eigenvalues of elliptic operators", *SIAM J. Numer. Anal.* 4, 1, 89-102. (6.1)

Francis, J., 1962, "The QR transformation. A unitary analogue to the LR transformation", *Comp. J.* 4, 265-271. (7.4)

Freudenstein, F. & Roth, B., 1963, "Numerical solution of systems of nonlinear equations", *J. ACM* 10, 550-556. (7.7)

Gauss, K. F., 1809, "Theoria motus corporum coelestium", *Werke*, Vol. 7, Book 2, Sec. 3. (7.1)

Gill, P. E. & Murray, W., 1970, "A numerically stable form of the simplex algorithm", Tech. Report Maths. 87, NPL, Teddington, England. (7.1)

Golab, S., 1966, "La comparaison de la rapidité de convergence des approximations successives de la méthode de Newton avec la méthode de "regula falsi"", Mathematica (Cluj) 8, 45-49. (5.1)

Goldfarb, D., 1966, "A conjugate gradient method for nonlinear programming", Ph. D. Thesis, Princeton Uni. (7.1)

Goldfarb, D., 1969a, "Extensions of Davidon's variable metric method to maximization under linear inequality and equality constraints", SIAM J. Appl. Math. 17, 4, 739-764. (7.1)

Goldfarb, D., 1969b, "Sufficient conditions for the convergence of a variable metric algorithm", In Fletcher (1969a). (7.1)

Goldfarb, D., 1970, "A family of variable-metric methods derived by variational means", Math. Comp. 24, 23-26. (7.1)

Goldfarb, D. & Lapidus, L., 1968, "A conjugate gradient method for nonlinear programming problems with linear constraints", Indust. Eng. Chem. Fundamentals 7, 142-151. (7.1)

Goldfeld, S. M., Quandt, R. E. & Trotter, H. F., 1968, "Maximization by improved quadratic hill-climbing and other methods", Econometrics Research Program Res. Mem. 95, Princeton Uni. (7.1)

Goldstein, A. A., 1962, "Cauchy's method of minimization", Numer. Math. 4, 146-150. (7.1)

Goldstein, A. A., 1965, "On steepest descent", SIAM J. on Control, Ser. A 3, 147-151. (7.1)

Goldstein, A. A. & Price, J. F., 1967, "An effective algorithm for minimization", Numer. Math. 10, 184-189. (7.1, 7.7)

Golub, G. H., 1965, "Numerical methods for solving linear least squares problems", Numer. Math. 7, 206-216. (7.1)

Golub, G. H., 1968, "Least squares, singular values, and matrix approximations", Aplikace Matematiky 13, 44-51. (7.1)

Golub, G. H., see Businger & Golub (1965), Bartels & Golub (1969), Bartels, Golub & Saunders (1970).

Golub, G. H. & Kahan, W., 1965, "Calculating the singular values and pseudo-inverse of a matrix", J. SIAM Numer. Anal., Ser. B 2, 205-224. (7.4)

Golub, G. H. & Reinsch, C., 1970, "Singular value decomposition and least squares solutions", Handbook Series Linear Algebra, Numer. Math. 14, 403-420. (7.4, 7.9)

Golub, G. H. & Saunders, M., 1969, "Linear least squares and quadratic programming", Report CS 134, Stanford Uni. (7.1)

Golub, G. H. & Smith, L. B., 1967, "Chebyshev approximation of continuous functions by a Chebyshev system of functions", Tech. Report CS 72, Stanford Uni. (5.4)

Golub, G. H. & Wilkinson, J. H., 1966, "Note on the iterative refinement of least squares solution", Numer. Math. 9, 139-148. (7.1)

Goto, K., see Tokumaru, Adachi & Goto (1970).

Gould, F. J., see Evans & Gould (1970).

