# DETERMINATION OF EIGENSOLUTIONS OF ARBITRARY 

MATRICES USING SIMULTANEOUS ITERATION

ACCELERATED BY JACOBI-IIKE METHODS.

A thesis submitted at the University of London for the degree of Doctor of Philosophy (Computer Science)


#### Abstract

The direct methods of obtaining the eigenvalues and eigenvectors of a matrix, such as the QR algorithm of Francis, are certainly to be recommended when it is necessary to compute all the eigenvalues and corresponding eigenvectors of relatively small matrices. However, for larger matrices iterative techniques may be the only feasible methods. Iterative methods particularly come into their own when: 1) the required number of eigensolutions is substantially smaller than the dimension of the matrix, 2) initial estimates of the eigenvectors are available, 3) the matrix is sparse.

It is often the case that many technical problems give rise to very large sparse matrices. The author has been involved in marine engine vibration problems and this gave rise to an interest in the methods of obtaining eigensolutions of the matrices involved. It is also usually the case that only a few eigenvalues and eigenvectors need to be determined accurately and that experience with similar problems enables good initial approximations to the eigenvectors to be made. Hence we see that these are ideal conditions in which to use iterative methods.


The best known iterative method is the power method in which a trial vector is continually premultiplied by the matrix until the iterates become proportional to each other. This process can often yield an eigenvector in a very short time but this cannot be guaranteed even with improvements such as shift of origin and acceleration techniques. To overcome possible poor convergence the computation is applied to general iteration vectors between which an orthogonality or biorthogonality relation is maintained. Such methods and the developments thereof are the subject of this thesis.

## CONTENTS



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In quoting from a number of papers in French and German the author lays no claim to any ability to read them and frankly confesses that they were translated for him by his father, to whom he is grateful.

For such imperfections as the reader may find the author alone takes responsibility; he only hopes that they will not be too numerous.

## 1. INTRODUCTION

In this brief introduction we give many of the definitions and fundamental results upon which the following chapters are based. In general, proofs are given only if they are pertinent to later results. The (i,j) element of a matrix $A$ will be denoted by $a_{i j}$. Vectors will be represented by lower case letters; we shall very frequently be concerned with systems of vectors which will be denoted by $x_{1}, x_{2}, \ldots$ ..., $x_{n}$. We shall refer to the matrix having $x_{i}$ as its i-th column as X. Matrices of eigenvectors will usually be denoted by the letters $U, V, W, X$ or $Y$. In particular, matrices of right-hand eigenvectors will be denoted by $X$ and matrices of left-hand eigenvectors by $Y$.

The notation $|A|$ is reserved exclusively to denote the matrix the elements of which are $\left|a_{i j}\right|$. The determinant of a matrix is represented by det(A) and the norm of a matrix by $\|A\|$.

The conjugate of the matrix $A=\left(a_{i j}\right)$ is represented by $\bar{A}=\left(\bar{a}_{i j}\right)$. The transpose of $A$ is denoted by $A^{T}$ and is such that its ( $i, j$ ) element is equal to $a_{j i}$. Similarly, the Hermitian transpose of A is denoted by $A^{H}$ and is such that its (i,j) element is equal to $\bar{a}_{j i}$.

A diagonal matrix with the (i,i) element equal to $\lambda_{i}$ will be denoted by $\operatorname{diag}\left(\lambda_{i}\right)$ or, if no confusion can arise, $\Lambda$ or $D$ may be used to represent diagonal
matrices.

## 2. DEFINITIONS

The fundamental algebraic eigenproblem with which we are concerned is determining some or all of those values $\lambda$ for which the set of $n$ homogeneous linear equations in $n$ unknowns

$$
\begin{equation*}
(A-\lambda I) x=0 \tag{2.1}
\end{equation*}
$$

has a non-trivial solution. Equation (2.1) may be rewritten as

$$
\begin{equation*}
A x=\lambda x \tag{2.2}
\end{equation*}
$$

The theory of simultaneous linear algebraic equations shows that there is a solution, other than the trivial $x=0$, if, and only if, the matrix (A- $\lambda I$ ) is singular. That is

$$
\begin{equation*}
\operatorname{det}(A-\lambda I)=0 \tag{2.3}
\end{equation*}
$$

The polynomial $f(\lambda)=\operatorname{det}(A-\lambda I)$ is called the characteristic polynomial and the equation $f(\lambda)=0$ is called the characteristic equation of $A$. Theorem 2.1 The characteristic polynomial of a matrix of order $n$ is a polynomial of degree $n$ with leading coefficient (-1) ${ }^{n}$; i.e.,

$$
f(\lambda)=a_{0}+a_{1} \lambda+\ldots+a_{n-1} \lambda^{n-1}+(-1)^{n} \lambda^{n} \cdot \text { (2.4) }
$$

If the n solutions of

$$
\begin{equation*}
f(\lambda)=0 \tag{2.5}
\end{equation*}
$$

are $\lambda_{1}, \lambda_{2}, \ldots, \lambda_{n}$, then

$$
\begin{equation*}
\lambda_{1} \lambda_{2} \ldots \lambda_{n}=\operatorname{det}(A) \tag{2.6}
\end{equation*}
$$

Proof: The proof follows by expanding $\operatorname{det}(A-\lambda I)$ in terms of elements in the first row. A rigorous treatment is to be found in Noble (1969).

Since the coefficient of $\lambda^{n}$ is non-zero and we are working in the field of complex numbers the equation always has n roots. In general the roots will be complex and of any multiplicity up to $n$. These n roots are called the eigenvalues of the matrix $A$.

Corresponding to any eigenvalue $\lambda$ the equation (2.2) has at least one non-trivial solution. This solution is called the eigenvector of $A$ corresponding to the given value of $\lambda$. We refer to the pair $(\lambda, x)$ as an eigensolution of the matrix $A$. Theorem 2.2 (i) There exists at least one eigenvector, corresponding to each eigenvalue.
(ii) The eigenvectors corresponding to a given eigenvalue constitute a vector space. Prof: To find an eigenvector corresponding to $\lambda_{i}$ we solve

$$
\begin{equation*}
\left(A-\lambda_{i} I\right) x=0 \tag{2.7}
\end{equation*}
$$

Since $\operatorname{det}\left(A-\lambda_{i} I\right)=0$, this is a set of $n$ homogeneous equations in $n$ unknowns, the coefficient matrix having rank less than $n$. Hence a non-zero solution exists, which gives an eigenvector. This proves (i). To prove (ii) suppose that $u$ and $v$ are two eigenvectors corresponding to $\lambda_{i}$, then

$$
\begin{equation*}
A u=\lambda_{i} u, \quad A v=\lambda_{i} v \tag{2.8}
\end{equation*}
$$

so that

$$
\begin{align*}
A(\alpha u+\beta v) & =a \lambda_{i} u+\beta \lambda_{i} v \\
& =\lambda_{i}(\alpha u+\beta v) \tag{2.9}
\end{align*}
$$

Hence, $a u+\beta v$ is also an eigenvector and this proves (ii).

We note in particular that any eigenvector is arbitrary to the extent of a constant multiplier, for if

$$
\begin{equation*}
A x=\lambda x \tag{2.10}
\end{equation*}
$$

then

$$
\begin{equation*}
A(k x)=\lambda(k x) \tag{2.11}
\end{equation*}
$$

for some scalar k. It is often convenient to choose k such that the eigenvector has a particular numerical property. We refer to such eigenvectors as normalised. The most convenient forms of normalisation are those for which

$$
\begin{align*}
& \text { (i) } x^{H} x=\sum_{i=1}^{n}\left|x_{i}\right|^{2}=1  \tag{2.12}\\
& \text { (ii) if }\left|x_{i}\right| \geqslant\left|x_{j}\right|, \quad j=1, \ldots, n \\
& \text { then } k x_{i}=1 \tag{2.13}
\end{align*}
$$

## 3. EIGENSOLUTIONS OF THE TRANSPOSED MATRIX

We now consider the eigenvalues and eigenvectors of the transpose of a matrix A. By our previous definitions the eigenequation for the transpose $A^{T}$ is

$$
\begin{equation*}
A^{T} z=\lambda z \tag{3.1}
\end{equation*}
$$

where we seek those values of $\lambda$ for which (3.1) has a non-trivial solution. Following (2.3) these are the values for which

$$
\begin{equation*}
\operatorname{det}\left(A^{T}-\lambda I\right)=0 \tag{3.2}
\end{equation*}
$$

and since the determinant of a matrix is equal to that of its transpose the eigenvalues of $A$ are the same as those of $A^{T}$. We denote the eigenvector of $A^{T}$ corresponding to $\lambda_{i}$ as $z_{i}$, so that we have

$$
\begin{equation*}
A^{T} z_{i}=\lambda_{i} z_{i} \tag{3.3}
\end{equation*}
$$

Note that in general $x_{i} \neq z_{i}$. Equation (3.3) may be written as

$$
\begin{equation*}
z_{i}^{T} A=\lambda_{i} z_{i}^{T} \tag{3.4}
\end{equation*}
$$

To distinguish these vectors from the vectors $x_{i}$, where

$$
\begin{equation*}
A x_{i}=\lambda_{i} x_{i} \tag{3.5}
\end{equation*}
$$

the $z_{i}^{T}$ are called the left-eigenvectors of $A$ and the $x_{i}$ the right-eigenvectors of $A$. If we speak of just the eigenvectors of $A$ the meaning will be apparent from the context. These are the classical definitions as given in, for example, Wilkinson (1965) but for a lot of the work that follows it is convenient to adopt the following slightly modified definition of a left-hand eigenvector.

Instead of (3.4) we consider the equation

$$
\begin{equation*}
y_{i}^{H} A=\lambda_{i} y_{i}^{H} \tag{3.6}
\end{equation*}
$$

which may be rewritten as

$$
\begin{equation*}
A^{H} y_{i}=\bar{\lambda}_{i} y_{i} \tag{3.7}
\end{equation*}
$$

Note that $Y_{i}=\bar{z}_{i}$. We prefer to use $y^{H}$ and $A^{H}$ rather than $\mathrm{y}^{\mathrm{T}}$ and $\mathrm{A}^{\mathrm{T}}$ because we shall make extensive use of inner-products and in this case

$$
\begin{equation*}
(x, y) \equiv x^{H_{y}}=\overline{y^{H_{x}}}=\overline{(y, x)} \tag{3.8}
\end{equation*}
$$

and

$$
\begin{equation*}
x^{H} x>0 \tag{3.9}
\end{equation*}
$$

for all non-zero $x$.
We illustrate this further by using both the classical and modified definitions to prove the following theorem.
Theorem 3.1 A right eigenvector $x_{i}$ and a left eigenvector $\mathrm{y}_{\mathrm{j}}$ corresponding to distinct eigenvalues $\lambda_{i}$ and $\lambda_{j}$ respectively are orthogonal.
Proof (i): We may rewrite equation (3.5) as

$$
\begin{equation*}
x_{i}^{T} A^{T}=\lambda_{i} x_{i}^{T} \tag{3.10}
\end{equation*}
$$

and from (3.3)

$$
\begin{equation*}
A^{T} z_{j}=\lambda_{j} z_{j} \tag{3.11}
\end{equation*}
$$

Hence by postmultiplying (3.10) by $z_{j}$ and premultiplying (3.11) by $x_{i}^{T}$ we obtain

$$
\begin{equation*}
x_{i}^{T} A^{T} z_{j}=\lambda_{i} x_{i}^{T} z_{j} \tag{3.12}
\end{equation*}
$$

and

$$
\begin{equation*}
x_{i}^{T} A^{T} z_{j}=\lambda_{j} x_{i}^{T} z_{j} \tag{3.13}
\end{equation*}
$$

Subtracting gives

$$
\begin{equation*}
0=x_{i}^{T} z_{j}\left(\lambda_{i}-\lambda_{j}\right) \tag{3.14}
\end{equation*}
$$

which proves that

$$
\begin{equation*}
x_{i}^{T} z_{j}=0, \quad \text { if } \lambda_{i} \neq \lambda_{j} \tag{3.15}
\end{equation*}
$$

We note that as $x_{i}$ and $z_{j}$ are, in general,
complex vectors, $x_{i}^{T}{ }_{j}$ is not an inner-product as
is usually understood; for, in this case, we have

$$
\begin{equation*}
x_{i}^{T} z_{j}=z_{j}^{T} x_{i} \tag{3.16}
\end{equation*}
$$

and not

$$
\begin{equation*}
x_{i}^{T} z_{j}=\overline{z_{j}^{T} x_{i}} \tag{3.17}
\end{equation*}
$$

We note also that if x is complex we may have

$$
\begin{equation*}
x^{T} x \leq 0 \tag{3.18}
\end{equation*}
$$

In fact $x^{T} x$ may even be a complex number:
Proof (ii): We may rewrite equation (3.5) as

$$
\begin{equation*}
x_{i}^{H} A^{H}=\bar{\lambda}_{i} x_{i}^{H} \tag{3.19}
\end{equation*}
$$

and from (3.7)

$$
\begin{equation*}
A^{H} y_{j}=\bar{\lambda}_{j} \mathrm{y}_{j} \tag{3.20}
\end{equation*}
$$

Hence by postmultiplying (3.19) by $y_{j}$ and premultiplying (3.20) by $x_{i}^{H}$ we obtain

$$
\begin{equation*}
x_{i}^{H} A^{H} y_{j}=\bar{\lambda}_{i} x_{i}^{H} y_{\cdot j} \tag{3.21}
\end{equation*}
$$

and

$$
\begin{equation*}
x_{i}^{H} A^{H} y_{j}=\bar{\lambda}_{j} x_{i}^{H} y_{j} . \tag{3.22}
\end{equation*}
$$

Subtracting gives

$$
\begin{equation*}
0=x_{i}^{H} y_{j}\left(\bar{\lambda}_{i}-\bar{\lambda}_{j}\right) \tag{3.23}
\end{equation*}
$$

which proves that

$$
\begin{equation*}
x_{i}^{H} y_{j}=0, \quad \text { if } \lambda_{i} \neq \lambda_{j} \tag{3.24}
\end{equation*}
$$

This seems to us to be rather neater than the previous result as $X_{i} \mathrm{y}_{j}$ is an inner-product as usually understood. In particular

$$
\begin{equation*}
x_{i}^{H} y_{j}=\overline{y_{j}^{H} x_{i}} \tag{3.25}
\end{equation*}
$$

and

$$
\begin{equation*}
x^{H} x>0 \tag{3.26}
\end{equation*}
$$

for all non-zero $x$.
4. EIGENSYSTEMS WITH DISTINCT EIGENVALUES

Firstly we consider the theory of the system of eigenvectors in the case of distinct eigenvalues. The equation

$$
\begin{equation*}
\left(A-\lambda_{i} I\right) x_{i}=0 \tag{4.1}
\end{equation*}
$$

certainly has at least one solution for each value of $\lambda_{i}$ and therefore we are justified in assuming the existence of a set of eigenvectors $x_{1}, x_{2}, \ldots, x_{n}$. Theorem 4.1 The eigenvectors $x_{i}$ corresponding to distinct eigenvalues $\lambda_{i}$ are linearly independent. Proof: We assume that they are not independent and let $s$ be the smallest number of linearly dependent vectors such that $x_{1}, x_{2}, \ldots, x_{s}$ are eigenvectors corresponding to distinct eigenvalues $\lambda_{1}, \lambda_{2}, \ldots, \lambda_{5}$ of $A$. Then
and

$$
\begin{equation*}
\sum_{i=1}^{s} a_{i} x_{i}=0 \tag{4.2}
\end{equation*}
$$

$$
\begin{equation*}
a_{i} \neq 0, \quad i=1,2, \ldots, s \tag{4.3}
\end{equation*}
$$

Premultiplying (4.2) by A gives

$$
\begin{equation*}
\sum_{i=1}^{s} a_{i} \lambda_{i} x_{i}=0 \tag{4.4}
\end{equation*}
$$

Multiplying (4.2) by $\lambda_{S}$ and subtracting (4.4) gives

$$
\begin{equation*}
\sum_{i=1}^{s-1} a_{i}\left(\lambda_{s}-\lambda_{i}\right) x_{i}=0 \tag{4.5}
\end{equation*}
$$

and

$$
\begin{equation*}
a_{i} \neq 0 \quad \text { and } \quad \lambda_{i} \neq \lambda_{s}, \quad i=1,2, \ldots, s-1 \tag{4.6}
\end{equation*}
$$

Equation (4.5) implies that $x_{1}, x_{2}, \ldots, x_{s-1}$
are linearly dependent which is contrary to our hypothesis. Therefore there is no $s \leq n$ and hence the $n$ eigenvectors are linearly independent and span the whole n-dimensional space. From this result we may easily prove the following theorem.

Theorem 4.2 Each of the vectors $x_{i}$ is unique, apart from an arbitrary multiplier.

Proof: Suppose that corresponding to $\lambda_{1}$ there is an eigenvector $x_{1}$ and a second $x_{1}^{\prime}$. Then we may write

$$
\begin{equation*}
x_{i}^{\prime}=\sum_{i=1}^{n} a_{i} x_{i}, \tag{4.7}
\end{equation*}
$$

where at least one of the $\alpha_{i}$ is non-zero.
Multiplying (4.7) by A gives

$$
\begin{equation*}
\lambda_{1} x_{1}^{\prime}=\sum_{i=1}^{n} a_{i} \lambda_{i} x_{i} . \tag{4.8}
\end{equation*}
$$

Multiplying (4.7) by $\lambda_{1}$ and subtracting from (4.8) gives

$$
\begin{equation*}
0=\sum_{i=2}^{n} a_{i}\left(\lambda_{i}-\lambda_{1}\right) x_{i} \tag{4.9}
\end{equation*}
$$

But as the $x_{i}$ are independent we must have

$$
\begin{equation*}
\mathbf{a}_{i}\left(\lambda_{i}-\lambda_{1}\right)=0, \quad i=2,3, \ldots, n ; \tag{4.10}
\end{equation*}
$$

$$
\begin{equation*}
\Longrightarrow a_{i}=0, \quad i=2,3, \ldots, n \tag{4.11}
\end{equation*}
$$

as the eigenvectors are distinct. However, as at least one of the $a_{i}$ was non-zero it must have been
$a_{1}$ showing that $x_{1}$ is a multiple of $x_{1}$. Similar results hold for the left-hand eigenvectors.