- Graham, S., see Bauer, Becker & Graham (1968).
- Green, D. R., see Bennett & Green (1966).
- Greenstadt, J. L., 1967, "On the relative efficiencies of gradient methods", Math. Comp. 21, 360-367. (1.2, 7.1)
- Greenstadt, J. L., 1970, "Variations on variable metric methods", Math. Comp. 24, 1-22 (appendix by Y. Bard). (7.1)
- Gregory, R. T. & Karney, D. L., 1969, "A collection of matrices for testing computational algorithms", Interscience, New York. (7.7, 7.9)
- Gross, O. & Johnson, S. M., 1959, "Sequential minimax search for a zero of a convex function", MTAC (now Math. Comp.) 13, 44-51. (1.2, 4.1)
- Haarhoff, P. C. & Buys, J. D., 1970, "A new method for the optimization of a nonlinear function subject to nonlinear constraints", Comp. J. 13, 2, 178-184. (7.1)
- Hadley, G., 1964, "Nonlinear and dynamic programming", Addison Wesley, Reading, Massachusetts. (7.1)
- Hanson, R. J., 1970, "Computing quadratic programming problems: linear inequality and equality constraints", Tech. Memo. 240, JPL, Pasadena. (7.1)
- Hartley, H. O., 1961, "The modified Gauss-Newton method for fitting of nonlinear regression functions by least squares", Technometrics 3, 269-280. (7.1)
- Henrici, P., see Dejon & Henrici (1969), Fox, Henrici & Moler (1967).
- Hestenes, M. R., 1956, "The conjugate gradient method for solving linear systems", Proc. Symp. Appl. Math. 6, Amer. Math. Soc., Providence, 83-102. (7.3)
- Hestenes, M. R., 1969, "Multiplier and gradient methods", J. Optzn. Thry. & Apps. 4, 303. Also in Zadeh (1969). (7.1)
- Hestenes, M. R. & Stiefel, E. L., 1952, "Method of conjugate gradients for solving linear systems", J. Res. Nat. Bur. Standards, Sect. B, 49, 409-436. (7.3)
- Hext, G. R., see Spendley, Hext & Himsworth (1962).
- Hill, I. D., see Pike, Hill & James (1967).
- Hillstrom, K. E., see Clark, Cody, Hillstrom & Thieleker (1967).
- Himsworth, F. R., see Spendley, Hext & Himsworth (1962).
- Hoare, C., see Wirth & Hoare (1966).
- Hooke, R. & Jeeves, T. A., 1961, "Direct search solution of numerical and statistical problems", J. ACM 8, 212-229. (7.1)
- Householder, A. S., 1964, "The theory of matrices in numerical analysis", Blaisdell, New York. (7.4)
- Householder, A. S., 1971, "The numerical treatment of a single nonlinear equation", to appear. (3.1)
- Huang, H. Y., 1970, "Unified approach to quadratically convergent algorithms for function minimization", J. Optzn. Thry. & Apps. 5, 405-423. (7.1)
- Isaacson, E. & Keller, H. B., 1966, "Analysis of numerical methods", Wiley, New York. (2.2, 2.4)
- Jacoby, S. L. S., Kowalik, J. S. & Pizzo, J. T., 1971,

"Iterative methods for nonlinear optimization problems",
Prentice-Hall, Englewood Cliffs, New Jersey (to appear).
(5.4, 7.1, 8)

James, F. D., see Pike, Hill & James (1967).

Jarratt, P., 1967, "An iterative method for locating turning
points", Comp. J. 10, 82-84. (1.2, 3.1, 3.2, 3.6, 3.7,
3.8, 3.9, 5.1)

Jarratt, P., 1968, "A numerical method for determining points
of inflexion", BIT 8, 31-35. (1.2, 3.1, 3.2, 3.6, 3.9)

Jeeves, T. A., see Hooke & Jeeves (1961).

Jenkins, M. A., 1969, "Three-stage variable-shift iterations
for the solution of polynomial equations with a posteriori
bounds for the zeros", Tech. Report CS 138, Stanford
University. (3.5)

Johnsen, S. E. J., see Allran & Johnsen (1970).

Johnson, I. L. & Myers, G. E., 1967, "One-dimensional
minimization using search by golden section and cubic fit
methods", Report N68-18823 (NASA), Manned Spacecraft
Center, Houston. (5.7)

Johnson, S. M., 1955, "Best exploration for maximum is
Fibonacci", RAND Corp. RM-1590. (5.3)

Johnson, S. M., see Gross & Johnson (1959), Bellman (1957),
Bellman & Dreyfus (1962).

Jones, A. P., 1970, "SPIRAL - a new algorithm for non-linear
parameter estimation using least squares", Comp. J. 13, 3,
301-308. (7.1)

Jones, A. P., see Fiacco & Jones (1969).

Jones, A. P. & McCormick, G. P., 1969, "Penalty methods in
optimal control theory", RAC-TP-371, Res. Anal. Corp.,
McLean, Virginia. (7.1)

Jordan, T. L., 1968, "Experiments on error growth associated
with some linear least-squares procedures", Math. Comp. 22,
579-588. (7.1)

Kahan, W., see Golub & Kahan (1965).

Kaifon, P., Ribiere, G. & Sogno, J. C., 1968, "A method of
feasible directions using projection operators", presented
at IFIPS Congress, Edinburgh, 1968. (7.1)

Kantorovich, L. V. & Akilov, G. P., 1959, "Functional analysis
in normed spaces", Moscow (translation by D. Brown, edited
by A. Robertson, MacMillan, New York, 1964). (3.1)

Kaplan, J. L., see Mitchell & Kaplan (1968).

Karney, D. L., see Gregory & Karney (1969).