We showed earlier that

$$
\begin{equation*}
x_{i}^{H} y_{j}=0, \quad \lambda_{i} \neq \lambda_{j} \tag{4.12}
\end{equation*}
$$

and it follows that

$$
\begin{equation*}
x_{i}^{H} y_{i} \neq 0, \quad i=1,2, \ldots \ldots, n . \tag{4.13}
\end{equation*}
$$

If this were not so and $x_{i}$ was orthogonal to $y_{i}$ it would be orthogonal to $y_{1}, y_{2}, \ldots, y_{n}$ and hence to the whole n-dimensional space. This is not possible as we demand that $x_{i}$ is not the null vector.

## 5. SIMILARITY TRANSFORMATIONS

If we choose the arbitrary multipliers associated with each $x_{i}$ and $y_{j}$ so that

$$
\begin{equation*}
y_{i}^{H} x_{i}=1, \quad i=1,2, \ldots, n \tag{5.1}
\end{equation*}
$$

this, together with (4.12), implies that the matrix $Y^{H}$, which has $y_{i}^{H}$ as its i-th row, is the inverse of the matrix $X$, which has $x_{i}$ as its i-th column. The $n$ equations

$$
\begin{equation*}
A x_{i}=\lambda_{i} x_{i}, \quad i=1,2, \ldots, n \tag{5.2}
\end{equation*}
$$

may be written as

$$
\begin{equation*}
\operatorname{AX}=\operatorname{Xdiag}\left(\lambda_{i}\right) . \tag{5.3}
\end{equation*}
$$

We have just seen that the inverse of the matrix X exists and is equal to $\mathrm{Y}^{\mathrm{H}}$. Hence we have

$$
\begin{equation*}
X^{-1} A X=Y^{H} A X=\operatorname{diag}\left(\lambda_{i}\right)=\Lambda \tag{5.4}
\end{equation*}
$$

where

$$
\begin{equation*}
Y^{H} X=X^{-1} X=I \tag{5.5}
\end{equation*}
$$

A transformation of the type $X^{-1}$ AX where $X$ is nonsingular is known as a similarity transformation. Equations (5.4) and (5.5) will be of the upquost importance in the work that follows.

## 6. MULTIPLE EIGENVALUES

We have just considered the case of distinct eigenvalues and we now look at the situation that arises if one or more of the eigenvalues is repeated. Unfortunately the position with respect to the eigenvectors is usually much more complicated than that outlined in sections 4 and 5. However it may still be the case that for a particular matrix A there does indeed exist a similarity transformation which reduces $A$ to diagonal form. That is, there exists an $X$, implicitly non-singular, such that

$$
\begin{equation*}
X^{-1} A X=\operatorname{diag}\left(\lambda_{i}\right)=\Lambda \tag{6.1}
\end{equation*}
$$

Lemma 6.1 The determinant of the product of two square matrices is equal to the product of the determinants, thus

$$
\begin{equation*}
\operatorname{det}(A B)=\operatorname{det}(A) \operatorname{det}(B) \tag{6.2}
\end{equation*}
$$

A complete proof is to be found in Noble (1969).

Theorem 6.2 If equation (6.1) is true the $\lambda_{i}$ are the eigenvalues of $A$ and each $\lambda_{i}$ occurs with the appropriate multiplicity. In addition the columns of $X$ are the eigenvectors of $A$.
Proof: $X^{-1}(A-\lambda I) X=X^{-1} A X-\lambda X^{-1} I X$

$$
\begin{equation*}
=\operatorname{diag}\left(\lambda_{i}-\lambda\right) \tag{6.3}
\end{equation*}
$$

Taking determinants of both sides and using lemma 6.1 we obtain

$$
\begin{array}{r}
\operatorname{det}\left(X^{-1}\right) \operatorname{det}(A-\lambda I) \operatorname{det}(X) \\
=\prod_{i=1}^{n}\left(\lambda_{i}-\lambda\right) \tag{6.4}
\end{array}
$$

giving

$$
\begin{equation*}
\operatorname{det}(A-\lambda I)=\prod_{i=1}^{n}\left(\lambda_{i}-\lambda\right) \tag{6.5}
\end{equation*}
$$

Hence, from theorem 2.1, the $\lambda_{i}$ are the roots of the characteristic equation of $A$. Writing (6.1) as

$$
\begin{equation*}
\mathrm{AX}=\mathrm{X} \Lambda \tag{6.6}
\end{equation*}
$$

we see that the columns of $X$ are eigenvectors of $A$. Since $X$ is non-singular, its columns are independent. Note that if $\lambda_{1}$ is, say, a double root then we have

$$
\begin{equation*}
A x_{1}=\lambda_{1} x_{1} \text { and } A x_{2}=\lambda_{1} x_{2} \tag{6.7}
\end{equation*}
$$

where $x_{1}$ and $x_{2}$ are independent. Equations (6.7) imply that any vector in the two-dimensional subspace spanned by $x_{1}$ and $x_{2}$ is also an eigenvector. For

$$
\begin{align*}
A\left(\beta_{1} x_{1}+\beta_{2} x_{2}\right) & =\beta_{1} \lambda_{1} x_{1}+\beta_{2} \lambda_{1} x_{2} \\
& =\lambda_{1}\left(\beta_{1} x_{1}+\beta_{2} x_{2}\right) \tag{6.8}
\end{align*}
$$

It is the case that for any matrix which can be reduced to diagonal form by a similarity transformation and which has multiple eigenvalues of multiplicity $m$, say, that there is a certain amount of indeterminacy associated with the corresponding m eigenvectors. However, it is always possible to select m vectors which span the mdimensional subspace and thus it is always possible to choose the complete set of eigenvectors to span the whole n-dimensional space.

We showed in theorem 2.2 that there exists at least one eigenvector corresponding to each eigenvalue and thus far we have only considered the case of m eigenvectors corresponding to an eigenvalue of multiplicity m. We now consider when this is not the case.
7. SIMPLE JORDAN SUBMATRICES

We consider the following very simple example. Let

$$
A(a, b)=\left(\begin{array}{ll}
a & \varepsilon  \tag{7.1}\\
0 & b
\end{array}\right), \quad \text { where } b \neq a
$$

This matrix has the two eigenvalues a and b and the corresponding eigenvectors are

$$
\left[\begin{array}{l}
\varepsilon \\
0
\end{array}\right] \text { and } \quad\left[\begin{array}{c}
\varepsilon \\
b \\
-a
\end{array}\right] .
$$

As $\mathrm{b} \rightarrow \mathrm{a}$ the eigenvalues become closer and the eigenvectors more and more parallel. In the limit $b=a$ and we have an eigenvalue a of multiplicity two and
corresponding to it only one eigenvector. The matrix $A(a, a)$ is usually denoted by $C_{2}(a)$ and in general we define

$$
G_{1}(a)=(a)
$$

and

$$
C_{s}(a)=\left[\begin{array}{llllll}
a & \varepsilon & & & & \\
& a & \varepsilon & & & \\
& & a & \varepsilon & & \\
& & & \cdots & \\
& & & & a & \varepsilon \\
& & & & & a
\end{array}\right], \text { for } s>1
$$

where $C_{s}$ is of order $s$.
The matrix $\mathrm{C}_{\mathrm{S}}(\mathrm{a})$ is normally defined to have $\varepsilon=1$ (see, for example, Wilkinson (1965)) but we feel this to be too specific a choice for our application as will be shown later.
Theorem 7.1 The matrix $C_{S}(a)$ has an eigenvalue a of multiplicity s but corresponding to these eigenvalues there is only one eigenvector, namely $\mathrm{x}=\mathrm{e}_{1}$, where we use $e_{i}$ to denote the i-th column of the identity matrix.
Proof: Consider the set of equations

$$
\begin{equation*}
\left(C_{s}(a)-a I\right) x=0, \tag{7.3}
\end{equation*}
$$


These equations have only the one solution $x_{2}=x_{3}=\ldots .=x_{s}=0$ with $x_{1}$ arbitrary. Hence $e_{1}$ is the
only eigenveator of $C_{S}(a)$.
Theorem 7.2 The matrix $C_{S}(a)(s>1)$, cannot be reduced to diagonal form by a similarity transformation. Proof: Suppose there exists a non-singular X for which

$$
\begin{equation*}
X^{-1} C_{S} X=\operatorname{diag}\left(\lambda_{i}\right) \tag{7.5}
\end{equation*}
$$

that is

$$
\begin{equation*}
\mathrm{C}_{\mathrm{S}} \mathrm{X}=\mathrm{X} \Lambda, \tag{7.6}
\end{equation*}
$$

then as we have shown in section 6 , the $\lambda_{i}$ must be equal to the eigenvalues of. $C_{S}(a)$ and therefore we must have

$$
\begin{equation*}
\lambda_{i}=a, \quad i=1,2, \ldots, s \tag{7.7}
\end{equation*}
$$

Equation (7.6) then shows that the columns of $X$ are all eigenvectors of $C_{S}(a)$ and these columns must be independent. The hypothesis that such an $X$ exists is therefore false and the theorem is proved.

The matrix $C_{S}(a)$ is of a special type which plays a major role in the theory of the eigenproblem.

## 8. JORDAN CANONICAL FORM

The matrix $C_{S}(a)$ of the previous section is called a simple Jordan Submatrix of order s. A block diagonal matrix consisting of only simple Jordan submatrices such as

$$
C=\left[\begin{array}{lllll}
c_{3}\left(\lambda_{1}\right) & & & &  \tag{8.1}\\
& c_{3}\left(\lambda_{2}\right) & & & \\
& & & c_{2}\left(\lambda_{2}\right) & \\
\\
& & & & c_{2}\left(\lambda_{2}\right) \\
& & & & \\
& & & & \\
& & & \\
& & & & \\
& & & & \\
& & &
\end{array}\right]
$$

is refered to as a Jordan canonical form and $C$ is said to be the direct sum of the simple Jordan submatrices. The importance of the Jordan canonical form is shown by the following fundamental theorem. Theorem 8.1 Let A be a matrix of order $n$ with $r$ distinct eigenvalues $\lambda_{1}, \lambda_{2}, \ldots, \lambda_{r}$ of multiplicities $m_{1}, m_{2}, \ldots, m_{r}$ where, obviously,

$$
\begin{equation*}
\sum_{i=1}^{r} m_{i}=n . \tag{8.2}
\end{equation*}
$$

Then there exists a similarity transformation such that

$$
\begin{equation*}
X^{-1} A X=C . \tag{8.3}
\end{equation*}
$$

The sum of the order of the submatrices associated with $\lambda_{i}$ is equal to $m_{i}$ and, apart from the ordering of the submatrices along the diagonal, the transformed matrix $C$ is unique. Although this theorem is of fundamental importance the proof makes little use of the techniques with which we shall be later concerned but full details are to be found in Noble (1969).

From this theorem and the results of section 7
we see that the total number of eigenvectors of a matrix $A$ is equal to the number of simple submatrices
in the Jordan canonical form. Thus the matrix $C$ defined in equation (8.1) has five eigenvectors, namely $e_{1}, e_{4}, e_{7}, e_{9}$ and $e_{11}$. The eigenvectors of $A$ are given by $\mathrm{Xe}_{1}, \mathrm{Xe}_{4}, \mathrm{Xe}_{7}, \mathrm{Xe}_{9}$ and $\mathrm{Xe}_{11}$. Note that in this example $\lambda_{1}$ is an eigenvalue of multiplicity three and has one eigenvector; $\lambda_{2}$ is of multiplicity seven and has three eigenvectors and finally $\lambda_{3}$ is an isolated eigenvalue.

We see also that although we defined the elements of the super diagonals of simple Jordan submatrices to be ' $\varepsilon$ ' it is possible by a suitable similarity transformation to give these elements any non-zero value. Furthermore the matrices of the similarity transformation are diagonal. For example, take

$$
C_{4}=\left[\begin{array}{llll}
a & \varepsilon & & \\
& a & \varepsilon & \\
& & a & \varepsilon \\
& & & a
\end{array}\right] \text { and } X=\left[\begin{array}{llll}
x_{1} & & & \\
& x_{2} & & \\
& & x_{3} & \\
& & & x_{4}
\end{array}\right] \cdot \text { (8.4) }
$$

Hence

$$
\begin{align*}
& =\left[\begin{array}{ccccc}
a & \varepsilon x_{2} / x_{1} & & \\
& \text { a } & \varepsilon x_{3} / x_{2} & & \\
& & & a & \varepsilon x_{4} / x_{3} \\
& & & & \\
& & & &
\end{array}\right] \tag{8.5}
\end{align*}
$$

Notice that by a suitable choice of the $x_{i}$ we can
theoretically make $\mathrm{X}^{-1} \mathrm{CX}$ arbitrarily close to (but never equal to as shown in theorem 7.2) a diagonal matrix.

Finally we note that if the Jordan canonical form of a matrix consists only of submatrices of order one then the matrix can be diagonalised by a similarity transformation.

## 9. ELEMENTARY DIVISORS

Let $C$ be the Jordan canonical form corresponding to $A$ and consider the matrix $C-\lambda I$. Defining $C$ as in (8.1), for example, we see that

$$
(c-\lambda I)=\left[\begin{array}{lllll}
c_{3}\left(\lambda_{1}-\lambda\right) & & & & \\
& c_{3}\left(\lambda_{2}-\lambda\right) & & & \\
& & c_{2}\left(\lambda_{2}-\lambda\right) & & \\
& & & c_{2}\left(\lambda_{2}-\lambda\right) & \\
& & & & c_{1}\left(\lambda_{3}-\lambda\right)
\end{array}\right] .
$$

The determinants of these submatrices of the matrix (C- $\lambda I$ ) are called the elementary divisors of $A$. Thus, in the example of (8.1), the elementary divisors of any matrix $A$ similar to $C$ are

$$
\left(\lambda_{1}-\lambda\right)^{3},\left(\lambda_{2}-\lambda\right)^{3},\left(\lambda_{2}-\lambda\right)^{2},\left(\lambda_{2}-\lambda\right)^{2} \text { and }\left(\lambda_{3}-\lambda\right)
$$

Clearly, the characteristic polynomial of a matrix is the product of the elementary divisors. If the Jordan canonical form is diagonal we see that the elementary divisors must be linear. We have already seen that a matrix with distinct eigenvalues must
have linear elementary divisors but if it has one or more multiple eigenvalues it may or may not have linear elementary divisors. If a matrix $A$ has one or more non-linear elementary divisors then one or more of the simple Jordan submatrices is of order two or more and hence $A$ has less than $n$ independent eigenvectors. A matrix with fewer than $n$ independent eigenvectors is said to be defective.
10. DEROGATORY MATRICES

A matrix is said to be derogatory if there is more than one Jordan submatrix (and therefore more than one eigenvector) associated with $\lambda_{i}$ for some i. Conversely a matrix is said to be nonderogatory if there is only one Jordan submatrix (and hence only one eigenvector) associated with each distinct $\lambda_{i}$ for some i. A very thorough and readable treatment of derogatory matrices is to be found in Wilkinson (1965).

## 11. DEFFCTIVE AND DEROGATORY MATRICES

In order to illustrate the four cases of matrices classified according to their defective and derogatory nature we give examples taken from Gregory (1960), to which reference may be made for further details on classification of matrices.
(i) Non-defective and non-derogatory,

$$
A=\left[\begin{array}{llll}
\lambda_{1} & & &  \tag{11.1}\\
& \lambda_{2} & & \\
& & \lambda_{3} & \\
& & & \lambda_{4}
\end{array}\right]
$$

This matrix has four distinct eigenvalues $\lambda_{1}, \lambda_{2}$, $\lambda_{3}$ and $\lambda_{4}$ and four linearly independent eigenvectors

$$
\left[\begin{array}{c}
x_{1} \\
0 \\
0 \\
0
\end{array}\right],\left[\begin{array}{c}
0 \\
x_{2} \\
0 \\
0
\end{array}\right],\left[\begin{array}{c}
0 \\
0 \\
x_{3} \\
0
\end{array}\right] \text { and }\left[\begin{array}{c}
0 \\
0 \\
0 \\
x_{4}
\end{array}\right] .
$$

(ii) Non-defective and derogatory,

$$
A=\left[\begin{array}{llll}
\lambda_{1} & & & \\
& \lambda_{1} & & \\
& & \lambda_{3} & \\
& & & \\
& & & \lambda_{4}
\end{array}\right]
$$

This matrix has three distinct eigenvalues $\lambda_{1}, \lambda_{3}$ and $\lambda_{4}$ with $\lambda_{1}$ of multiplicity two. There are four linearly independent eigenvectors where the two eigenvectors associated with $\lambda_{1}$ may be any two linearly independent vectors lying in the two dimensional subspace spanned by

$$
\left[\begin{array}{c}
1 \\
0 \\
0 \\
0
\end{array}\right] \text { and }\left[\begin{array}{c}
0 \\
1 \\
0 \\
0
\end{array}\right]
$$

The other two eigenvectors are

$$
\left[\begin{array}{c}
0 \\
0 \\
x_{3} \\
0
\end{array}\right] \text { and }\left[\begin{array}{c}
0 \\
0 \\
0 \\
x_{4}
\end{array}\right]
$$

(iii) Defective and non-derogatory,

$$
A=\left[\begin{array}{llll}
\lambda_{1} & 1 & & \\
& \lambda_{1} & & \\
& & \lambda_{3} & \\
& & & \lambda_{4}
\end{array}\right]
$$

Again the matrix has three distinct eigenvalues $\lambda_{1}, \lambda_{3}$ and $\lambda_{4}$ with $\lambda_{1}$ of multiplicity two. However there are only three linearly independent eigenvectors

$$
\left[\begin{array}{c}
x_{1} \\
0 \\
0 \\
0
\end{array}\right],\left[\begin{array}{c}
0 \\
0 \\
x_{3} \\
0
\end{array}\right] \text { and }\left[\begin{array}{c}
0 \\
0 \\
0 \\
x_{4}
\end{array}\right]
$$

(iv) Defective and derogatory,
$A=\left[\begin{array}{llll}\lambda_{1} & 1 & & \\ & \lambda_{1} & & \\ & & \lambda_{1} & \\ & & & \lambda_{4}\end{array}\right]$.
This matrix has only two distinct eigenvalues $\lambda_{1}$ and $\lambda_{4}$ with $\lambda_{1}$ having multiplicity three. Again there are only three linearly independent eigenvectors. The two eigenvectors corresponding to $\lambda_{1}$ may be any two linearly independent vectors
lying in the two dimensional subspace spanned by

$$
\left[\begin{array}{c}
1 \\
0 \\
0 \\
0
\end{array}\right] \text { and }\left[\begin{array}{c}
0 \\
0 \\
1 \\
0
\end{array}\right]
$$

The third eigenvector is

$$
\left[\begin{array}{c}
0 \\
0 \\
0 \\
x_{4}
\end{array}\right] .
$$

## 12. SOME PROPERTIES OF HERMITIAN MATRICES

We have seen already the fundamental importance of similarity transformations and we now look at a special type of these transformations which plays a vital role in both the theoretical and practical aspects of the eigenproblem. Our motivation for considering these transformations comes from considering some properties of Hermitian matrices. Lemma 12.1 The eigenvalues of a Hermitian matrix are real.