Karp, R. M. & Miranker, W. L., 1968, "Parallel minimax search
for a maximum", J. Comb. Thry. 4, 1, 19-35. (5.7)

Kaupe, A. F., 1964, "On optimal search techniques", Comm. ACM
7, 38. (6.7)

Keller, H. B., see Isaacson & Keller (1966).

Kelley, H. J. & Myers, G. E., 1967, "Conjugate direction
methods for parameter optimization", presented at the 18th
Congress of the International Astronautical Federation,
Belgrade. (7.1)

Kempthorne, O., see Shah, Buehler & Kempthorne (1964).

Kettler, P. C., see Shanno & Kettler (1969).

Khabaza, I. M., 1963, "An iterative least-square method suitable for solving large sparse matrices", *Comp. J.* 6, 202-206. (7.1)

Kiefer, J., 1953, "Sequential minimax search for a maximum", *Proc. Amer. Math. Soc.* 4, 503-506. (1.2)

Kiefer, J., 1957, "Optimal sequential search and approximation methods under minimum regularity assumptions", *SIAM J. Appl. Math.* 5, 105-136. (6.7)

King, R. P., 1966, "Necessary and sufficient conditions for inequality constrained extreme values", *Ind. Eng. Chem. (Fund.)* 5, 484. (7.1)

Knuth, D. E., 1969, "The art of computer programming", Vol. 2, Addison-Wesley, Reading, Massachusetts. (7.9)

Kogbetliantz, E. G., 1955, "Solution of linear equations by diagonalization of coefficients matrix", *Quart. Appl. Math.* 13, 123-132. (7.4)

Kowalik, J. S. & Osborne, M. R., 1968, "Methods for unconstrained optimization problems", Elsevier, New York. (1.2, 2.6, 3.7, 5.3, 5.4, 7.1, 7.3, 7.7, 7.9)

Kowalik, J. S., Osborne, M. R. & Ryan, D. M., 1969, "A new method for constrained optimization problems", *Oper. Res.* 17, 973. (7.1)

Kowalik, J. S., see Jacoby, Kowalik & Pizzo (1971).

Krolak, P. D., 1968, "Further extensions of Fibonacci search to nonlinear programming problems", *SIAM J. Control* 6, 2,

258-265. (5.3)

Krolak, P. D. & Cooper, L., 1963, "An extension of Fibonacci search to several variables", *Comm. ACM* 6, 639. (6.7)

Kublanovskaya, V. N., 1961, "On some algorithms for the solution of the complete eigenvalue problem", *Zh. Vych. Mat.* 1, 555-570. (7.4)

Künzi, H. P. & Oettli, W., 1970, "Nichtlineare Optimierung: Neuere Verfahren Bibliographie", Springer-Verlag, Berlin. (8)

Künzi, H. P., Tzschach, H. G. & Zehnder, C. A., 1968, "Numerical methods of mathematical optimization", Academic Press, New York. (7.1)

Lancaster, P., 1966, "Error analysis for the Newton-Raphson method", *Numer. Math.* 9, 55-68. (5.2)

Lapidus, I., see Goldfarb & Lapidus (1968).

Lavi, A. & Vogl, T. P. (eds.), 1966, "Recent advances in optimization techniques", Wiley, New York. (7.1, 8)

Lawson, C. L., 1968, "Bibliography of recent publications in approximation theory with emphasis on computer applications", *Tech. Mem.* 201, JPL, Pasadena. (8)

Leon, A., 1966, "A comparison of eight known optimizing procedures", in Lavi & Vogl (1966). (7.7, 7.9)

Levenberg, K. A., 1944, "A method for the solution of certain non-linear problems in least squares", *Quart. Appl. Math.* 2, 164-168. (7.1)

Levy, A. V., see Cragg & Levy (1969).

Lill, S. A., 1970, "A modified Davidon method for finding the

minimum of a functions using difference approximations for derivatives", Algorithm 46, Comp. J. 13, 111-113. (7.1)

Lootsma, F. A., 1968, "Constrained optimization via penalty functions", Philips Res. Report. 23, 408. (7.1)

Lootsma, F. A., 1970, "Boundary properties of penalty functions for constrained minimization", Thesis, Eindhoven, Holland. (7.1)

Luenberger, D. G., 1969a, "Optimization by vector space methods", Wiley, New York. (7.1, 7.3)

Luenberger, D. G., 1969b, "Hyperbolic pairs in the method of conjugate gradients", SIAM J. Appl. Math. 17, 6, 1263-1267. (7.1)

Luenberger, D. G., 1970, "The conjugate residual method for constrained minimization problems", SIAM J. Numer. Anal. 7, 3, 390-398. (7.1)

Maddison, R., 1966, "A procedure for nonlinear least squares refinement in adverse practical conditions", J. ACM 13, 124-134. (7.1)

Magee, E. J., 1960, "An empirical investigation of procedures for locating the maximum peak of a multiple-peak regression function", Lincoln Lab. Report 22G-0046. (1.2)

Mangasarian, O. L., 1969, "Nonlinear programming", McGraw Hill, New York. (7.1)

Marquardt, D. W., 1963, "An algorithm for least squares estimation of nonlinear parameters", J. SIAM 11, 431-441. (7.1)

Martin, R. S., see Bowdler, Martin, Reinsch & Wilkinson (1968).

Martin, R. S., Reinsch, C. & Wilkinson, J. H., 1968, "Householder's tridiagonalization of a symmetric matrix", Numer. Math. 11, 181-195. (7.4)

Matthews, A. & Davies, D., 1969, "A comparison of modified Newton methods for unconstrained optimization", ICI Management Services Report MSDH/69/94. (7.1)

McCann, A. P., see Fletcher & McCann (1969).

McCormick, G. P., 1969, "The rate of convergence of the reset Davidon variable metric method", MRC Report 1012, Uni. of Wisconsin. (1.2, 7.1, 7.8)

McCormick, G. P., see Fiacco & McCormick (1968), Jones & McCormick (1969).

McCormick, G. P. & Pearson, J. D., 1969, "Variable metric methods and unconstrained optimization", in Fletcher (1969a). (1.2, 7.1, 7.7, 7.9)

Mead, R., see Nelder & Mead (1965).

Meinardus, G., 1967, "Approximation of functions: theory and numerical methods", Springer-Verlag, Berlin & New York. (3.7)

Mendelsohn, J., see Flanagan, Vitale & Mendelsohn (1969).

Miele, A. & Cantrell, J. W., 1969, "Study on a memory gradient method for the minimization of functions", J. Optzn. Thry. & Apps. 3, 459-470. (7.1)

Miele, A. & Cantrell, J. W., 1970, "Memory gradient method for

the minimization of functions", in Balakrishnan (1970). (7.1)

Milne, W. E., 1949, "Numerical calculus", Princeton Uni. Press, Princeton, New Jersey. (2.2)

Milne-Thomson, L. M., 1933, "The calculus of finite differences", MacMillan, London. (2.2)

Miranker, W. L., 1969, "Parallel methods for approximating the root of a function", IBM Jour. Res. & Dev. 13, 3, 297-301. (4.5, 5.7)

Miranker, W. L., see Chazan & Miranker (1970), Karp & Miranker (1968).

Mitchell, R. A. & Kaplan, J. L., 1968, "Nonlinear constrained optimization by a non-random complex method", J. Res. NBS (Engr. and Instr.) 72C, 249. (7.1)

Moler, C. B., see Forsythe & Moler (1967), Fox, Henrici & Moler (1967).

Morrison, D. D., 1968, "Optimization by least squares", SIAM J. Numer. Anal. 5, 83. (7.1)

Murray, W., 1969a, "Ill-conditioning in barrier and penalty functions arising in constrained nonlinear programming", in "Proceedings of the sixth international symposium on mathematical programming", Princeton, New Jersey, 1967. (7.1)

Murray, W., 1969b, "An algorithm for constrained minimization", in Fletcher (1969a). (7.1)

Murray, W., see Gill & Murray (1970).

Murtagh, B. A., 1969, "Optimization methods with applications

to chemical engineering design", Ph. D. Thesis, Uni. of London. (7.1)

Murtagh, B. A. & Sargent, R. W. H., 1969, "A constrained minimization method with quadratic convergence", in Fletcher (1969a). (7.1)

Murtagh, B. A. & Sargent, R. W. H., 1970, "Computational experience with quadratically convergent minimization methods", Comp. J. 13, 2, 185-194. (7.1)

Myers, G. E., 1968, "Properties of the conjugate gradient and Davidon methods", J. Optzn. Thry. & Apps. 2, 209-219. (7.1)

Myers, G. E., see Johnson & Myers (1967), Kelley & Myers (1967).

Naur, P. (ed.), 1963, "Revised report on the algorithmic language ALGOL 60", Comm. ACM 6, 1, 1-17. (1.1)

Nelder, J. A. & Mead, R., 1965, "A simplex method for function minimization", Comp. J. 7, 308-313. (7.1, 7.4)

Newman, D. J., 1965, "Location of the maximum on unimodal surfaces", J. ACM 12, 395-398. (1.2, 5.3, 6.7)

Nörlund, N. E., 1954, "Vorlesungen über Differenzenrechnung", (reprinted), New York. (3.1)

Oettli, W., see Künzi & Oettli (1970).