Proof: If

$$
\begin{equation*}
A x=\lambda x \tag{12.1}
\end{equation*}
$$

then

$$
\begin{equation*}
x^{H} A x=\lambda x^{H} x . \tag{12.2}
\end{equation*}
$$

Now $\mathrm{x}^{H} \mathrm{x}$ is real and positive for $\mathrm{x} \neq 0$. Further

$$
\begin{equation*}
\left(x^{H} A x\right)^{H}=x^{H} A^{H} x=x^{H} A x \tag{12.3}
\end{equation*}
$$

and since $\mathrm{x}^{\mathrm{H}} \mathrm{Ax}$ is a scalar it must be real. Hence from (12.2) $\lambda$ must be real. We note however that,
in general, the eigenvectors are complex. If A is real the eigenvectors are always real.

Consider now the left-hand eigenvectors of a
Hermitian matrix. From (3.7) we have

$$
\begin{equation*}
A y_{i}=A^{H} y_{i}=\bar{\lambda}_{i} y_{i} \tag{12.4}
\end{equation*}
$$

and from (12.1)

$$
\begin{equation*}
A x_{i}=\lambda_{i} x_{i} \tag{12.5}
\end{equation*}
$$

As the $\lambda_{i}$ are real we see that $y_{i}=x_{i}$ for all $i$. Thus the quantities $\mathrm{X}_{i} \mathrm{H}_{i}$ which we saw to be of importance in section 3 become $x_{i}^{H} x_{i}$ for Hermitian matrices and it follows immediately that if a Hermitian matrix has distinct eigenvalues then its eigenvectors satisfy

$$
\begin{equation*}
x_{i}^{H} x_{j}=0, \quad i \neq j \tag{12.6}
\end{equation*}
$$

If we normalise the $\mathrm{x}_{\mathrm{i}}$ so that

$$
\begin{equation*}
x_{i}^{H} x_{i}=1 \tag{12.7}
\end{equation*}
$$

we see that in the equation

$$
\begin{equation*}
Y^{H} A X=\Lambda \tag{12.8}
\end{equation*}
$$

we may write

$$
\begin{equation*}
X^{H} A X=\Lambda \tag{12.9}
\end{equation*}
$$

where, from equations (5.4) and (5.5),

$$
\begin{equation*}
X^{H} X=X X^{H}=I \text { and } X^{H}=X^{-1} \tag{12.10}
\end{equation*}
$$

A matrix which satisfies equation (12.10) is called a unitary matrix. A real unitary matrix is called an orthogonal matrix. We shall see in the next section that equation (12.9) in fact holds for
any Hermitian matrix $A$ irrespective of the multiplicity of its eigenvalues. Unitary transformations have desirable numerical properties and we now consider the effect of applying a unitary transformation to a general matrix.

## 13. REDUCTION OF A GENERAL SQUARE MATRIX TO

 TRIANGULAR FORMBefore the main theorem of this section we prove two lemmas.

Lemma 13.1 If $u_{1}, \ldots . u_{s}$ is an orthonormal set of vectors of order $n(s<n)$, then vectors $v_{1}, \ldots, v_{n-s}$ exist such that

$$
\begin{equation*}
Q=\left(u_{1}, \ldots, u_{s}, v_{1}, \ldots, v_{n-s}\right) \tag{13.1}
\end{equation*}
$$

is a unitary matrix.
Proof: Suppose $w_{1}, \ldots . w_{n}$ are any linearly
independent vectors of order $n$. Consider the set of $n+s$ vectors

$$
\left(u_{1}, \ldots, u_{s}, w_{1}, \ldots, w_{n}\right)
$$

We reduce this to a linearly independent set by an accept or reject procedure. The vectors $u_{1}, \ldots, u_{s}$ we know are linearly independent; $w_{1}$ may or may not be independent of them. If it is we shall include it but let us assume that it is dependent and is not therefore included. We shall now look to see whether $w_{2}$ is or is not independent of $u_{1}, \ldots, u_{s} ;$ again let us assume that it.is
dependent and not included. Proceeding in this way we arrive at the "worst possible case" where we have found ( $w_{1}, w_{2}, \ldots . w_{s}$ ) to be linearly dependent upon $\left(u_{1}, u_{2}, \ldots, u_{s}\right)$. It now remains to show that $\left(w_{s+1}, \ldots, w_{n}\right)$ cannot be linearly dependent upon $\left(u_{1}, \ldots, u_{s}\right)$. By hypothesis ( $w_{1}, \ldots, w_{n}$ ) are linearly independent and hence $\left(w_{s+1}, \ldots ., w_{n}\right)$ are also. Suppose $w_{s+1}$ is linearly dependent upon ( $u_{1}, \ldots, u_{s}$ ). This means that corresponding to the s-dimensional subspace spanned by $\left(u_{1}, \ldots ., u_{s}\right)$ we are able to choose from ( $w_{1}, \ldots, w_{n}$ ) s+1 independent vectors that span this space. This is a contradicftion and hence $W_{s+1}$ cannot be linearly dependent upon $\left(u_{1}, \ldots, u_{s}\right)$. Continuing in this manner we find that ( $w_{s+1}, \ldots, w_{n}$ ) are all linearly independent of $\left(u_{1}, \ldots, u_{s}\right)$. Hence we have obtained a set of $n$ vectors, say

$$
\left(u_{1}, \ldots, u_{s}, z_{1}, \ldots, z_{n-s}\right)
$$

where

$$
\begin{equation*}
\left(z_{1}, \ldots, z_{n-s}\right) \subseteq\left(w_{1}, \ldots, w_{n}\right) \tag{13.2}
\end{equation*}
$$

such that any vector is linearly independent of the preceding vectors in the set. By means of the GramSchmidt orthogonalisation procedure we may orthonormalise this set of vectors.

Lemma 13.2 The product of two unitary matrices is itself unitary.

Proof: Let L . and $V$ be two unitary matrices such that

$$
\begin{equation*}
U^{H_{U}}=V^{H_{V}}=I \tag{13.3}
\end{equation*}
$$

Then

$$
\begin{equation*}
(\mathrm{VU})^{\mathrm{H}}(\mathrm{VU})=U^{\mathrm{H}^{\mathrm{H}}} \mathrm{VU}=I \tag{13.4}
\end{equation*}
$$

We are now in a position to prove the following theorem.

Theorem 13.3 Any square matrix A can be reduced by a unitary transformation to an upper triangular matrix with the eigenvalues of A on the diagonal. Proof: Let $A$ have an eigenvalue $\lambda_{1}$ with a corresponding eigenvector $\mathrm{x}_{1}$ which is normalised such that $\left\|x_{1}\right\|_{2}=1$. We have shown that vectors $w_{2}, \ldots, w_{n}$ exist such that

$$
\begin{equation*}
Q=\left(x_{1}, w_{2}, \ldots, w_{n}\right)=\left[x_{1}, W\right] \tag{13.5}
\end{equation*}
$$

is a unitary matrix. Hence

$$
\begin{align*}
Q^{H_{Q}} & =\left[\begin{array}{l}
x_{1}^{H} \\
W^{H}
\end{array}\right]\left[x_{1}, W\right] \\
& =\left[\begin{array}{ll}
x_{1}^{H} x_{1} & x_{1}^{H} W \\
W^{H} x_{1} & W^{H}
\end{array}\right] \\
& =\left[\begin{array}{cc}
1 & 0 \\
0 & I_{n-1}
\end{array}\right] \tag{13.6}
\end{align*}
$$

so that $W^{H} x_{1}=0$. Thus, since

$$
\begin{equation*}
A x_{1}=\lambda_{1} x_{1} \tag{13.7}
\end{equation*}
$$

$$
\begin{align*}
Q^{H} A Q & =\left[\begin{array}{l}
x_{1}^{H} \\
W^{H}
\end{array}\right] A\left(x_{1}, W\right) \\
& =\left[\begin{array}{l}
x_{1}^{H} \\
W^{H}
\end{array}\right]\left(\lambda_{1} x_{1}, A W\right) \\
& =\left(\begin{array}{ll}
\lambda_{1} & x_{1}^{H} A W \\
0 & W^{H} A W
\end{array}\right) \\
& =\left(\begin{array}{ll}
\lambda_{1} & B \\
0 & C
\end{array}\right), \text { say. } \tag{13.8}
\end{align*}
$$

We now proceed by induction. If $n=2$ the theorem is true as (13.8) is already in upper triangular form. Now assume that A is $\mathrm{n} * \mathrm{n}$ and the theorem is true for $n-1$. Then $C=W^{H}$ AW of (13.8) is of order $n-1$, and a unitary matrix $V$ exists such that $V^{H} C V$ is upper triangular. The matrix

$$
U=\left(\begin{array}{ll}
1 & 0  \tag{13.9}\\
0 & v
\end{array}\right)
$$

is unitary and

$$
\begin{align*}
\mathrm{U}^{\mathrm{H}_{\mathrm{Q}} \mathrm{H}_{\mathrm{AQU}}} & =\left[\begin{array}{ll}
1 & 0 \\
0 & \mathrm{~V}^{\mathrm{H}}
\end{array}\right]\left[\begin{array}{ll}
\lambda_{1} & \mathrm{~B} \\
0 & \mathrm{C}
\end{array}\right]\left[\begin{array}{ll}
1 & 0 \\
0 & \mathrm{~V}
\end{array}\right] \\
& =\left[\begin{array}{cc}
\lambda_{1} & \mathrm{BV} \\
0 & \mathrm{~V}^{\mathrm{H}} \mathrm{CV}
\end{array}\right] . \tag{13.10}
\end{align*}
$$

Hence $(Q U)^{H} A(Q U)$ is upper triangular. Since, from lemma 13.2, $Q U$ is unitary, $A$ has been reduced to
upper triangular form by a unitary transformation. We have shown that if the result is true for a matrix of order ( $n-1$ ) it is true for one of order $n$. However, it is true for $2 * 2$ matrices and the result is proved by induction.

## 14. SOME SPECIAL CASES

We have just proved that for any matrix A there exists a unitary matrix $R$ such that

$$
\begin{equation*}
\mathrm{R}^{\mathrm{H}_{\mathrm{AR}}}=\mathrm{T} \tag{14.1}
\end{equation*}
$$

where $T$ is upper triangular.
Suppose A is Hermitian. Then, as $R^{H} A R$ is Hermitian, $T$ must be Hermitian and hence $T$ must be diagonal. This proves the result that we stated at the end of section 12 , that whatever the multiplicity of the eigenvalues a Hermitian matrix can always be reduced to diagonal form by a unitary transformation. Note also that if $A$ is real symmetric its eigenvalues and eigenvectors are real and hence it may be reduced to diagonal form by an orthogonal transformation.

It also follows immediately that the elementary divisors of a Hermitian matrix are all linear and hence it cannot be defective. If a Hermitian matrix has any multiple eigenvalues then it is derogatory.

## 15. NORMAL MATRICES

We now ask if there is a more general class
of matrix, other than a Hermitian, which can be reduced to diagonal form by a unitary transformation. Thus far we have considered

$$
\begin{equation*}
\mathrm{R}^{\mathrm{H}_{\mathrm{AR}}}=\mathrm{D} \tag{15.1}
\end{equation*}
$$

where $D$ has always been real. We now consider (15.1) in the case of $D$ complex. From equation (15.1) we obtain

$$
\begin{equation*}
A=R D R^{H} \tag{15.2}
\end{equation*}
$$

and hence

$$
\begin{equation*}
A^{H}=R D^{H} R^{H} \tag{15.3}
\end{equation*}
$$

Consider

$$
\left.\begin{array}{rl}
A A^{H} & =R D R^{H_{R D}} H^{H} \\
& =R D D^{H} R^{H} \\
& =R D^{H} D R^{H} \text { (as diagonal matrices } \\
\text { commute) }
\end{array}\right)
$$

We show conversely that if $A A^{H}=A^{H} A$, then $A$ may be factorised as in (15.2). From (14.1) any matrix A may be expressed in the form

$$
\begin{equation*}
\mathrm{A}=\mathrm{RTR}^{\mathrm{H}} \tag{15.5}
\end{equation*}
$$

where $R$ is unitary and $T$ upper triangular. Hence we have

$$
\begin{equation*}
A A^{H}=R T R^{H} R T^{H_{R}}{ }^{H}=R T^{H} R_{R T R}{ }^{H}=A^{H} \tag{15.6}
\end{equation*}
$$

giving

$$
\begin{equation*}
\mathrm{RTT}^{\mathrm{H}_{\mathrm{R}} \mathrm{H}}=\mathrm{RT}^{\mathrm{H}_{\mathrm{PR}}}{ }^{\mathrm{H}} \tag{15.7}
\end{equation*}
$$

hence

$$
\begin{equation*}
T T^{H}=T^{H} T \tag{15.8}
\end{equation*}
$$

Equating the elements in equation (15.8) we find that all the off-diagonal elements of $T$ are zero, so that $T$ is diagonal. Hence the most general class of matrices which can be factorised as in (15.2) is the same as that class of matrices for which

$$
\begin{equation*}
\mathrm{AA}^{\mathrm{H}}=\mathrm{A}^{\mathrm{H}} \mathrm{~A} \text {. } \tag{15.9}
\end{equation*}
$$

Such matrices are said to be normal. Obvious examples of normal matrices are Hermitian, skew-Hermitian., and unitary matrices; also all diagonal matrices. We now prove the following theorem which gives an alternative definition of a normal matrix. Theorem 15.1 A matrix $A$ is normal if and only if

$$
\begin{equation*}
A=B+C \tag{15.10}
\end{equation*}
$$

where $B$ is Hermitian, C is skew-Hermitian and

$$
\begin{equation*}
B C=C B . \tag{15.11}
\end{equation*}
$$

Proof: (i) If equations (15.10) and (15.11) hold then

$$
\begin{align*}
A A^{H} & =(B+C)\left(B^{H}+C^{H}\right) \\
& =B B^{H}+B C^{H}+C B^{H}+C C^{H} \\
& =B^{H} B-B C+C B-C \cdot C \\
& =B^{H} B-C B+B C+C^{H} C \\
& =B^{H} B+C^{H} B+B^{H} C+C^{H} C \\
& =\left(B^{H}+C^{H}\right)(B+C) \\
& =A^{H} A . \tag{15.12}
\end{align*}
$$

(ii) If $A A^{H}=A^{H} A$ then, for any matrix $A$, we
may write

$$
\begin{equation*}
A=B+C \tag{15.13}
\end{equation*}
$$

where $B$ is Hermitian and $C$ is a skew-Hermitian matrix. This is seen by considering the ( $i, j$ ) and (j,i) elements of A.

$$
\begin{equation*}
a_{i j}=b_{i j}+c_{i j} \tag{15.14}
\end{equation*}
$$

and

$$
\begin{equation*}
a_{j i}=\bar{b}_{i j}-\bar{c}_{i j} . \tag{15.15}
\end{equation*}
$$

These equations always have a solution, namely

$$
\begin{equation*}
b_{i j}=\frac{1}{2}\left(a_{i j}+\bar{a}_{j i}\right) \tag{15.16}
\end{equation*}
$$

and

$$
\begin{equation*}
c_{i j}=\frac{1}{2}\left(a_{i j}-\bar{a}_{j i}\right) \tag{15.17}
\end{equation*}
$$

Obviously we take $b_{i i}=\operatorname{Re}\left(a_{i i}\right)$ and $c_{i i}=i * \operatorname{Im}\left(a_{i i}\right)$.
From (15.13) we obtain

$$
\begin{align*}
A A^{H} & =(B+C)\left(B^{H}+C^{H}\right) \\
& =B^{H} B-B C+C B+C^{H} C \tag{15.18}
\end{align*}
$$

and

$$
\begin{align*}
\mathrm{A}^{\mathrm{H}} & =\left(\mathrm{B}^{\mathrm{H}}+\mathrm{C}^{\mathrm{H}}\right)(\mathrm{B}+\mathrm{C}) \\
& =\mathrm{B}^{\mathrm{H}} \mathrm{~B}-\mathrm{CB}+\mathrm{BC}+\mathrm{C}^{\mathrm{H}} \mathrm{C} . \tag{15.19}
\end{align*}
$$

Hence we must have

$$
\begin{equation*}
-\mathrm{BC}+\mathrm{CB}=-\mathrm{CB}+\mathrm{BC} \tag{15.20}
\end{equation*}
$$

or

$$
\begin{equation*}
B C=C B \tag{15.21}
\end{equation*}
$$

which proves sufficiency.
16. PRINCIPAL VECTORS

Finally in this introductory section we mention, mainly for the sake of completeness, the idea of principal vectors. We saw that a matrix A with linear elementary divisors has $n$ eigenvectors spanning the whole $n$-space. If $A$ has non-linear divisors this is not true as there are fewer than $n$ independent eigenvectors. It is often convenient however to have a set of vectors which spansthe whole $n$-space and which reduces to the eigenvectors of $A$ when $A$ has linear elementary divisors. We saw that if a matrix can be diagonalised then

$$
\begin{equation*}
A X=\operatorname{Xdiag}\left(\lambda_{i}\right) \tag{16.1}
\end{equation*}
$$

If it cannot be we take as a basis the n columns of a matrix $X$ which is such that

$$
\begin{equation*}
A X=X C \tag{16.2}
\end{equation*}
$$

where $C$ is the Jordan canonical form of $A$. To illustrate the importance of these vectors we give an example used by Wilkinson (1965), where a fuller treatment of the subject is to be found.

Suppose A is such that

$$
\operatorname{AX}=X\left[\begin{array}{llll}
c_{3}\left(\lambda_{1}\right) & & &  \tag{16.3}\\
& c_{2}\left(\lambda_{1}\right) & & \\
& & c_{2}\left(\lambda_{2}\right) & \\
& & & c_{1}\left(\lambda_{3}\right)
\end{array}\right]
$$

then in the usual notation for the columns of $X$, and letting $\varepsilon=1$ for simplicity in equation (7.2),
we obtain

$$
\begin{array}{lll}
A x_{1}=\lambda_{1} x_{1} & A x_{4}=\lambda_{1} x_{4} \\
A x_{2}=\lambda_{1} x_{2}+x_{1} & A x_{5}=\lambda_{1} x_{5}+x_{4} & A x_{7}=\lambda_{2} x_{6} \\
A x_{3}=\lambda_{1} x_{7}+x_{3}+x_{2} \tag{16.4}
\end{array} \quad A x_{8}=\lambda_{3} x_{8}
$$

from which we see that

$$
\begin{align*}
& \left(A-\lambda_{1} I\right) x_{1}=0 \quad\left(A-\lambda_{1} I\right) x_{4}=0 \quad\left(A-\lambda_{2} I\right) x_{6}=0 \quad\left(A-\lambda_{3} I\right) x_{8}=0 \\
& \left(A-\lambda_{1} I\right)^{2} x_{2}=0 \quad\left(A-\lambda_{1} I\right)^{2} x_{5}=0\left(A-\lambda_{2} I\right)^{2} x_{7}=0 \\
& \left(A-\lambda_{1} I\right)^{3} x_{3}=0 \tag{16.5}
\end{align*}
$$

Each of the vectors therefore satisfies a relation of the form

$$
\begin{equation*}
\left(A-\lambda_{i} I\right)^{j_{x}}{ }_{k}=0 \tag{16.6}
\end{equation*}
$$

A vector which satisfies equation (16.6) for a given value of $j$, but does not satisfy it for any lower value of $j$, is called a principal vector of grade $j$ corresponding to $\lambda_{i}$. Eigenvectors are principal vectors of grade one. Note that, although there exists a set of principal vectors which spans the whole $n$-space, in general principal vectors are not unique. If x is a principal vector of grade $j$ corresponding to $\lambda_{i}$ then the same is true of any other vector obtained by adding to $x$ multiples of any principal vectors of grade $j$ or less corresponding to $\lambda_{i}$.

CHAPTER 2

JACOBI-LIKE METHODS FOR REDUCING MATRICES
TO DIAGONAL FORM

## 1. INTRODUCTION

In this chapter we describe techniques for solving the eigenproblem for general complex matrices by methods related to the Jacobi method for real symmetric matrices. These techniques are applicable to any form of matrix but are of particular relevance in the case of small dense diagonally dominant matrices. Determining the eigensolutions of such matrices forms a vital part in the acceleration of simultaneous iteration and hence their relevance to our work.

Historically, the method for real symmetric matrices discovered by Jacobi (1846) is the oldest process for determining eigensolutions which is applicable for use on an electronic computer. The extension of this method to deal with Hermitian matrices is simple and it is then a relatively easy step to consider normal matrices.

We saw earlier that for a normal matrix $A$ there is always a unitary matrix $V$ such that

$$
\begin{equation*}
V^{H} A V=\operatorname{diag}\left(\lambda_{i}\right) \tag{1.1}
\end{equation*}
$$

However for an arbitrary matrix $A$ this is not in general true but having considered normal matrices we are well placed to tackle the problem of general matrices.

All of the methods we consider depend upon the application of a series of similarity transformations to convert the matrix A ịnto a
special forme In the simplest cases the similarity transformations are unitary matrices which reduce A directly to diagonal or, in practice, to nearly diagonal form. In the general case we shall use similarity transformations to reduce the matrix to normal form before applying unitary transformations to further reduce $A$ to diagonal form.

Finally in this chapter we give brief details of an abortive attempt to use an algorithm proposed by Rutishauser.
2. THE CLASSICAL JACOBI METHOD FOR REAL SYMMETRIC

## MATRICES

In the method of Jacobi the original matrix is transformed to diagonal form by a sequence of plane, rotations. In fact, to complete the diagonalisation would require an infinite number of such rotations but in practice the process is triminated when the off-diagonal elements are negligible to working accuracy. As we are considering real symmetric matrices, which we know have real eigenvalues and eigenvectors, we use real plane rotations.

Let the matrix $V$ of order $n$ be such that

$$
\begin{align*}
& v_{p p}=v_{q q}=\cos \phi \\
& v_{p q}=-v_{q P}=\sin \phi \\
& v_{i i}=1, \quad i \neq p, q \\
& v_{i j}=0 \text { otherwise. } \tag{2.1}
\end{align*}
$$

We note that

$$
\begin{equation*}
\mathrm{VV}^{\mathrm{T}}=\mathrm{V}^{\mathrm{T}} \mathrm{~V}=\mathrm{I} \tag{2.2}
\end{equation*}
$$

If we denote the original matrix by $A_{O}$ then we may describe the Jacobi process as follows. A sequence of matrices $A_{k}$ is produced satisfying the relations

$$
\begin{equation*}
A_{k}=V_{k}^{T} A_{k-1} V_{k}, \quad k=1,2, \ldots \tag{2.3}
\end{equation*}
$$

We note that as $A_{k-1}$ is symmetric, so too is $A_{k}$. The matrix $\mathrm{V}_{\mathrm{k}}$ is determined by the rules which follow. If no confusion can arise we shall denote the elements of $A_{k-1}$ by $a_{i j}$ and those of $A_{k}$ by $a_{i j}^{\prime}$. Using this notation we consider the details of equation (2.3). The only elements of $A_{k-1}$ that are altered are those in rows $p$ and $q$ and in columns $p$ and $q$. Hence the modified elements are given by

$$
\begin{align*}
& a_{i j}^{\prime}=a_{i j}, \quad i, j \neq p, q  \tag{2.4}\\
& \left.\begin{array}{l}
a_{p j}^{\prime}=a_{p j} \cos \phi-a_{q j} \sin \phi \\
a_{q j}^{\prime}=a_{q j} \cos \phi+a_{p j} \sin \phi
\end{array}\right\} \quad j \neq p, q  \tag{2.5}\\
& \left.\begin{array}{l}
a_{p p}^{\prime}=a_{p p} \cos ^{2} \phi+a_{q q} \sin ^{2} \phi-2 a_{p q} \sin \phi \cos \phi \\
a_{q q}^{\prime}=a_{q q} \cos ^{2} \phi+a_{p p} \sin ^{2} \phi+2 a_{p q} \sin \phi \cos \phi
\end{array} \right\rvert\,  \tag{2.6}\\
& a_{p q}^{\prime}=a_{p q}\left(\cos ^{2} \phi-\sin ^{2} \phi\right)+\left(a_{p p}-a_{q q}\right) \sin \phi \cos \phi \\
& =a_{q p}^{\prime} . \tag{2.7}
\end{align*}
$$

We do not explicitly state the form of $a_{j p}^{\prime}$, ajq or
$a_{q}^{\prime}$ p since these follow by symmetry.
We now introduce two functions which we shall use extensively in what follows. Firstly the function defined by

$$
\begin{equation*}
N^{2}\left(A_{k}\right)=\sum_{i=1}^{n} \sum_{j=1}^{n}\left|a_{i j}^{(k)}\right|^{2} \tag{2.8}
\end{equation*}
$$

and secondly

$$
\begin{equation*}
t^{2}\left(A_{k}\right)=\sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n}\left|a_{i j}^{(k)}\right|^{2} \tag{2.9}
\end{equation*}
$$

We note that $t^{2}\left(A_{k}\right)=N^{2}\left(A_{k}\right)-\sum_{i}\left|a_{i i}^{(k)}\right|^{2}$.
We notice that the transformations given by (2.3) leave $N^{2}\left(A_{k-1}\right)$ unaltered and that $A_{k}$ will tend to diagonal form if and only if $t^{2}\left(A_{k}\right) \rightarrow 0$. We therefore need only consider the effect of the offdiagonal elements and noting from equation (2.5) that

$$
\begin{equation*}
a_{p j}^{\prime 2}+a_{q j}^{\prime 2}=a_{p j}^{2}+a_{q j}^{2}, \quad j \neq p, q \tag{2.10}
\end{equation*}
$$

we see that the only reduction in $t^{2}\left(A_{k}\right)$ that can take place is through the reduction of $\left|a_{p q}^{\prime}\right|$ (and $\left.\left|a_{q p}^{\prime}\right|\right)$.

Hence it is clear that the maximum reduction in $t^{2}\left(A_{k}\right)$ will occur if we use (2.3) to reduce $\left|a_{p q}\right|$ as much as possible. In fact it is possible to make $a_{p q}$ zero at any stage. For if

$$
a_{p q}^{\prime}=a_{p q}\left(\cos ^{2} \phi-\sin ^{2} \phi\right)+\left(a_{p p}-a_{q q}\right) \sin \phi \cos \phi
$$

$$
\begin{align*}
& =a_{p q} \cos 2 \phi+\left(a_{p p}-a_{q q}\right) \frac{1}{2} \sin 2 \phi \\
& =0 \tag{2.11}
\end{align*}
$$

then

$$
\begin{equation*}
\tan 2 \phi=\frac{2 a_{p q}}{\left(a_{q q}-a_{p p}\right)} . \tag{2.12}
\end{equation*}
$$

We shall always restrict $\varnothing$ such that

$$
\begin{equation*}
-\pi / 4 \leq \varnothing \leq \pi / 4 \tag{2.13}
\end{equation*}
$$

and if $a_{p p}=a_{q q}$ we take $\varnothing$ to be $\pm \pi / 4$ according to the sign of $a_{p q}$.

It is clear that in order to obtain the maximum reduction of $t^{2}(A)$ at every stage we should choose p and q such that

$$
\begin{equation*}
a_{p q}=\max \left(a_{i j}\right) . \tag{2.14}
\end{equation*}
$$

With the choice of $\varnothing$ given by (2.12) we reduce $a_{p q}^{\prime}$ to zero and hence at the $k$-th stage

$$
\begin{equation*}
t^{2}\left(A_{k}\right)=t^{2}\left(A_{k-1}\right)-2\left(a_{p q}^{(k-1)}\right)^{2} \tag{2.15}
\end{equation*}
$$

Since $a_{p q}$ was the absolutely largest of all the $n(n-1)$ off-diagonal elements of $A$ we have

$$
\begin{equation*}
\left.t^{2}\left(A_{k}\right) \leq\left(1-2 /\left(n^{2}-n\right)\right) t^{2}\left(A_{k-1}\right)\right) \tag{2.16}
\end{equation*}
$$

Hence, at the k-th stage

$$
\begin{equation*}
t^{2}\left(A_{k}\right) \leq\left(1-2 /\left(n^{2}-n\right)\right)^{k} t^{2}\left(A_{0}\right) . \tag{2.17}
\end{equation*}
$$

If we let $N=\frac{1}{2}\left(n^{2}-n\right)$ we obtain

$$
\begin{equation*}
t^{2}\left(A_{k}\right)<e^{-k / N_{t}^{2}}\left(A_{0}\right) \tag{2.18}
\end{equation*}
$$

This shows that the process is convergent although
in practice (2.18) is a very crude bound as we shall see later. Suppose we define r by

$$
\begin{equation*}
k=r \mathbb{N} \tag{2.19}
\end{equation*}
$$

then

$$
\begin{align*}
t^{2}\left(A_{r N}\right) & <e^{-r_{t}^{2}\left(A_{0}\right)}  \tag{2.20}\\
& <\varepsilon^{2} t^{2}\left(A_{0}\right) \tag{2.21}
\end{align*}
$$

if

$$
\begin{equation*}
r>2 \ln (1 / \varepsilon) . \tag{2.22}
\end{equation*}
$$

If, for example, $\varepsilon=2^{-t}$, then

$$
\begin{equation*}
r>2 \ln 2^{t} \simeq 1.39 t \tag{2.23}
\end{equation*}
$$

3. CONVERGENCE TO A FIXED DIAGONAL MATRIX

We still have to show that $A_{k}$ tends to a fixed diagonal matrix with the eigenvalues of A on the diagonal. Suppose the iteration is at a stage such that

$$
\begin{equation*}
t\left(A_{k}\right)<\varepsilon \tag{3.1}
\end{equation*}
$$

and suppose the eigenvalues $\lambda_{i}$ of $A_{k}$ (and hence of
A) are arranged in non-increasing order. If we similarly arrange the diagonal elements of $A_{k}$ to be in non-increasing order it may be seen that the elements in the two sequences differ by less than $\varepsilon$. This follows from the minimax characterisation of the eigenvalues of the sum of two symmetric matrices as given by, for example, Wilkinson (1965). Thus the $a_{i i}^{(k)}$, arranged in some order, lie in intervals of width $2 \varepsilon$ centred on the $\lambda_{i}$. Since we may make
$\varepsilon$ arbitrarily small, the eigenvalues can be located to any desired accuracy.

It remains to show that each $\mathrm{a}_{\mathrm{ii}}^{(\mathrm{k})}$ does indeed converge to a specified $\lambda_{i}$. We firstly consider the case of distinct eigenvalues and define $\varepsilon$ by the relation

$$
\begin{equation*}
0<4 \varepsilon=\min _{\substack{i \neq j}}\left|\lambda_{i}-\lambda_{j}\right| \tag{3.2}
\end{equation*}
$$

Let $k$ be chosen so that (3.1) is true, then from (2.16) it is satisfied for all subsequent values of $k$. With this choice of $\varepsilon$ the intervals centred on the $\lambda_{i}$ are clearly disjoint and hence there is just one of the $a_{i i}^{(k)}$ in each interval. We assume the $\lambda_{i}$ and the $a_{i i}^{(k)}$ have been ordered as before and now show that each $a_{i i}^{(k)}$ lies in the same interval at all later stages of the iteration.

Suppose the next iteration is in the ( $p, q$ ) plane. The only diagonal elements to be altered are $\mathrm{a}_{\mathrm{pp}}^{(\mathrm{k}-1)}$ and $\mathrm{a}_{\mathrm{qq}}^{(\mathrm{k}-1)}$; hence $\mathrm{a}_{\mathrm{pp}}^{(\mathrm{k})}$ and $\mathrm{a}_{\mathrm{qq}}^{(\mathrm{k})}$ must still be the two diagonal elements in the intervals centred on $\lambda_{p}$ and $\lambda_{q}$. We show that it must be $a_{p p}^{(k)}$ which lies in the interval containing $\lambda_{p}$. For, reverting to our earlier prime notation

$$
a_{q q}^{1}-\lambda_{p}=a_{q q} \cos ^{2} \phi+a_{p p} \sin ^{2} \phi+2 a_{p q} \sin \phi \cos \phi-\lambda_{p}
$$

$$
\begin{align*}
= & \left(a_{q q}-\lambda_{q}+\lambda_{q}-\lambda_{p}\right) \cos ^{2} \phi . \\
& +\left(a_{p p}-\lambda_{p}\right) \sin ^{2} \phi+2 a_{p q} \sin \phi \cos \phi . \tag{3.3}
\end{align*}
$$

Hence

$$
\begin{align*}
\left|a_{q q}^{\prime}-\lambda_{p}\right| \geq & \left|\lambda_{q}-\lambda_{p}\right| \cos ^{2} \phi-\left|a_{p p}-\lambda_{p}\right| \sin ^{2} \phi \\
& -\left|a_{q q}-\lambda_{q}\right| \cos ^{2} \phi-\left|a_{p q}\right| \\
\geq & 4 \varepsilon \cos ^{2} \phi-\varepsilon \sin ^{2} \phi-\varepsilon \cos ^{2} \phi-\varepsilon \\
= & 2 \varepsilon \cos 2 \phi . \tag{3.4}
\end{align*}
$$

However,

$$
\begin{align*}
|\tan 2 \phi| & =\left|2 a_{p q} /\left(a_{p p}-a_{q q}\right)\right| \\
& \leq 2 \varepsilon / 2 \varepsilon \\
& =1 \tag{3.5}
\end{align*}
$$

Hence for $\phi$ in the range given by (2.13) we have $|2 \phi| \leq \pi / 4$ and hence

$$
\begin{equation*}
\left|a_{q q}^{\prime}-\lambda_{p}\right| \geq 2^{\frac{1}{2}} \varepsilon \tag{3.6}
\end{equation*}
$$

showing that $a_{q q}^{\prime}$ is not in the interval centred on $\lambda_{p}$.

The result is not substantially altered if there are multiple eigenvalues present. We define $\varepsilon$ such that (3.2) is true for all distinct $\lambda_{i}$ and $\lambda_{j}$. If $\lambda_{i}$ is an eigenvalue of multiplicity $m$, then precisely $m$ of the $a_{i i}^{(k)}$ lie in the interval containing $\lambda_{i}$ and the proof that none of the $a_{p p}$ and $a_{q q}$ lying in different intervals centred on distinct values of $\lambda$ can move out of those intervals remains valid.