Ortega, J. M., 1968, "The Newton-Kantorovich theorem", Amer. Math. Monthly 75, 658-660. (3.1)

Ortega, J. M., 1970, "Solution of nonlinear systems of equations", Notes for Uni. of Michigan Conf. on Numerical Analysis, June 1970. (7.1)

Ortega, J. M. & Rheinboldt, W. C., 1970, "Iterative solution

- of nonlinear equations in several variables", Academic Press, New York. (3.1, 3.2, 3.6, 7.1, 8)
- Osborne, M. R., 1969, "A note on Powell's method for calculating orthogonal vectors", Austral. Comp. J. 1, 216. (7.5)
- Osborne, M. R., see Kowalik & Osborne (1968), Kowalik, Osborne & Ryan (1969).
- Osborne, M. R. & Ryan, D. M., 1970, "An algorithm for nonlinear programming", Tech. Report 35, Computer Centre, Australian National Uni., Canberra. (7.1)
- Osborne, M. R. & Ryan, D. M., 1971, "On penalty function methods for nonlinear programming problems", J. Math. Anal. Apps. (to appear). (7.1)
- Ostrowski, A. M., 1966, "Solution of equations and systems of equations", Academic Press, New York (2nd edition). (1.2, 3.1, 3.2, 3.6, 3.7, 4.2, 5.1, 7.1)
- Ostrowski, A. M., 1967a, "Contributions to the theory of the method of steepest descent", Arch. Rational Mech. Anal. 26, 257-280. (7.1)
- Ostrowski, A. M., 1967b, "The round-off stability of iterations", Z. Angew. Math. Mech. 47, 77-82. (5.2)
- Overholt, K. J., 1965, "An instability in the Fibonacci and the golden section search methods" BIT 5, 284. (5.3)
- Overholt, K. J., 1967, "Note on Algorithm 2, Algorithm 16 and Algorithm 17", Comp. J. 9, 414. (5.3)
- Palmer, J. R., 1969, "An improved procedure for orthogonalising the search vectors in Rosenbrock's and Swann's direct search optimization methods", Comp. J. 12, 69. (7.5)
- Pearson, J. D., 1969, "Variable metric methods of minimization", Comp. J. 12, 2, 171-178. (7.1)
- Pearson, J. D., see McCormick & Pearson (1969).
- Peckham, G., 1970, "A new method for minimizing a sum of squares without calculating gradients", Comp. J. 13, 4, 418-420. (7.1)
- Peters, G. & Wilkinson, J. H., 1969, "Eigenvalues of $Ax = \lambda Bx$ with band symmetric A and B", Comp. J. 12, 398-404. (1.2, 4.1, 4.2)
- Pierre, D. A., 1969, "Optimization theory with applications", Wiley, New York. (5.4)
- Pietrzykowski, T., 1969, "An exact potential method for constrained maxima", SIAM J. Numer. Anal. 6, 229. (7.1)
- Pike, M. C., Hill, I. D. & James, F. D., 1967, "Note on Algorithm 2, FIBONACCI SEARCH and on Algorithm 7, MINX", Comp. J. 9, 416. (5.2)
- Pike, M. C. & Pixner, J., 1967, "Algorithm 2, FIBONACCI SEARCH", Comp. Bulletin 8, 147. (5.3)
- Pike, M. C., see Bell & Pike (1966).
- Pixner, J., see Pike & Pixner (1967).
- Pizzo, J. T., see Jacoby, Kowalik & Pizzo (1971).
- Powell, M. J. D., 1962, "An iterative method for finding stationary values of a function of several variables",

Comp. J. 5, 147-151. (7.7, 7.9)

Powell, M. J. D., 1964, "An efficient method for finding the minimum of a function of several variables without calculating derivatives", Comp. J. 7, 155-162. (1.1, 1.2, 5.4, 7.1, 7.3, 7.5, 7.6, 7.7, 7.8, 7.9)

Powell, M. J. D., 1965, "A method of minimizing a sum of squares of non-linear functions without calculating derivatives", Comp. J. 7, 303-307. (7.1, 7.7)

Powell, M. J. D., 1966, "Minimization of functions of several variables", in Walsh (1966). (7.1)

Powell, M. J. D., 1968a, "On the calculation of orthogonal vectors", Comp. J. 11, 3, 302-304. (7.5)

Powell, M. J. D., 1968b, "A FORTRAN subroutine for solving systems of non-linear equations", Report R-5947, AERE, Harwell, England. (7.1)

Powell, M. J. D., 1969a, "A hybrid method for nonlinear equations", Report TP 364, AERE, Harwell, England. (7.1)

Powell, M. J. D., 1969b, "Rank one methods for unconstrained optimization", Report TP 372, AERE, Harwell, England. (7.1)

Powell, M. J. D., 1969c, "On the convergence of the variable metric algorithm", Report TP 382, AERE, Harwell, England. (7.1)

Powell, M. J. D., 1969d, "A method for nonlinear constraints in minimization problems", in Fletcher (1969a). (7.1)

Powell, M. J. D., 1969e, "A theorem on rank one modifications to a matrix and its inverse", Comp. J. 12, 3, 288-290. (7.1)