Hence, whatever the multiplicity of the eigenvalues, after a certain stage of the iteration each diagonal element of $A_{k}$ remains in a fixed interval centred on $\lambda_{i}$ as $k$ is increased and the width of that interval tends to zero as k tends to infinity.
4. THE GERSCHGORIN DISCS

Suppose the eigenvalues $\lambda_{i}$ of $A$ are distinct and that

$$
\begin{equation*}
\min _{i \neq j}\left|\lambda_{i}-\lambda_{j}\right|=2 \delta \tag{4.1}
\end{equation*}
$$

and we have reached, at the $k$-th stage, a matrix $A_{k}$ for which

$$
\begin{equation*}
\left|a_{i i}^{(k)}-\lambda_{i}\right|<\delta / 4, \quad \max _{i \neq j}\left|a_{i j}\right|=\varepsilon \tag{4.2}
\end{equation*}
$$

together with

$$
\begin{equation*}
(n-1) \varepsilon<\delta / 4 . \tag{4.3}
\end{equation*}
$$

The Gerschgorin discs are definitely disjoint, since

$$
\begin{aligned}
\left|a_{i i}^{(k)}-a_{j j}^{(k)}\right| \geq\left|\lambda_{i}-\lambda_{j}\right| & -\left|a_{i i}^{(k)}-\lambda_{i}\right| \\
& -\left|a_{j j}^{(k)}-\lambda_{j}\right|
\end{aligned}
$$

$$
\begin{equation*}
>3 \delta / 2 \tag{4.4}
\end{equation*}
$$

Hence we have

$$
\begin{equation*}
\left|a_{i i}^{(k)}-\lambda_{i}\right|<(n-1) \varepsilon . \tag{4.5}
\end{equation*}
$$

If we perform upon $A$ the similarity transformation corresponding to multiplying the i-th row by $\varepsilon / \delta$ and the i-th column by $\delta / \varepsilon$, then the i-th Gerschgorin
disc is certainly contained in the circle

$$
\begin{equation*}
\left|a_{i i}^{(k)}-\lambda\right|<(n-1) \varepsilon^{2} / \delta \tag{4.6}
\end{equation*}
$$

while the remainder are contained in the discs

$$
\left|a_{j j}^{(k)}-\lambda\right|<(n-2) \varepsilon+\delta, \quad j \neq i
$$

The i-th disc is certainly isolated from the others, so from (4.6) we see that when the absolute values of the off-diagonal elements have become less than $\varepsilon$ then, for sufficiently small $\varepsilon$, the diagonal elements differ from the eigenvalues by quantities of order $\varepsilon^{2}$. This result holds for the simple eigenvalues even if A has some multiple eigenvalues. We see that we can obtain very good estimates of the eigenvalues when the off-diagonal elements have become small. It is therefore important that the convergence of the Jacobi method should become more rapid in the later stages of the iteration. Some results on quadratic convergence are known but before considering these we consider different forms of the Jacobi method.
5. VARIANTS OF THE JACOBI METHOD

The process we have outlined so far depends upon determining at each step the absolutely largest off-diagonal element. Searching for this element is fairly time consuming on an automatic computer and so it is usual to select the elements to be eliminated in some simpler manner.

Any method in which each of the off-diagonal elements is eliminated just once until all $n(n-1) / 2$ elements have been chosen as pivot is called a generalised serial Jacobi method. Each sequence of $n(n-1) / 2$ rotations is called a sweep. The special serial Jacobi method is the particular case of a generalised serial method in which the order of elimination of elements in each sweep is given by $(1,2),(1,3), \ldots,(1, n) ;(2,3),(2,4), \ldots,(2, n)$; .... ; ( $n-1, n$ ). The special serial method is particularly suited to imp $\neq$ mentation on an electronic computer. Forsythe and Henrici (1960) have shown that the special serial Jacobi method does in fact converge but the proof is quite involved. We do not consider it here as the algorithm we have actually used is slightly different and is referred to as the threshold Jacobi method.

The maximum reduction that can be achieved in $t^{2}\left(A_{k}\right)$ at any stage by a rotation in the ( $p, q$ ) plane is given by $2\left(a_{p q}^{(k-1)}\right)^{2}$. If $a_{p q}^{(k-1)}$ is much smaller than the average value of the other offdiagonal elements then there is little point in performing the ( $p, q$ ) rotation. This idea leads to the threshold Jacobi method. With each sweep there is an associated threshold value and any rotation based on an off-diagonal element which is below the threshold value is omitted. We may
assume without loss of generality that the offdiagonal elements are of order unity and typically we might then choose the set of threshold values $2^{-2}, 2^{-4}, 2^{-8}, 2^{-12}$. Assuming that $2^{-12}$ is the smallest number $m$ on the machine for which

$$
\begin{equation*}
1.0+m \neq 1.0 \tag{5.1}
\end{equation*}
$$

we select all subsequent threshold values to be $2^{-12}$. This means that only zeros are skipped in the fourth and later sweeps. A suitable criterion for terminating the process is to stop when $n(n-1) / 2$ successive elements have been skipped. We give later the details of the implementation of the algorithm that we have used. It is important to notice that, with the threshold Jacobi method, termination is guaranteed as there are only a finite number of iterations corresponding to any given threshold value. From the analysis of section 4 we see that the diagonal elements of $A$ then differ from the eigenvalues by less than $(n-1) \varepsilon^{2} / \delta$.

## 6. ULTIMATE QUADRATIC CONVERGENCE OF JACOBI METHODS

We showed in section 4 that we would expect a Jacobi method to be ultimately quadratically convergent. It has been shown that several variants of the Jacobi method do indeed have ultimate quadratic convergence when the eigenvalues are distinct. The first result in this field was obtained by Henrici (1958). For completeness we
summarise, using the notation of sections 2 and 4 , the best results obtained so far.

For the classical Jacobi method, Schönage (1961)
has shown that if

$$
\begin{equation*}
\left|\lambda_{i}-\lambda_{j}\right| \geq 2 \delta, \quad i \neq j \tag{6.1}
\end{equation*}
$$

and if we have reached a stage at which

$$
\begin{equation*}
t\left(A_{r}\right)<\frac{1}{2} \delta \tag{6.2}
\end{equation*}
$$

then

$$
\begin{equation*}
t\left(A_{r+N}\right) \leq\left(\frac{1}{2} n-1\right)^{\frac{1}{2}} t^{2}\left(A_{r}\right) / \delta, \tag{6.3}
\end{equation*}
$$

where $N=\frac{1}{2} n(n-1)$.
For the general serial Jacobi method Wilkinson (1962) has shown that, subject to (6.1) and (6.2)

$$
\begin{equation*}
t\left(A_{r+N}\right) \leq \frac{1}{2}\left(n^{2}-n\right)^{\frac{1}{2}} t^{2}\left(A_{r}\right) / \delta \tag{6.4}
\end{equation*}
$$

For the special serial Jacobi method Wilkinson (1962) has shown that

$$
\begin{equation*}
t\left(A_{r+N}\right) \leq t^{2}\left(A_{r}\right) /\left(2^{\frac{1}{2}} \delta\right) \tag{6.5}
\end{equation*}
$$

We discuss only (6.5) in detail.
7. BOUND FOR THE SPECIAL SERIAL JACOBI METHOD

As before we assume that the eigenvalues $\lambda_{i}$
of $A_{O}$ satisfy

$$
\begin{equation*}
\left|\lambda_{i}-\lambda_{j}\right| \geq 2 \delta, \quad i \neq j \tag{7.1}
\end{equation*}
$$

Following Wilkinson (1962) we let

$$
\begin{equation*}
S_{k}=2^{-\frac{1}{2}} t\left(A_{k}\right) \tag{7.2}
\end{equation*}
$$

Suppose we have reached the stage when

$$
\begin{equation*}
S_{k}<\delta / 4 \tag{7.3}
\end{equation*}
$$

Then from the precelding sections we have that

$$
\begin{equation*}
\left\|A_{k}-\operatorname{diag}\left(a_{i i}^{(k)}\right)\right\|_{E}<\delta / 2 \tag{7.4}
\end{equation*}
$$

and hence for some ordering of the $\lambda_{i}$

$$
\begin{align*}
\left|a_{i j}^{(k)}-a_{j j}^{(k)}\right|= & \mid\left(a_{i i}^{(k)}-\lambda_{i}\right)-\left(a_{j j}^{(k)}-\lambda_{j}\right) \\
& +\left(\lambda_{i}-\lambda_{j}\right) \mid \\
\geq & \left|\lambda_{i}-\lambda_{j}\right|-\left|a_{i i}^{(k)}-\lambda_{i}\right| \\
& -\left|a_{j j}^{(k)}-\lambda_{j}\right| \\
& >2 \delta-\frac{1}{2} \delta-\frac{1}{2} \delta \\
& =\delta . \tag{7.5}
\end{align*}
$$

We recall that the effect of a plane rotation is to reduce $\left(S_{k}\right)^{2}$ by the square of the element which is reduced to zero and hence, if (7.3) holds for any k , it holds for all subsequent $k$. For convenience we assume that equation (7.3) holds when $k=0$.

In the special serial Jacobi method the elements are annihilated in the row order given in section 5 . We denote the $N$ off-diagonal elements in their correct order by $\boldsymbol{\alpha}_{1}, \mathbf{x}_{2}, \ldots, \boldsymbol{x}_{\mathrm{N}}$ and the angles of rotation corresponding to them by $\phi_{1}, \phi_{2}, \ldots, \phi_{N}$. If $\alpha_{i}$ is annihilated by a rotation in the ( $p, q$ ) plane we have

$$
\left|\tan 2 \phi_{i}\right|=\left|\frac{2 \alpha_{i}}{a_{p p}^{(i)}-a_{q q}^{(i)}}\right|
$$

$$
\begin{equation*}
\leq \frac{2\left|\alpha_{i}\right|}{\delta} \tag{7.6}
\end{equation*}
$$

and hence

$$
\begin{align*}
\left|\sin \phi_{i}\right| & \leq\left|\phi_{i}\right| \\
& =\frac{1}{2}\left|2 \phi_{i}\right| \\
& \leq \frac{1}{2}\left|\tan 2 \phi_{i}\right| \\
& \leq\left|\alpha_{i}\right| / \delta . \tag{7.7}
\end{align*}
$$

Since

$$
\begin{equation*}
s_{i+1}^{2}-s_{i}^{2}=-\alpha_{i}^{2} \tag{7.8}
\end{equation*}
$$

we have

$$
\begin{equation*}
0 \leq S_{N}^{2}=S_{0}^{2}-\sum_{i=1}^{N} \alpha_{i}^{2} . \tag{7.9}
\end{equation*}
$$

Hence, from (7.7)

$$
\begin{equation*}
\sum_{i=1}^{N} \sin ^{2} \phi_{i} \leq \frac{1}{\delta^{2}} \sum_{i=1}^{N} \alpha_{i}^{2} \leq s_{0}^{2} / \delta^{2} \tag{7.10}
\end{equation*}
$$

We now consider the effect of the rotations on the element $\alpha_{i}$ after it has been annihilated. It is only affected by a subset of the later rotations - namely those in the ( $p, q$ ) plane where $\mathcal{X}_{i}$ lies in the $p$ or $q-t h$ row or column. In order to simplify the resulting analysis we consider firstly the following particular case. We let $p=1$ and consider what happens to $a_{p q}$ as $q=2,3, \ldots, n$. From equations (2.5) and (2.7) we see that

$$
\begin{array}{ll}
a_{12}^{(1)}=0, & q=2 \\
a_{12}^{(2)}=0 \cdot \cos \phi_{2}-a_{32}^{(1)} \sin \phi_{2}, & q=3
\end{array}
$$

$$
\begin{align*}
& a_{12}^{(3)}=a_{12}^{(2)} \cos \phi_{3}-a_{42}^{(1)} \sin \phi_{3}, q=4 \\
& \cdots \cdots \cdots \cdot \cdots \\
& a_{12}^{(n-1)}=\cdots a_{12}^{(n-2)} \cos \phi_{n-1}-a_{n 2}^{(1)} \sin \phi_{n-1},  \tag{7.11}\\
& q=n,
\end{align*}
$$

where we use $\phi_{i}$ to denote in the correct order each of the $\mathbb{N}$ angles needed in one complete sweep. Since $\left|\cos \phi_{i}\right| \leq 1$ we have

$$
\begin{align*}
\left|a_{12}^{(n-1)}\right| \leq & \left|a_{32}^{(1)}\right|\left|\sin \phi_{2}\right|+\left|a_{42}^{(1)}\right|\left|\sin \phi_{3}\right|+\ldots \\
& \ldots+\left|a_{n 2}^{(1)}\right|\left|\sin \phi_{n-1}\right| \tag{7.12}
\end{align*}
$$

Similarly we may consider the history of the other elements in the first row. In particular

$$
\begin{array}{ll}
a_{13}^{(1)}=a_{13}^{(0)} \cos \phi_{1}-a_{23}^{(0)} \sin \phi_{1}, & q=2 \\
a_{13}^{(2)}=0, & q=3 \\
a_{13}^{(3)}=0 \cdot \cos \phi_{3}-a_{43}^{(1)} \sin \phi_{3}, & q=4 \\
a_{13}^{(4)}=a_{13}^{(3)} \cos \phi_{4}-a_{53}^{(1)} \sin \phi_{4}, & q=5 \\
\cdots \cdots \cdots \cdot \cdots \\
a_{13}^{(n-1)}=a_{13}^{(n-2)} \cos \phi_{n-1}-a_{n 3}^{(1)} \sin \phi_{n-1}, & q=n . \tag{7.13}
\end{array}
$$

Hence we have

$$
\begin{gather*}
\left|a_{13}^{(n-1)}\right| \leq\left|a_{43}^{(1)}\right|\left|\sin \phi_{3}\right|+\left|a_{53}^{(1)}\right|\left|\sin \phi_{4}\right|+\ldots \\
\ldots+\left|a_{n 3}^{(1)}\right|\left|\sin \phi_{n-1}\right| \tag{7.14}
\end{gather*}
$$

In general

$$
\begin{align*}
& \left|a_{1 j}^{(n-1) \mid \leq} \sum_{k=j+1}^{n}\right| a_{k j}^{(1)}| | \sin \phi_{k-1} \mid \\
& \\
& \quad j=2,3, \ldots, n-1 \quad(7.15)  \tag{7.16}\\
& a_{1 n}^{(n-1)}=0 .
\end{align*}
$$

Hence

$$
\begin{equation*}
\sum_{j=2}^{n-1}\left(a_{1 j}^{(n-1)}\right)^{2} \leq\left(\sum_{j=2}^{n-1} \sum_{k=j+1}^{n}\left(a_{k j}^{(1)}\right)^{2}\right)\left(\sum_{j=2}^{n-1} \sin ^{2} \phi_{j}\right) \tag{7.17}
\end{equation*}
$$

Now, as each rotation alters only two elements in each of the relevant rows and leaves the sum of their squares unaltered we have

$$
\begin{align*}
\left(a_{k 1}^{(k-2)}\right)^{2}+\sum_{j=2}^{k-1}\left(a_{k j}^{(1)}\right)^{2}= & \sum_{j=1}^{k-1}\left(a_{k j}^{(0)}\right)^{2},  \tag{7.18}\\
& k=3,4, \ldots, n
\end{align*}
$$

Hence, certainly

$$
\begin{align*}
\sum_{j=2}^{n-1}\left(a_{1 j}^{(n-1)}\right)^{2} & \leq\left(\sum_{k=3}^{n} \sum_{j=1}^{k-1}\left(a_{k j}^{(0)}\right)^{2}\right)\left(\sum_{j=2}^{n-1} \sin ^{2} \phi_{j}\right) \\
& \leq s_{0}^{2} \cdot \sum_{j=2}^{n-1} \sin ^{2} \phi_{j} . \tag{7.19}
\end{align*}
$$

We note that this sum of squares of the first row is unaltered by subsequent transformations in this sweep.

Secondly we consider the sum of the squares of the super-diagonal elements of the second row on completion of their succesive annihilation.

From a discussion similar to that for the first row we obtain

$$
\sum_{j=3}^{n-1}\left(a_{2 j}^{(n)}\right)^{2} \leq s_{n-1}^{2} \sum_{j=n+1}^{2 n-3} \sin ^{2} \phi_{j}
$$

$$
\begin{equation*}
\leq s_{0}^{2} \sum_{j=n+1}^{2 n-3} \sin ^{2} \phi_{j} \tag{7.20}
\end{equation*}
$$

and this sum then remains constant.

> In general, for the k-th row we have

$$
\begin{array}{r}
\sum_{j=k+1}^{n-1}\left(a_{k j}^{(n+k-2))^{2} \leq} \leq s_{f(n)}^{2} \sum_{j=0}^{n-k-2} \sin ^{2} \phi_{g(j)}\right. \\
\leq s_{0}^{2} \sum_{j=0}^{n-k-2} \sin ^{2} \phi_{g(j)} \\
k=1,2, \ldots, n-2 \tag{7.21}
\end{array}
$$

where the exact form of $f(n)$ and $g(j)$ are defined by

$$
\begin{equation*}
f(n)=\sum_{i=1}^{k-1}(n-i) \tag{7.22}
\end{equation*}
$$

and

$$
\begin{equation*}
g(j)=2+\sum_{i=1}^{k-1}(n-i)+j \ldots \tag{7.23}
\end{equation*}
$$

Adding equations (7.21) for $k=1,2, \ldots, n-2$ we obtain

$$
\begin{align*}
S_{N}^{2} & \leq S_{0}^{2} \cdot \sum_{j=1}^{N} \sin ^{2} \phi_{j} \\
& \leq S_{O}^{2} \cdot \frac{S_{0}^{2}}{s^{2}} \\
& =\frac{S_{0}^{4}}{\delta^{2}} \tag{7.24}
\end{align*}
$$

Clearly a similar result must hold for each of the rows in every sweep and hence in general we have

$$
\begin{equation*}
S_{N} \leq S_{0}^{2} / \delta \tag{7.25}
\end{equation*}
$$

Thus, from (7.2)

$$
\begin{equation*}
\frac{t\left(A_{N}\right)}{2^{\frac{1}{2}}} \leq \frac{t^{2}\left(A_{0}\right)}{2 \delta} \tag{7.26}
\end{equation*}
$$

or

$$
\begin{equation*}
t\left(A_{N}\right) \leq \frac{t^{2}\left(A_{0}\right)}{2^{\frac{1}{2}} \boldsymbol{\sigma}} \tag{7.27}
\end{equation*}
$$

as stated in (6.5).
In fact (7.27) is often a bad estimate in reality, for we have replaced

$$
\left|a_{i j}^{(k)}-a_{j j}^{(k)}\right|, \quad i \neq j
$$

by $\delta$ whereas some may be much larger. We also replaced all $S_{k}$ by $S_{0}$ and finally it is usually the case that some of the contributions made to an element after annihilation are positive and some negative.

## 8. MULTIPLE EIGENVALUES

In all the foregoing we have assumed that

$$
\begin{equation*}
\left|\lambda_{i}-\lambda_{j}\right| \neq 0, \quad i \neq j \tag{8.1}
\end{equation*}
$$

and all the convergence proofs have contained a factor $1 / \delta$. Obviously all the proofs break down if $\delta$ is zero and even if $\delta$ is small we would expect the rate of convergence to be slow. In fact it has been shown, see for example Schönage (1951), that if none of the eigenvalues is of multiplicity greater than two then quadratic convergence can be guaranteed for the classical Jacobi method. Little theoretical progress seems to have been made in the case of eigenvalues of multiplicity greater than two. However, our experience sucgests that convergence is usually just as fast if there are
repeated eigenvalues. Wilkinson (1965) reports similar findings and justifies them on the following grounds.

In the first place if all the eigenvalues are equal to $\lambda_{1}$ then the matrix is diagonal and no iterations are required. Now suppose the eigenvalues are all very close so that

$$
\begin{equation*}
\lambda_{i}=a+\delta_{i} \tag{8.2}
\end{equation*}
$$

where the $\delta_{i}$ are small compared with a. Then we have

$$
\begin{equation*}
A=\operatorname{Vdiag}\left(a+\delta_{i}\right) V^{T} \tag{8.3}
\end{equation*}
$$

for some orthogonal $V$, and hence

$$
\begin{equation*}
A=a I+\operatorname{Vdiag}\left(\delta_{i}\right) V^{T} \tag{8.4}
\end{equation*}
$$

Now

$$
\begin{equation*}
t\left(\operatorname{Vdiag}\left(\delta_{i}\right) V^{T}\right) \leqq\left(\sum \delta_{i}^{2}\right)^{\frac{1}{2}} \tag{8.5}
\end{equation*}
$$

which shows that the oif-diagonal elements must be small initially. Computation with A is identical to computation with (A-aI), and this matrix is no longer special in the original sense. However, as all the elements of (A-aI) are small to start with we may expect that the reduction of the off-diagonal elements below a prescribed level will require less operations for this matrix than for a general symmetric matrix. In fact if $\max \left|\delta_{i}\right|=O\left(10^{-r}\right)$, then we would expect to reduce the off-diagonal elements of A below $10^{-t-r}$ in the time it usually takes to
reduce them to $10^{-t}$.

## 9. CALCULATION OF THE EIGENVECTORS

If the last rotation to be performed is $V_{S}$ then we have

$$
\begin{equation*}
\left(v_{s}^{T} \ldots v_{2}^{T} v_{1}^{T}\right) A_{0}\left(V_{1} V_{2} \ldots V_{s}\right)=\operatorname{diag}\left(\lambda_{i}\right) \tag{9.1}
\end{equation*}
$$

to working accuracy. The eigenvectors of $A_{0}$ are therefore the columns of the matrix $X$ defined by

$$
\begin{equation*}
x=v_{1} v_{2} \ldots v_{s} . \tag{9.2}
\end{equation*}
$$

If the eigenvectors are required, then at each stage of the process we may store the current product $V_{1} V_{2} \ldots V_{i}$. This requires $n^{2}$ storage locations in addition to the $\frac{1}{2}\left(n^{2}+n\right)$ needed for the upper triangles of the $A_{i}$. This scheme automatically gives all n eigenvectors.

## 10. COMPUTATIONAL ASPECTS OF THE ALGORITHM

We are now in a position to discuss in detail the implementation of the algorithm that we have used. Various schemes have been proposed in the past; Jacobi (1846) inspected the absolutely largest off-diagonal element $a_{p q}$ and then chose the angle of rotation $\varnothing$ such that in the matrix $A_{k+1}$ the ( $p, q$ ) element was zero. After the rediscovery of the method by Gregory (1953), when for the first time it was used in automatic computing, it was
applied in such a way that $p$ and $q$ ran row-wise through all super-diagonal elements of the matrix and again the rotation angle $\varnothing$ was chosen every time to annihilate the ( $p, q$ ) element of the matrix $A_{k+1}:$ Later Pope and Tompkins (1957) suggested a strategy which tended to avoid inefficient rotations and thus achieved diagonalisation with less effort. In practice we have found the proposals of Pope and Tompkins to be of little application and our basịc algorithm is due to Rutishauser (1966).

The pivots of the Jacobi rotations are chosen by row-wise scanning of the upper triangle of $A$. Before each sweep we calculate

$$
\begin{equation*}
\sigma=\sum_{p=1}^{n-1} \sum_{q=p+1}^{n}\left|a_{p q}\right| \tag{10.1}
\end{equation*}
$$

and during the first three sweeps it performs only those rotations for which

$$
\begin{equation*}
\left|a_{p q}\right|>0.2 \sigma / n^{2}=h . \tag{10.2}
\end{equation*}
$$

In the later sweeps $h$ is set to zero. If $\sigma$ is less than or equal to some preset tolerance the process is terminated. The tolerance may be altered by the user but we have taken a typical value to be $\frac{1}{2} n(n-1) \cdot m$ where $m$ is the smallest number for which

$$
\begin{equation*}
1.0+m \neq 1.0 \tag{10.3}
\end{equation*}
$$

on the machine being used.
If before the $(p, q)$ rotation the element $a_{p q}$
is small compared to $a_{p p}$ and small compared to $a_{q q}$,
then $a_{p q}^{\prime}$ is set to zero and the transformation is skipped. By small we mean that the addition of 100. $\left|a_{p q}\right|$ to both $a_{p p}$ and $a_{q q}$ does not alter the two diagonal elements on the machine being used. This is certainly meaningful as it produces an error no larger than would be produced if the rotation had been performed. However, in order that the procedure can be used on perturbed diagonal matrices this device is suppressed during the first four sweeps.

In order to illustrate the difference between our stopping criteria and Rutishauser's consider the following example of order 2. Let

$$
A=\left(\begin{array}{ll}
a & \varepsilon  \tag{10.4}\\
\varepsilon & b
\end{array}\right)
$$

where

$$
\begin{equation*}
\varepsilon=m / 2 \tag{10.5}
\end{equation*}
$$

and $a$ and $b$ are approximately of order unity. Based on our stopping criteria the matrix $A$ is diagonal and we should accept the eigenvalues

$$
\begin{equation*}
\lambda_{1}=a, \quad \lambda_{2}=b \tag{10.6}
\end{equation*}
$$

and the corresponding matrix of eigenvectors

$$
V=\left(\begin{array}{ll}
1 & 0  \tag{10.7}\\
0 & 1
\end{array}\right)
$$

Rutishauser's algorithm would however perform a rotation to give, to machine precision, the eigen-
values

$$
\lambda_{1}=a, \quad \lambda_{2}=b
$$

and the corresponding matrix of eigenvectors

$$
V=\left(\begin{array}{cc}
2^{-\frac{1}{2}} & 2^{-\frac{1}{2}}  \tag{10.9}\\
2^{-\frac{1}{2}} & -2^{-\frac{1}{2}}
\end{array}\right)
$$

We think it unlikely that there would be many instances in which it was advantageous to perform the extra rotation and in our particular application to simultaneous iteration it is often disastrous.

In order to annihilate the ( $p, q$ ) element the rotation parameters $c(=\cos \phi)$ and $s(=\sin \phi)$ are computed as follows. Firstly, instead of taking

$$
\begin{equation*}
\tan 2 \phi=\frac{2 a_{p q}}{a_{q q}-a_{p p}} \tag{10.10}
\end{equation*}
$$

we compute

$$
\begin{equation*}
\theta=\cot 2 \phi=\left(a_{q q}-a_{p p}\right) / 2 a_{p q} \tag{10.11}
\end{equation*}
$$

giving

$$
\begin{equation*}
\frac{1}{\theta}=\tan 2 \phi=\frac{2 t}{1-t^{2}} \quad \text { where } t=\tan \phi \tag{10.12}
\end{equation*}
$$

From (10.12) we have

$$
\begin{equation*}
1-t^{2}=2 \theta t \tag{10.13}
\end{equation*}
$$

or

$$
\begin{equation*}
t^{2}+2 \theta t-1=0 \tag{10.14}
\end{equation*}
$$

We take

$$
\begin{equation*}
t=-\theta \pm\left(1+\theta^{2}\right)^{\frac{1}{2}} \tag{10.15}
\end{equation*}
$$

where we require the smaller (in modulus) root.

If $|\theta|$ is large we do not use the above but instead we take

$$
\begin{equation*}
t=1 / 2 \theta \tag{10.16}
\end{equation*}
$$

To find whether $|\theta|$ is large we form

$$
\begin{equation*}
h=a_{q q}-a_{p p} \tag{10.17}
\end{equation*}
$$

and test if

$$
\begin{equation*}
h+100 \cdot\left|a_{p q}\right|=h \tag{10.18}
\end{equation*}
$$

to machine precision.
The solution of (10.15) which we require is
given by

$$
\begin{align*}
t=-\theta+\left(1+\theta^{2}\right)^{\frac{1}{2}}= & 1 /\left(\theta+\left(1+\theta^{2}\right)^{\frac{1}{2}}\right) \\
& \text { if } \theta \geq 0 \tag{10.19}
\end{align*}
$$

and

$$
\begin{gather*}
t=|\theta|-\left(1+\theta^{2}\right)^{\frac{1}{2}}=-1 /\left(|\theta|+\left(1+\theta^{2}\right)^{\frac{1}{2}}\right) \\
 \tag{10.20}\\
\text { if } \theta<0 .
\end{gather*}
$$

From $t$ we easily calculate

$$
\begin{equation*}
c=\cos \phi=1 /\left(1+t^{2}\right)^{\frac{1}{2}} \tag{10.21}
\end{equation*}
$$

whence

$$
\begin{equation*}
s=\sin \phi=t \cdot \cos \phi \tag{10.22}
\end{equation*}
$$

and

$$
\begin{equation*}
r=\tan (\phi / 2)=\sin \phi /(1+\cos \phi) \tag{10.22}
\end{equation*}
$$

Finally we mention that the program does not operate directly on the diagonal elements of the matrix $A$ but transfers them to a one-dimensional array $d$ and then acts upon this. In order to ensure maximum accuracy of the eigenvalues, as well as updating a at each rotation (for the purposes of
calculations performed during any particular sweep), the alterations to $d$ are also accumulated separately and at the end of each sweep these totalled increments of all the diagonal elements during the sweep are used to compute new and better values of the latter. We give more details in chapter 5 .

## 11. NUMERICAL DETAILS

In an attempt to diminish the accumulation of round-off errors the following computational formulae are used. To calculate $c, s$ and $\tau$ we proceed as follows. Let

$$
\begin{align*}
& \mathrm{h}=\mathrm{a}_{\mathrm{qq}}-\mathrm{a}_{\mathrm{pp}}  \tag{11.1}\\
& \theta=\frac{1}{2} \mathrm{~h} / \mathrm{a}_{\mathrm{pq}}  \tag{11.2}\\
& \mathrm{t}=1 /\left(|\theta|+\left(1+\theta^{2}\right)^{\frac{1}{2}}\right) \text { if } \theta \geqslant 0 \text { or } \\
& \mathrm{t}=-1 /\left(|\theta|+\left(1+\theta^{2}\right)^{\frac{1}{2}}\right) \text { if } \theta<0 \\
& \mathrm{c}=1 /\left(1+\mathrm{t}^{2}\right)^{\frac{1}{2}}  \tag{11.4}\\
& \mathrm{~s}=\mathrm{t} \cdot \mathrm{c}  \tag{11.5}\\
& \tau=\mathrm{s} /(1+\mathrm{c}) . \tag{11.6}
\end{align*}
$$

If $\theta$ is large we replace (11.3) by $t=1 / 2 \theta$. We modify the formulae (2.6) and (2.7) as follows. We know

$$
\begin{equation*}
\tan 2 \phi=2 a_{p q} /\left(a_{q q}-a_{p p}\right) \tag{11.7}
\end{equation*}
$$

therefore

$$
\begin{equation*}
\frac{\tan \phi}{1-\tan ^{2} \phi}=\frac{a_{p q}}{a_{q q}-a_{p p}} \tag{11.8}
\end{equation*}
$$

Hence, from

$$
\begin{equation*}
a_{p p}^{\prime}=a_{p p} \cos ^{2} \phi+a_{q q} \sin ^{2} \phi-2 a_{p q} \sin \phi \cos \phi \tag{11.9}
\end{equation*}
$$

we have

$$
\begin{align*}
a_{p p}^{\prime} & =a_{p p}+\left(a_{q q}-a_{p p}\right) \sin ^{2} \phi-2 a_{p q} \sin \phi \cos \phi \\
& =a_{p p}+a_{p q}\left(1-\tan ^{2} \phi\right) \frac{\sin ^{2} \phi}{\tan \phi}-2 a_{p q} \sin \phi \cos \phi \\
& =a_{p p}-a_{p q} \sin \phi \cos \phi-a_{p q} \tan ^{2} \phi \sin \phi \cos \phi \\
& =a_{p p}-a_{p q} \sin \phi \cos \phi \sec ^{2} \phi \\
& =a_{p p}-a_{p q} \tan \phi . \tag{11.10}
\end{align*}
$$

Hence, we use the computational formulae

$$
\begin{align*}
& a_{p p}^{\prime}=a_{p p}-t \cdot a_{p q}  \tag{11.11}\\
& a_{q q}^{\prime}=a_{q q}+t \cdot a_{p q}  \tag{11.12}\\
& a_{p q}^{\prime}=0 . \tag{11.13}
\end{align*}
$$

Similarly for the off-diagonal elements of A , and also for the components of $V$, we do not use equations (2.5) but instead modify them in a similar manner. For if

$$
\begin{equation*}
a_{p j}^{\prime}=a_{p j} \cos \phi-a_{q j} \sin \phi \tag{11.14}
\end{equation*}
$$

we have

$$
\begin{align*}
a_{p j}^{\prime} & =a_{p j}\left(1-2 \sin ^{2} \frac{1}{2} \phi\right)-a_{q j} \sin \phi \\
& =a_{p j}\left(1-\frac{\sin \phi}{\cos \frac{1}{2} \phi} \cdot \sin \frac{1}{2} \phi\right)-a_{q j} \sin \phi \\
& =a_{p j}-\sin \phi\left(a_{q j}+a_{p j} \tan \frac{1}{2} \phi\right) . \tag{11.15}
\end{align*}
$$

It might be thought that analagously to (11.11) we would use

$$
\begin{equation*}
a_{p j}^{\prime}=\cos \phi\left(a_{p j}-a_{q j} \tan \phi\right) \tag{11.16}
\end{equation*}
$$

offers no advantage since its rounding error but this euffons from the disedvantage that tant is similar to that of (11.i4). wher $\phi$ is small, oan take all values in the nange $[-\infty, \infty]$. Fquation
smaller
(11.15) has a mind rounding error that of
(11.14). Hence, we use the computational formulae

$$
\begin{align*}
& a_{p j}^{\prime}=a_{p j}-s \cdot\left(a_{q j}+\tau \cdot a_{p j}\right) \\
& a_{q j}^{\prime}=a_{q j}+s \cdot\left(a_{p j}-r \cdot a_{q j}\right) \tag{11.17}
\end{align*}
$$

In the program we work only with the upper triangle of elements of A and hence.equations (11.17) are only used if the appropriate $a_{p j}$ and $a_{q j}$ are in this upper triangle. In fact we use three pairs of equations to modify the elements of the $p$ - and $q$-th row and column as follows. For $1 \leqslant j \leqslant p-1$ we take

$$
\begin{align*}
& a_{j p}^{\prime}=a_{j p}-s \cdot\left(a_{j q}+a_{j p} \cdot \tau\right) \\
& a_{j q}^{\prime}=a_{j q}+s \cdot\left(a_{j p}-a_{j q} \cdot \tau\right), \tag{11.18}
\end{align*}
$$

for $p+1 \leqslant j \leqslant q-1$

$$
\begin{align*}
& a_{p j}^{\prime}=a_{p j}-s \cdot\left(a_{j q}+a_{p j} \cdot r\right) \\
& a_{j q}^{\prime}=a_{j q}+s \cdot\left(a_{p j}-a_{j q} \cdot r\right), \tag{11.19}
\end{align*}
$$

and for $q+1 \leqslant j \leqslant n$

$$
\begin{align*}
& a_{p j}^{\prime}=a_{p j}-s \cdot\left(a_{q j}+a_{p j} \cdot \tau\right) \\
& a_{q j}^{\prime}=a_{q j}+s \cdot\left(a_{p j}-a_{q j} \cdot \tau\right) . \tag{11.20}
\end{align*}
$$

This completes the details of the algorithm; we discuss the programming aspects in chapter 5 and a listing of the program is given in appendix 1.