Powell, M. J. D., 1970a, "A survey of numerical methods for unconstrained optimization", SIAM Review 12, 79-97. (7.1)

Powell, M. J. D., 1970b, "A new algorithm for unconstrained optimization", Report TP 393, AERE, Harwell, England. (7.1)

Powell, M. J. D., 1970c, "Rank one methods for unconstrained optimization", in Abadie (1970). (7.1)

Powell, M. J. D., 1970d, "A FORTRAN subroutine for unconstrained minimization, requiring first derivatives of the objective function", Report R-6469, AERE, Harwell, England. (7.1)

Powell, M. J. D., 1970e, "Recent advances in unconstrained optimization", Report TP 430, AERE, Harwell, England. (7.1, 7.7)

Powell, M. J. D., see Fletcher & Powell (1963).

Powell, M. J. D. & Reid, J. K., 1968, "On applying Householder transformations to linear least squares problems", Report TP 322, AERE, Harwell, England. (7.1)

Price, J. F., see Goldstein & Price (1967).

Quandt, R. E., see Goldfeld, Quandt & Trotter (1968).

Rabinowitz, P. (ed.), 1969, "Proceedings of the conference on numerical methods for nonlinear algebraic equations". (7.1, 8)

Rall, L. B. (ed.), 1965, "Error in digital computation", Vol. 2, Wiley, New York. (8)

Rall, L. B., 1966, "Convergence of the Newton process to multiple solutions", Numer. Math. 9, 23-37. (7.1)

Rall, L. B., 1969, "Computational solution of nonlinear

operator equations", Wiley, New York. (7.1)

Ralston, A., 1963, "On differentiating error terms", Amer. Math. Monthly 70, 187-188. (1.2, 2.1, 2.6)

Ralston, A., 1965, "A first course in numerical analysis", McGraw Hill, New York. (1.2, 2.6)

Ralston, A. & Wilf, H. S. (eds.), 1960, "Mathematical methods for digital computers", Vol. 1, Wiley, New York. (7.1, 8)

Ralston, A. & Wilf, H. S. (eds.), 1967, "Mathematical methods for digital computers", Vol. 2, Wiley, New York. (8)

Ramsay, J. O., 1970, "A family of gradient methods for optimization", Comp. J. 13, 4, 413-417. (7.1)

Reeves, C. M., see Fletcher & Reeves (1964).

Reid, J. K., see Powell & Reid (1968).

Reinsch, C., see Golub & Reinsch (1970), Martin, Reinsch & Wilkinson (1968), Bowdler, Martin, Reinsch & Wilkinson (1968).

Rheinboldt, W. C., see Ortega & Rheinboldt (1970).

Ribiere, G., see Kalfon, Ribiere & Sogno (1968).

Rice, J. R., 1966, "Experiments on Gram-Schmidt orthogonalization", Math. Comp. 20, 325-328. (7.5)

Rice, J. R., 1970, "Minimization and techniques in nonlinear approximation", SIAM Studies in Numer. Anal. 2, 80-98. (7.1)

Richman, P. L., 1968, " ϵ -calculus", Tech. Report CS 105, Stanford Uni. (1.2, 5.3)

Rivlin, T. J., 1970, "Bounds on a polynomial", J. Res. Nat. Bureau of Standards-B, 74B, 1, 47-54. (1.2, 6.1)

Robbins, H., 1952, "Some aspects of the sequential design of experiments", Bull. Amer. Math. Soc. 58, 527-536. (1.2)

Rosen, J. B., 1960, "The gradient projection method for nonlinear programming. Part 1. Linear constraints", J. SIAM 8, 181. (7.1)

Rosen, J. B., 1961, "The gradient projection method for nonlinear programming. Part 2. Nonlinear constraints", J. SIAM 9, 514. (7.1)

Rosen, J. B. & Suzuki, S., 1965, "Construction of nonlinear programming test problems", Comm. ACM 8, 113. (7.1)

Rosenbrock, H. H., 1960, "An automatic method for finding the greatest or least value of a function", Comp. J. 3, 175-184. (6.8, 7.5, 7.7, 7.9)

Roth, B., see Freudenstein & Roth (1963).

Ryan, D. M., see Osborne & Ryan (1970, 1971), Kowalik, Osborne & Ryan (1969).

Sargent, R. W. H., see Murtagh & Sargent (1969, 1970).

Satterthwaite, E., see Bauer, Becker & Graham (1968).

Saunders, M., see Golub & Saunders (1969), Bartels, Golub & Saunders (1970).