## 12. THE JACOBI METHOD FOR HERMITIAN MATRICES

Nearly all of the results we obtained in the previous sections for real symmetric matrices carry over to the case when $A$ is Hermitian. We define the rotation matrix $V$ of order $n$ such that

$$
\begin{align*}
& v_{p p}=v_{q q}=\cos \phi \\
& v_{p q}=e^{i \theta} \sin \phi \\
& v_{q p}=-e^{-i \theta} \sin \phi \\
& v_{i i}=1, \quad i \neq p, q \\
& v_{i j}=0 \quad \text { otherwise. } \tag{12.1}
\end{align*}
$$

We note that

$$
\begin{equation*}
V V^{H}=V^{H} V^{H} \tag{12.2}
\end{equation*}
$$

Denoting the original matrix by $A_{0}$ we may describe the process by the sequence of matrices

$$
\begin{equation*}
A_{k}=V_{k}^{H} A_{k-1} V_{k} \tag{12.3}
\end{equation*}
$$

As $A_{k-1}$ is Hermitian we see that $A_{k}$ is also. In a similar notation to section 2 the modified elements are given by

$$
\begin{align*}
& a_{i j}^{\prime}=a_{i j}, \quad i, j \neq p, q  \tag{12.4}\\
& \left.\begin{array}{l}
a_{p j}^{\prime}=a_{p j} \cos \phi-a_{q j} e^{i \theta} \sin \phi \\
a_{q j}^{\prime}=a_{q j} \cos \phi+a_{p j} e^{-i \theta} \sin \phi
\end{array}\right\} j \neq p, q  \tag{12.5}\\
& a_{p p}^{\prime}=a_{p p} \cos ^{2} \phi+a_{q q} \sin ^{2} \phi \\
& -\sin \phi \cos \phi\left(a_{p q} e^{-i \theta}+a_{q p} e^{i \theta}\right)
\end{align*}
$$

$$
\begin{align*}
a_{q q}^{\prime}= & a_{q q} \cos ^{2} \phi+a_{p p} \sin ^{2} \phi \\
& +\sin \phi \cos \phi\left(a_{p q} e^{-i \theta}+a_{q p} e^{i \theta}\right)  \tag{12.6}\\
a_{p q}^{\prime}= & a_{p q} \cos ^{2} \phi-a_{q p} e^{2 i \theta} \sin ^{2} \phi \\
& +e^{i \theta} \sin \phi \cos \phi\left(a_{p p}-a_{q q}\right) \tag{12.7}
\end{align*}
$$

Again we notice that the transformation given by (12.3) leaves $N^{2}(A)$ invariant and that $A$ tends to diagonal form if and only if $t^{2}(A) \rightarrow 0$. Again it is possible to reduce $a_{p q}$ to zero at any stage. For if

$$
\begin{align*}
a_{p q}^{\prime}= & a_{p q} \cos ^{2} \phi-a_{q p} e^{2 i \theta} \sin ^{2} \phi \\
& +e^{i \theta} \sin \phi \cos \phi\left(a_{p p}-a_{q q}\right) \\
= & 0 . \tag{12.8}
\end{align*}
$$

Then

$$
\begin{align*}
a_{p q} e^{-i \theta} \cos ^{2} \phi & -a_{q p} e^{i \theta} \sin ^{2} \phi \\
& =\left(a_{q q}-a_{p p}\right) \sin \phi \cos \phi \tag{12.9}
\end{align*}
$$

thus

$$
\begin{align*}
& a_{p q}(\cos \theta-i \sin \theta) \cos ^{2} \phi-a_{q p}(\cos \theta+i \sin \theta) \sin ^{2} \phi \\
&=\frac{1}{2}\left(a_{q q}-a_{p p}\right) \sin 2 \phi \tag{12.10}
\end{align*}
$$

Therefore

$$
\begin{gather*}
\left(\cos ^{2} \phi-\sin ^{2} \phi\right)\left(\operatorname{Re}\left(a_{p q}\right) \cos \theta+\operatorname{Im}\left(a_{p q}\right) \sin \theta\right) \\
+i\left[\left(\cos ^{2} \phi+\sin ^{2} \phi\right)\left(\operatorname{Im}\left(a_{p q}\right) \cos \theta-\operatorname{Re}\left(a_{p q}\right) \sin \theta\right)\right] \\
\quad=\frac{1}{2}\left(a_{q q}-a_{p p}\right) \sin 2 \phi \tag{12.11}
\end{gather*}
$$

Hence, taking

$$
\begin{equation*}
\operatorname{Im}\left(a_{p q}\right) \cos \theta=\operatorname{Re}\left(a_{p q}\right) \sin \theta \tag{12.12}
\end{equation*}
$$

gives

$$
\begin{equation*}
\tan \theta=\operatorname{Im}\left(a_{p q}\right) / \operatorname{Re}\left(a_{p q}\right) \tag{12.13}
\end{equation*}
$$

and

$$
\begin{equation*}
\tan 2 \phi=\frac{2\left(\operatorname{Re}\left(a_{p q}\right) \cos \theta+\operatorname{Im}\left(a_{p q}\right) \sin \theta\right)}{\left(a_{q q}-a_{p p}\right)} . \tag{12.14}
\end{equation*}
$$

Therefore

$$
\begin{equation*}
\frac{\tan \phi}{1-\tan ^{2} \phi}=\frac{\Omega}{a_{q q}-a_{p p}} \tag{12.15}
\end{equation*}
$$

where

$$
\begin{equation*}
\Omega=\operatorname{Re}\left(a_{p q}\right) \cos \theta+\operatorname{Im}\left(a_{p q}\right) \sin \theta: \tag{12.16}
\end{equation*}
$$

As before we restrict ourselves to implementing the threshold special serial method and rearrange equations (12.5), (12.6) and (12.7) into a more convenient computational form. These then become

$$
\begin{align*}
& a_{p p}^{\prime}=a_{p p}-\Omega \tan \phi \\
& a_{q q}^{\prime}=a_{q q}+\Omega \tan \phi  \tag{12.17}\\
& a_{p q}^{\prime}=0 \tag{12.18}
\end{align*}
$$

where $\Omega$ is defined as in (12.16). Analogously to equations (11.17) we obtain

$$
a_{p j}^{\prime}=a_{p j}-\sin \phi\left(a_{q j} e^{i \theta}+\tau \cdot a_{p j}\right)
$$

and

$$
a_{q j}^{\prime}=a_{q j}+\sin \phi\left(a_{p j} e^{-i \theta}-\tau . a_{q j}\right) \cdot(12.19)
$$

As before the program works only with the elements
in the upper triangle of $A$ and hence we again use three pairs of equations for computational purposes. These are similar to those employed in the symmetric case. For example, if $1 \leqslant j \leqslant p-1$ we use

$$
\begin{align*}
& a_{j p}^{\prime}=a_{j p}-s\left(a_{j q} e^{i \theta}+a_{j p} \cdot \tau\right) \\
& a_{j q}^{\prime}=a_{j q}+s\left(a_{j p} e^{i \theta}-a_{j q} \cdot \tau\right) \tag{12.20}
\end{align*}
$$

The complex arithmetic is performed by breaking all equations down into their real and imaginary parts.

The only other feature of the program which does not occur in the symmetric case is the computation of $\cos \theta$ and $\sin \theta$. From (12.13) we form

$$
\begin{equation*}
\mathrm{t}=\tan \theta \tag{12.21}
\end{equation*}
$$

If $|t| \leqslant 1$ then form

$$
\begin{equation*}
\cos \theta=1 /\left(1+t^{2}\right)^{\frac{1}{2}} \tag{12.22}
\end{equation*}
$$

and

$$
\begin{equation*}
\sin \theta=t \cdot \cos \theta \tag{12.23}
\end{equation*}
$$

If, however, $|t|>1$ we take

$$
\begin{equation*}
t_{1}=\frac{1}{t}=\frac{\operatorname{Re}\left(a_{p q}\right)}{\operatorname{Im}\left(a_{p q}\right)} \tag{12.24}
\end{equation*}
$$

and form

$$
\begin{align*}
& \sin \theta=1 /\left(1+t_{1}^{2}\right)^{\frac{1}{2}}  \tag{12.25}\\
& \cos \theta=t_{1} \cdot \sin \theta \tag{12.26}
\end{align*}
$$

The other computational details are identical with the symmetric case. Programming details are given in chapter 5 and a listing of the program is included in appendix 2.

All the convergence results given earlier carry"
over to the Fermitian case with little or no additional analysis. The results of sections 3 and 4 require no modification as the eigenvalues and diagonal elements of a Hermitian matrix are real. The proof given in section 7 also holds, for we note that all the equations and inequalities involving the offdiagonal elements rely not on these elements but on their moduli. In addition, the proof nowhere depends on any of the off-diagonal elements being real. In particular, $|\exp (i \theta)|=1$.

## 13. THE JACOBI METHOD FOR NORMAL MATRICES

We have shown in chapter 1 that a normal matrix
is the most general form for which there exists a unitary transformation such that

$$
\begin{equation*}
V^{H} A V=\operatorname{diag}\left(\lambda_{i}\right) \tag{13.1}
\end{equation*}
$$

We saw also that if $A$ is normal we may write

$$
\begin{equation*}
A=B+C^{\prime} \tag{13.2}
\end{equation*}
$$

where $B$ is Hermitian and $C^{\prime}$ is skew-Hermitian and

$$
\begin{equation*}
B C^{\prime}=C^{\prime} B \tag{13.3}
\end{equation*}
$$

If we now write

$$
\begin{equation*}
C^{\prime}=i C \tag{13.4}
\end{equation*}
$$

$C$ is a Hermitian matrix and we may replace equations (13.2) and (13.3) by

$$
\begin{equation*}
A=B+i C \tag{13.5}
\end{equation*}
$$

and

$$
\begin{equation*}
B C=C B \tag{13.6}
\end{equation*}
$$

respectively, where $B$ and $C$ are now both Hermitian
matrices. Hence in order to diagonalise a normal matrix it is only necessary to diagonalise two Hermitian matrices. We now consider some relations between commuting matrices and their eigenvectors. Lemma 13.1 If $A$ is normal then $A$ and $A^{H}$ have a common complete system of eigenvectors.

- Proof: From the relations

$$
\begin{equation*}
V^{H} A V=D \text { and } V^{H} A^{H} V=D^{H} \tag{13.7}
\end{equation*}
$$

where $\mathrm{D}=\operatorname{diag}\left(\lambda_{i}\right)$, we have

$$
\begin{align*}
A V & =V D \\
A^{H} & =V D^{H} \tag{13.8}
\end{align*}
$$

The matrices $A$ and $A^{H}$ therefore have a common complete system of eigenvectors, namely that formed by the columns of $V$.

Lemma 13.2 If any two matrices $B$ and $C$ have a common complete system of eigenvectors then they commute. Proof: Suppose the common system of eigenvectors forms the columns of the matrix $V$. Then we have

$$
\begin{equation*}
B=V_{1}^{\prime} V^{-1} \text { and } C=V D_{2} V^{-1} \tag{13.9}
\end{equation*}
$$

Hence

$$
\begin{equation*}
B C=V D_{1} V^{-1}{V D_{2}} V^{-1}=V D_{1} D_{2} V^{-1} \tag{13.10}
\end{equation*}
$$

and

$$
\begin{equation*}
C B=V D_{2} V^{-1} V D_{1} V^{-1}=V D_{2} D_{1} V^{-1} \tag{13.11}
\end{equation*}
$$

As diagonal matrices commute so do $B$ and $C$.
Theorem 13.3 If $B$ and C commute and have linear elementary divisors then they share a common system
of eigenvectors.
Proof: Suppose the eigenvectors of $B$ are $v_{1}, v_{2}, \ldots$
$\ldots, v_{n}$ and that these vectors form the columns of the matrix V. Then

$$
\begin{equation*}
V^{-1} B V=\operatorname{diag}\left(\lambda_{i}\right) \tag{13.12}
\end{equation*}
$$

where the $\lambda_{i}$ are not necessarily distinct. The manner of proof is dependent on the number of repeated eigenvalues and their respective multiplicities but an example will suffice to show the method. Let us suppose that

$$
\begin{align*}
\lambda_{1} & =\lambda_{2}=\cdots=\lambda_{I}  \tag{13.13}\\
\lambda_{I+1} & =\lambda_{I+2}=\cdots=\lambda_{m} \tag{13.14}
\end{align*}
$$

and that $\lambda_{m+1}, \lambda_{m+2}, \ldots, \lambda_{n}$ are all distinct. Equation (13.12) may then be written as

Since

$$
\begin{equation*}
B v_{i}=\lambda_{i} v_{i} \tag{13.16}
\end{equation*}
$$

we have

$$
\begin{equation*}
C B v_{i}=\lambda_{i} C v_{i} \tag{13.17}
\end{equation*}
$$

which gives

$$
\begin{equation*}
B\left(C v_{i}\right)=\lambda_{i}\left(C v_{i}\right) . \tag{13.18}
\end{equation*}
$$

Thus if $v_{i}$ is an eigenvector of $B$ corresponding to $\lambda_{i}$ then $\left(\mathrm{Cv}_{i}\right)$ lies in the subspace of eigenvectors corresponding to $\lambda_{i}$. Hence

$$
\begin{gather*}
C v_{1}=p_{11} v_{1}+p_{21} v_{2}+\ldots \cdot+p_{11} v_{1} \\
C v_{2}=p_{12} v_{1}+p_{22} v_{2}+\ldots+p_{12} v_{1} \\
\cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \\
C v_{1}=p_{11} v_{1}+p_{21} v_{2}+\ldots+p_{11} v_{1} \\
C v_{1+1}=q_{11} v_{1}+q_{21} v_{2}+\ldots+q_{m 11} v_{m} \\
\cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \cdot \\
C v_{m}=q_{1 m} v_{1}+q_{2 m} v_{2}+\ldots+q_{m m} v_{m}  \tag{13.19}\\
C v_{m+1}=\mu_{m+1} v_{m+1} \\
\cdot \cdot \cdot \cdot \cdot \cdot \cdot \\
C v_{n}=\mu_{n} v_{n} \cdot
\end{gather*}
$$

These equations may be written in matrix form as

$$
V^{-1} \mathrm{CV}=\left[\begin{array}{ccccc}
P & & & &  \tag{13.20}\\
& Q & & & \\
& & \mu_{\mathrm{m}+1} & & \\
& & & \cdots & \\
& & & & \mu_{\mathrm{n}}
\end{array}\right]
$$

Since C has linear elementary divisors it follows that so too must $P$ and $Q$. Hence there exist matrices $T$ and $U$ such that

$$
\mathrm{T}^{-1} \mathrm{PT}=\left[\begin{array}{ccc}
\mu_{1} & &  \tag{13.21}\\
& \cdots & \\
& \mu_{I}
\end{array}\right] \text { and } \quad \mathrm{U}^{-1} \mathrm{QU}=\left[\begin{array}{lll}
\mu_{I+1} & & \\
& & \\
& & \mu_{\mathrm{m}}
\end{array}\right]
$$

Writing

$$
W=\left[\begin{array}{lll}
T & &  \tag{13.22}\\
& U & \\
& & I_{n-m}
\end{array}\right]
$$

we have

$$
\begin{equation*}
W^{-1} V^{-1} C V W=\operatorname{diag}\left(\mu_{i}\right) \tag{13.23}
\end{equation*}
$$

However, from (13.15) we obtain

$$
\begin{equation*}
W^{-1} V^{-1} B V W=\operatorname{diag}\left(\lambda_{i}\right) \tag{13.24}
\end{equation*}
$$

Hence $B$ and $C$ share a common system of eigenvectors, namely the vectors which are the columns of VW.

We may make use of this theorem to enable us to diagonalise a normal matrix. In equations (13.5) and (13.6) the matrices B and C commute and, as they are Hermitian, both have linear elementary divisors. From (13.5) we may determine a matrix $V$ such that

$$
\begin{equation*}
\mathrm{v}^{\mathrm{H}_{\mathrm{BV}}}=\operatorname{diag}\left(\lambda_{i}(\mathrm{~B})\right) . \tag{13.25}
\end{equation*}
$$

Thus

$$
\begin{equation*}
V^{H} A V=\operatorname{diag}\left(\lambda_{i}(B)\right)+i V^{H_{C V}} \tag{13.26}
\end{equation*}
$$

From theorem (13.3) we see that $\mathrm{V}^{\mathrm{H}} \mathrm{CV}$ will be diagonal only if there are no repeated eigenvalues. If it is not diagonal however it follows that we can certainly find a matrix $W$ such that

$$
\begin{equation*}
W^{H} V^{H} A V W=\operatorname{diag}\left(\lambda_{i}(B)\right)+i \cdot \operatorname{diag}\left(\lambda_{i}(C)\right) \tag{13.27}
\end{equation*}
$$

A similar algorithm could be devised which was based upon first diagonalising the matrix C. In our algorithm we use, as before, the threshold
special serial Jacobi method on the matrix A but base the transformation on $B$ or $C$ depending upon which one gives the greater reduction in $t^{2}(A)$.

For a normal matrix $A$ it is necessary to operate on the whole of the matrix $A$ or on the two upper triangles of $B$ and $C$. We opt for the former as it is extremely easy to calculate the elements of $B$ and $C$ when they are required and much more economical to perform one set of rotations on $A$.

Computationally the program follows that for Hermitian matrices with only two exceptions. Firstly it is necessary to calculate $b_{p q}$ and $c_{p q}$; these follow directly from (15.16) and (15.17) of chapter 1. Secondly it is necessary to calculate $a_{p q}$ as we are not necessarily reducing this to zero. A full listing of the program is given in appendix 3. Convergence of our method for normal matrices relies only on the convergence of Jacobi's method for Hermitian matrices and this we have discussed in the previous section. We note that although a normal matrix may have complex eigenvalues these are dealt with as an ordered pair of reals thus enabling us to use the results from the Hermitian case.

Finally we must mention the work of Goldstine and Horwitz (1959) who developed an optimal algorithm for diagonalising normal matrices. Ruhe (1967) proved that for row cyclic choice of pivots
this algorithm was ultimately quadratically
convergent; Loizou (1972) established the same result for maximal pivot choice. Unfortunately the Golstine and Horwitz algorithm is difficult to implement and we believe our algorithm to be very competitive. This is because it is easy to implement, runs nearly as quickly as the algorithm for Hermitian matrices and is very close to being optimal.

## 14. GENERALISED JACOBI METHODS

Many attempts have been made to generalise the well-known Jacobi algorithm for the diagonalisation of a real symmetric matrix to arbitrary matrices. We have just discussed an extension for normal matrices but for a non-normal matrix it is no longer possible to use unitary transformations alone although, as we have shown in chapter 1, it is possible to use unitary transformations to triangularise an arbitrary matrix. Attempts to formulate computational methods for doing this have not been very successful as shown by Causey (1958), Greenstadt (1955), and Lotkin (1956). Another way of generalising the Jacobi method is to use both unitary and non-unitary transformations and attempt to diagonalise the matrix. It is essential to restrict the non-unitary transformations and use them only to bring the matrix closer to normal.