Schröder, E., 1870, "Über unendlich viele Algorithmen zur Auflösung der Gleichungen", Math. Ann. 2, 317-365. (3.1, 3.2)

Schubert, L. K., 1970, "Modification of a quasi-Newton method for nonlinear equations with a sparse Jacobian", Math. Comp. 24, 27-30. (7.1)

Shah, B. V., Buehler, R. J. & Kempthorne, O., 1964, "Some

algorithms for minimizing a function of several variables",
SIAM J. Appl. Math. 12, 74-92. (7.1)

Shanno, D. F., 1965, "An algorithm for the solution of
nonlinear estimation problems with linear constraints",
Gulf Research and Development Co. Tech. Memo 161. (7.1)

Shanno, D. F., 1969a, "Conditioning of quasi-Newton methods
for function minimization", Center for Math. Studies in
Business and Economics Report 6910 (revised), Uni. of
Chicago. (7.1)

Shanno, D. F., 1969b, "Inverse quasi-Newton methods", Center
for Math. Studies in Business and Economics Report 6938,
Uni. of Chicago. (7.1)

Shanno, D. F., 1970a, "Parameter selection for modified Newton
methods for function minimization", SIAM J. Numer. Anal.
7, 3, 366-372. (7.1)

Shanno, D. F., 1970b, "An accelerated gradient projection
method for linearly constrained nonlinear estimation", SIAM
J. Appl. Math. 18, 2, 322-334. (7.1)

Shanno, D. F. & Kettler, P. C., 1969, "Optimal conditioning of
quasi-Newton methods", Center for Math. Studies in Business
and Economics Report 6937, Uni. of Chicago. (7.1)

Smith, C. S., 1962, "The automatic computation of maximum
likelihood estimates", NCB Sci. Dept. Report SC 846/MR/40.
(7.1, 7.3, 7.8)

Smith, L. B., see Golub & Smith (1967).

Sobel, I., 1970, "Camera models and machine perception",

Stanford Artificial Intelligence Report AIM-121. (7.7)

Sogno, J. C., see Kalfon, Ribiere & Sogno (1968).

Sorensen, H. W., 1969, "Comparison of some conjugate direction
procedures for function minimization", J. Franklin
Institute 288, 421. (7.1)

Spang, H. A., 1962, "A review of minimization techniques for
nonlinear functions", SIAM Review 4, 343-365. (7.1)

Späth, H., 1967, "The damped Taylor series method for
minimizing a sum of squares and for solving systems of
nonlinear equations", Comm. ACM 10, 726-728. (7.1)

Spendley, W., 1969, "Nonlinear least squares fitting using a
modified simplex minimization technique", in Fletcher
(1969a). (7.1)

Spendley, W., Hext, G. R. & Himsworth, F. R., 1962,
"Sequential application of simplex designs in optimization
and evolutionary operation", Technometrics 4, 441. (7.1)

Sproull, R., see Swinehart & Sproull (1970).

Stewart, G. W., 1967, "A modification of Davidon's
minimization method to accept difference approximations of
derivatives", J. ACM 14, 72-83. (1.1, 1.2, 7.1, 7.7, 7.8)

Stiefel, E. L., see Hestenes & Stiefel (1952).

Sugie, N., 1964, "An extension of Fibonacci searching to
multidimensional cases", IEEE Trans. Control AC-9, 105. (6.7)

Suzuki, S., see Rosen & Suzuki (1965).

Swann, W. H., 1964, "Report on the development of a new direct
search method of optimization", ICI. Ltd. Cent. Inst. Lab.

Research Note 64/3. (1.2, 7.1, 7.5)

Swann, W. H., see Box, Davies & Swann (1969), Davies & Swann (1969).

Swinehart, D. & Sproull, R., 1970, "SAIL", Stanford Artificial Intelligence Project Operating Note 57.1, April 1970. (7.7)

Takahashi, I., 1965, "A note on the conjugate gradient method", Information Processing in Japan 5, 45-49. (7.1)

Thieleker, E. A., see Clark, Cody, Hillstrom & Thieleker (1967).

Tokumaru, H., Adachi, N. & Goto, K., 1970, "Davidon's method for minimization problems in Hilbert space with an application to control problems", SIAM J. Control 8, 2, 163-178. (7.1)

Tornheim, L., 1964, "Convergence of multipoint iterative methods", J. ACM 11, 210-220. (3.2)

Traub, J. F., 1964, "Iterative methods for solution of equations", Prentice-Hall, Englewood Cliffs, New Jersey. (2.2, 3.1, 3.2, 4.5)

Traub, J. F., 1967, "The solution of transcendental equations", in Ralston & Wilf (1967). (3.1, 3.2)

Trotter, H. F., see Goldfeld, Quandt & Trotter (1968).

Tzschach, H. G., see Künzi, Tzschach & Zehnder (1968).

Vercoustre, A. M., 1970, "Etude comparative des méthodes de minimization de Fletcher et Powell et de Davidon", Bulletin de la direction des études et recherches série C - Mathématiques, No. 1, 57-76. (7.1)

Vitale, P. A., see Flanagan, Vitale & Mendelsohn (1969).

Vogl, T. P., see Lavi & Vogl (1966).

Voigt, R. G., 1969, "Rates of convergence for iterative methods for nonlinear systems of equations", Uni. of Maryland Computer Sci. Center Report 69-97. (3.2, 7.1)

Wall, D., 1956, "The order of an iteration formula", Math. Comp. 10, 167-168. (3.2)

Walsh, J. (ed.), 1966, "Numerical analysis: an introduction", Academic Press, London & New York. (8)

Wells, M., 1965, "Algorithm 251: Function minimization", Comm. ACM 8, 3, 169-170. (7.1)

van Wijngaarden, A., Zonneveld, J. A. & Dijkstra, E. W., 1963, "Programs AP200 and AP230 de serie AP200", edited by T. J. Dekker, The Mathematical Centre, Amsterdam. (1.2, 4.1)

Wilde, D. J., 1964, "Optimum seeking methods", Prentice-Hall, Englewood Cliffs, New Jersey. (1.2, 4.5, 5.3, 5.7, 7.1, 7.5)

Wilde, D. J. & Beightler, C. S., 1967, "Foundations of optimization", Prentice-Hall, Englewood Cliffs, New Jersey. (7.1)

Wilde, D. J., see Avriel & Wilde (1966).

Wilf, H. S., see Ralston & Wilf (1960, 1967).

Wilkinson, J. H., 1963, "Rounding errors in algebraic processes", HMSO, London or Prentice Hall, New Jersey. (4.2, 6.3, 7.2)

Wilkinson, J. H., 1965a, "The algebraic eigenvalue problem", Oxford Uni. Press, Oxford. (7.2, 7.4)

Wilkinson, J. H., 1965b, "Error analysis of transformations based on the use of matrices of the form $I - 2ww^T$ ", in Rall (1965). (7.4)

Wilkinson, J. H., 1967, "Two algorithms based on successive linear interpolation", Tech. Report CS 60, Stanford Uni. (1.2, 4.1, 4.2)

Wilkinson, J. H., 1968, "Global convergence of QR algorithm", Proceedings of IFIPS Congress, 1968. (7.4)

Wilkinson, J. H., see Peters & Wilkinson (1969), Golub & Wilkinson (1966), Martin, Reinsch & Wilkinson (1968), Bowdler, Martin, Reinsch & Wilkinson (1968).

Winfield, D. H., 1967, "Function minimization without derivatives by a sequence of quadratic programming problems", Report 537, Engineering & Applied Physics Division, Harvard Uni. (7.1)

Wirth, N. & Hoare, C., 1966, "A contribution to the development of ALGOL", Comm. ACM 9, 6, 413-431. (1.1, 4.4, 5.6, 6.6, 7.9)

Witzgall, C., 1969, "Fibonacci search with arbitrary first evaluation", Report D1-82-0916, Boeing Scientific Research Labs., Seattle, Washington. (1.2, 5.3, 5.4)

Wolfe, P., 1959a, "The secant method for simultaneous non-linear equations", Comm. ACM 2, 12, 12-13. (7.1)

Wolfe, P., 1963, "Methods of nonlinear programming" in "Recent advances in nonlinear programming", edited by Graves & Wolfe, McGraw Hill. (7.1)

Wolfe, P., 1969, "Convergence conditions for ascent methods", SIAM Review 11, 226-235. (7.1)

Zadeh, L. A. (ed.), 1969, "Computing methods in optimization problems", Vol. 2, Academic Press, New York. (7.1, 8)

Zangwill, W. I., 1967a, "Minimizing a function without calculating derivatives", Comp. J. 10, 293-296. (7.1, 7.3)

Zangwill, W. I., 1967b, "Nonlinear programming via penalty functions", Mgmt. Sci. 13, 344-358. (7.1)

Zangwill, W. I., 1969a, "Nonlinear programming: a unified approach", Prentice-Hall, Englewood Cliffs, New Jersey. (7.1)

Zangwill, W. I., 1969b, "Convergence conditions for nonlinear programming algorithms", Mgmt. Sci. 16, 1. (7.1)

Zehnder, C. A., see Künzi, Tzsach & Zehnder (1968).

Zelevnik, F. J., 1968, "Quasi-Newton methods for nonlinear equations", J. ACM 15, 265-271. (7.1)

Zonneveld, J. A., see van Wijngaarden, Zonneveld & Dijkstra (1963).

Zoutendijk, G., 1960, "Methods of feasible directions", Elsevier, Amsterdam & New York. (7.1)

Zoutendijk, G., 1966, "Nonlinear programming: a numerical survey", J. SIAM Control 4, 194-210. (7.1)

Zoutendijk, G., 1970, "Nonlinear programming, computational methods", in Abadie (1970). (7.1)

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