Eberlein (1962) and Rutishauser (1964) have both proposed such methods, the former using non-unitary transformations and the latter using diagonal similarity transformations. Eberlein has proved the global convergence of her method and Ruhe (1968) has shown a slight modification of the algorithm to be ultimately quadratically convergent for nondefective matrices. No convergence proofs of Rutishauser's algorithm appear to exist and such attempts as we have made lead us to suspect that the method is not of general applicability.

## 15. MINIMISATION OF MATRIX NORMS

We prove firstly a theorem due to Mirsky (1958) upon which the attempts to diagonelise a matrix are based.

Iemma 15.1 Schur states that if A is a complex $(n * n)$ matrix with eigenvalues $\lambda_{1}, \lambda_{2}, \ldots, \lambda_{n}$ then

$$
\begin{equation*}
\|A\|_{E}^{2} \geqslant \sum_{i=1}^{n}\left|\lambda_{i}\right|^{2} \tag{15.1}
\end{equation*}
$$

There is equality if and only if $A$ is normal. Proof: For any matrix $A$ there exists a unitary matrix $R$ such that

$$
\begin{equation*}
\mathrm{R}^{\mathrm{H}_{\mathrm{AR}}}=\mathrm{T} \tag{15.2}
\end{equation*}
$$

where $T$ is a triangular matrix whose diagonal elements are the eigenvalues of A . We know that if $A$ is normal $T$ is diagonal.

From (15.2) we have

$$
\begin{equation*}
\mathrm{A}=\mathrm{RTR}^{\mathrm{H}} \tag{15.3}
\end{equation*}
$$

which gives us

$$
\begin{align*}
\|A\|_{E} & =\left\|R T R^{H}\right\|_{E} \\
& =\|T\|_{E} . \tag{15.4}
\end{align*}
$$

This follows because the Euclidean length of each column of $R T$ is equal to that of the corresponding column of $T$. Since

$$
\begin{equation*}
\|T\|_{E} \geqslant\left[\sum_{i=1}^{n}\left|\lambda_{i}\right|^{2}\right]^{\frac{1}{2}} \tag{15.5}
\end{equation*}
$$

with equality if and only if $T$ is diagonal the lemma is proved.

Theorem 15.2 Let $A$ be an ( $n * n$ ) arbitrary complex. matrix with eigenvalues $\lambda_{1}, \lambda_{2}, \ldots, \lambda_{n}$ then

$$
\begin{equation*}
\inf \left\|S^{-1} A S\right\|_{E}^{2}=\sum_{i=1}^{n}\left|\lambda_{i}\right|^{2} \tag{15.6}
\end{equation*}
$$

where the lower bound is taken with respect to all non-singular matrices $S$. Furthermore the lower bound is attained if and only if $A$ is normal. Proof: Denote by $T_{1}$ a matrix such that $T_{1}^{-1} A T_{1}$ is triangular, say

$$
\mathrm{T}_{1}^{-1} \mathrm{AT}_{1}=\left[\begin{array}{ccccc}
\lambda_{1} & b_{12} & \cdots & \cdot & b_{1 n}  \tag{15.7}\\
& \lambda_{2} & \cdots & \cdot & b_{2 n} \\
& & \cdots & \cdot & \\
& & & & \lambda_{n}
\end{array}\right]
$$

Let $|\delta|$ be not greater than unity and define

$$
\begin{equation*}
\mathrm{T}_{2}=\operatorname{diag}\left(1, \delta, \delta^{2}, \ldots, \delta^{\mathrm{n}-1}\right) . \tag{15.8}
\end{equation*}
$$

If $S_{0}=T_{1} T_{2}$ we have

$$
\begin{align*}
\left\|S_{O}^{-1} A S_{O}\right\|_{E}^{2} & =\left\|T_{2}^{-1} T_{1}^{-1} A T_{1} T_{2}\right\|_{E}^{2} \\
& =\sum_{i=1}^{n}\left|\lambda_{i}\right|^{2}+\sum_{1 \leqslant i<k \in n}\left|b_{i k}\right|^{2} 2(k-i) \\
& \leqslant \sum_{i=1}^{n}\left|\lambda_{i}\right|^{2}+\frac{1}{2} n(n-1) b^{2} \delta^{2} \tag{15.9}
\end{align*}
$$

where $\underset{i, k}{b=\max _{i k}}\left|b_{i k}\right|$. The relation (15.6) now follows since by (15.1)

$$
\begin{equation*}
\left\|S^{-1} A S\right\|_{E}^{2} \geqslant \sum_{i=1}^{n}\left|\lambda_{i}\right|^{2} \tag{15.10}
\end{equation*}
$$

for all non-singular S. Further, if $A$ is diagonaliṣable then the lower bound of $\left\|S^{-1} A S\right\|_{E}$ is clearly attained. If, on the other hand, the bound is attained so that, for some $S$,

$$
\begin{equation*}
\left\|S^{-1} A S\right\|_{E}^{2}=\sum_{i=1}^{n}\left|\lambda_{i}\right|^{2} \tag{15.11}
\end{equation*}
$$

then $S^{-1} A S$ is normal and $A$ is diagonalisable.

## 16. EBERLEIN'S ALGORITHM

Mirsky's theorem on the minimisation of matrix norms gave Eberlein (1962) the idea for a method of making complex matrices arbitrarily close to normal form. She proved global convergence, with some restriction on the choice of pivot elements, and found experimentally that an extension of the procedure produced a nearly diagonal matrix.

Ruhe (1968) has proved that slight modification of Eberlein's original 1962
algorithm is ultimately quadratically convergent for row cyclic choice of pivot. Using the 1962 paper Eberlein (1970) has published a program to reduce arbitrary complex matrices to nearly diagonal form. It is this algorithm which forms the basis of our program.

## 17. THE TRANSFORMATION MATRICES

As we have already mentioned the basic philosophy of Eberlein's method is to use shear matrices to reduce a matrix A arbitrarily close to normal form. It then may be made almost diagonal as we have shown previously. In practice the shears and rotations are performed together to minimise the arithmetic operations required but for theoretical purposes it is much more convenient to consider them separately. We shal". concertrate firstly on the effects of shearing. All the results that follow have been proved by Eberlein but we consider our proofs to be shorter and simpler to understand.

Define the shear matrix $S$ by

$$
\begin{align*}
& s_{p p}=s_{q q}=\cosh y \\
& s_{p q}=\bar{s}_{q p}=i e^{i \beta} \text { sinhy }, \quad y \text { and } \beta \text { real } \\
& s_{i j}=\delta_{i j}, \quad i, j \neq p, q . \tag{17.1}
\end{align*}
$$

For arbitrary $A$ the elements of the transformed
matrix $A^{\prime}$ defined by

$$
\begin{equation*}
A^{\prime}=S^{-1} A S \tag{17.2}
\end{equation*}
$$

are given by

$$
\begin{align*}
& a_{i j}=a_{i j} \quad i, j \neq p, q \\
& a_{p i}^{\prime}=a_{p i} \operatorname{coshy}-i a_{q i} e^{i \beta} \operatorname{sinhy} \\
& a_{i p}^{\prime}=a_{i p} \operatorname{coshy}-i a_{i q} e^{-i \beta_{\sinh y}} \\
& a_{q i}^{\prime}=a_{q i} \operatorname{coshy}+i a_{p i} e^{-i \beta} \sinh y  \tag{17.3}\\
& a_{i q}^{\prime}=a_{i q} \cosh y+i a_{i p} e^{i \beta} \sinh y \\
& a_{p p}^{\prime}=a_{p p} \cosh ^{2} y-a_{q q} \sinh ^{2} y \\
& -i \sinh y \operatorname{coshy}\left(a_{p q} e^{-i \beta}+a_{q p} e^{i \beta}\right)  \tag{17.4}\\
& a_{p q}^{\prime}=a_{p q} \cosh ^{2} y+a_{q p} e^{2 i \beta} \sinh ^{2} y \\
& +i e^{i \beta_{\sinh y \operatorname{coshy}}\left(a_{p p}-a_{q q}\right)}  \tag{17.5}\\
& a_{q p}^{\prime}=a_{q p} \cosh ^{2} y+a_{p q} e^{-2 i \beta} \sinh ^{2} y \\
& +i e^{-i \beta} \operatorname{sinhycoshy}\left(a_{p p}-a_{q q}\right)  \tag{17.6}\\
& a_{q q}^{\prime}=a_{q q} \cosh ^{2} y-a_{p p} \sinh ^{2} y \\
& +i \operatorname{sinhycoshy}\left(a_{p q} e^{-i \beta}+a_{q p} e^{i \beta}\right) \cdot
\end{align*}
$$

Equations (17.4) to (17.7) may be written more simply if we use the following substitutions. Let

$$
\begin{align*}
& D=a_{p p}-a_{q q}  \tag{17.8}\\
& E=a_{p q}+a_{q p}  \tag{17.9}\\
& F=a_{q p}-a_{p q} \tag{17.10}
\end{align*}
$$

$$
\begin{align*}
& B=a_{p q} e^{-i \beta}+a_{q p} e^{i \beta}  \tag{17.11}\\
& C=a_{p q} e^{-i \beta}-a_{q p} e^{i \beta} \tag{17.12}
\end{align*}
$$

From (17.4) we have

$$
\begin{align*}
a_{p p}^{\prime} & =a_{q q}-a_{q q} \cosh ^{2} y+a_{p p} \cosh ^{2} y-\frac{1}{2} i \sinh 2 y \cdot B \\
& =a_{q q}+D \cosh ^{2} y-\frac{1}{2} i \sinh 2 y \cdot B \\
& =a_{q q}+\frac{1}{2} D(1+\cosh 2 y)-\frac{1}{2} i B \sinh 2 y \\
& =\frac{1}{2}\left[\left(a_{p p}+a_{q q}\right)+D \cosh 2 y-i B \sinh 2 y\right] . \tag{17.13}
\end{align*}
$$

From (17.7) we have

$$
\begin{aligned}
a_{q q .}^{\prime} & =a_{q q}+a_{q q} \sinh ^{2} y-a_{p p} \sinh ^{2} y+\frac{1}{2} i \sinh 2 y \cdot B \\
& =a_{q q}-D \sinh ^{2} y+\frac{1}{2} i B \sinh 2 y \\
& =a_{q q}-\frac{1}{2} D(\cosh 2 y-1)+\frac{1}{2} i B \sinh 2 y \\
& =\frac{1}{2}\left[\left(a_{p p}+a_{q q}\right)-D \cosh 2 y+i B \sinh 2 y\right]
\end{aligned}
$$

From (17.5)

$$
\begin{align*}
a_{p q}^{\prime}= & e^{i \beta}\left(a_{p q} e^{-i \beta} \cosh { }^{2} y+a_{q p} e^{i \beta} \sinh { }^{2} y+\frac{1}{2} i D \sinh 2 y\right) \\
= & e^{i \beta}\left[\frac{1}{2} a_{p q} e^{-i \beta}-\frac{1}{2} a_{q p} e^{i \beta}\right. \\
& \left.+\frac{1}{2}\left(a_{p q} e^{-i \beta}+a_{q p} e^{i \beta}\right) \cosh 2 y+\frac{1}{2} i D \sinh 2 y\right] \\
= & \frac{1}{2} e^{i \beta}\left(a_{p q} e^{-i \beta}-a_{q p} e^{i \beta}+B \cosh 2 y+i D \sinh 2 y\right) \\
= & \frac{1}{2} e^{i \beta}(C+B \cosh 2 y+i D \sinh 2 y) . \tag{17.15}
\end{align*}
$$

From (17.6)

$$
a_{q p}^{\prime}=e^{-i \beta}\left(a_{q p} e^{i \beta} \cosh ^{2} y+a_{p q} e^{-i \beta} \sinh ^{2} y+\frac{1}{2} i D \sinh 2 y\right)
$$

$$
\begin{align*}
& =\frac{1}{2} e^{-i \beta}\left(a_{q p} e^{i \beta}-a_{p q} e^{-i \beta}+B \cosh 2 y+i D \sinh 2 y\right) \\
& =\frac{1}{2} e^{-i \beta}(-c+B \cosh 2 y+i D \sinh 2 y) \cdot(17 \cdot 16) \tag{17.16}
\end{align*}
$$

Hence we write equations (17.4) to (17.7) in the form

$$
\begin{align*}
& a_{p p}^{\prime}=\frac{1}{2}\left[\left(a_{p p}+a_{q q}\right)+D \cosh 2 y-i B \sinh 2 y\right]  \tag{17.17}\\
& a_{p q}^{\prime}=\frac{1}{2} e^{i \beta}(C+B \cosh 2 y+i D \sinh 2 y)  \tag{17.18}\\
& a_{q p}^{\prime}=\frac{1}{2} e^{-i \beta}(-C+B \cosh 2 y+i D \sinh 2 y)  \tag{17.19}\\
& a_{q q}^{\prime}=\frac{1}{2}\left[\left(a_{p p}+a_{q q}\right)-D \cosh 2 y+i B \sinh 2 y\right] . \tag{17.20}
\end{align*}
$$

We define the commutator matrix $C$ such that

$$
\begin{equation*}
C=A A^{H}-A_{A}^{H} \tag{17.21}
\end{equation*}
$$

and note that $C$ is Hermitian. An arbitrary matrix $A$ is normal if and only if

$$
\begin{equation*}
C \equiv 0 . \tag{17.22}
\end{equation*}
$$

We also introduce $\Delta$ defined by

$$
\begin{equation*}
\Delta \equiv \mathbb{N}^{2}(A)-\mathbb{N}^{2}\left(A^{\prime}\right) \tag{17.23}
\end{equation*}
$$

It is obvious that, to bring a matrix closer to normal form, we shall be interested in positive $\Delta$ at each step and ideally in maximising $\Delta$ at each step.

We now compute $\Delta$ for the single transformation of (17.2). Let

$$
\begin{aligned}
\Delta_{1} \equiv & \sum_{i \neq p, q}\left(\left|a_{p i}\right|^{2}+\left|a_{i p}\right|^{2}+\left|a_{q i}\right|^{2}+\left|a_{i q}\right|^{2}\right) \\
& -\sum_{i \neq p, q}\left(\left|a_{p i}^{\prime}\right|^{2}+\left|a_{i p}^{\prime}\right|^{2}+\left|a_{q i}^{\prime}\right|^{2}+\left|a_{i q}^{\prime}\right|^{2}\right) \cdot(17 \cdot 24)
\end{aligned}
$$

From equations (17.3) we obtain

$$
\begin{aligned}
\left|a_{p i}^{\prime}\right|^{2}= & \left(a_{p i} \operatorname{coshy}-i a_{q i} e^{i \boldsymbol{\beta}} \operatorname{sinhy}\right) \\
& *\left(\bar{a}_{p i} \operatorname{coshy}+i \bar{a}_{q i} e^{-i \boldsymbol{\beta}} \sinh y\right) \\
= & a_{p i} \bar{a}_{p i} \cosh ^{2} y+a_{q i} \bar{a}_{q i} \sinh ^{2} y \\
& +i \operatorname{sinhycoshy}\left(a_{p i} \bar{a}_{q i} e^{-i \boldsymbol{\beta}}-\bar{a}_{p i} a_{q i} e^{i \beta}\right)
\end{aligned}
$$

$$
\begin{align*}
\left|a_{i p}^{\prime}\right|^{2}= & a_{i p} \bar{a}_{i p} \cosh ^{2} y+a_{i q} \bar{a}_{i q} \sinh ^{2} y  \tag{17.25}\\
& +i \operatorname{sinhycoshy}\left(a_{i p} \bar{a}_{i q} e^{i \beta}-\bar{a}_{i p} a_{i q} e^{-i \beta}\right) \\
\left|a_{q i}^{\prime}\right|^{2}= & a_{q i} \bar{a}_{q i} \cosh ^{2} y+a_{p i} \bar{a}_{p i} \sinh ^{2} y  \tag{17.26}\\
& +i \operatorname{sinhycoshy}\left(a_{p i} \bar{a}_{q i} e^{\left.-i \beta-\bar{a}_{p i}{ }_{q i} e^{i \beta}\right)}\right. \tag{17.27}
\end{align*}
$$

and

$$
\begin{aligned}
\left|a_{i q}^{\prime}\right|^{2}= & a_{i q} \bar{a}_{i q} \cosh ^{2} y+a_{i p} \bar{a}_{i p} \sinh ^{2} y \\
& +i \operatorname{sinhycoshy}\left(a_{i p} \bar{a}_{i q} e^{i \beta}-\bar{a}_{i p} a_{i q} e^{-i \beta}\right)
\end{aligned}
$$

(17.28)

Hence

$$
\begin{aligned}
\Delta_{1}=\sum_{i \neq p, q} & {\left[a_{p i} \bar{a}_{p i}\left(1-\cosh ^{2} y-\sinh ^{2} y\right)\right.} \\
& +a_{i p} \bar{a}_{i p}\left(1-\cosh { }^{2} y-\sinh ^{2} y\right) \\
& +a_{q i} \bar{a}_{q i}\left(1-\cosh ^{2} y-\sinh ^{2} y\right) \\
& +a_{i q} \bar{a}_{i q}\left(1-\cosh ^{2} y-\sinh ^{2} y\right)
\end{aligned}
$$

$$
\begin{array}{r}
-2 i \operatorname{sinhycoshy}\left(a_{p i} \bar{a}_{q i} e^{-i \beta}-\bar{a}_{p i} a_{q i} e^{i \beta}\right. \\
\left.\left.+a_{i p} \bar{a}_{i q} e^{i \beta}-\bar{a}_{i p} a_{i q} e^{-i \beta}\right)\right] \tag{17.29}
\end{array}
$$

Some simple manipulation then gives us

$$
\begin{gathered}
\Delta_{1}=\sum_{i \neq p, q}\left\{\left(a_{p i} \bar{a}_{p i}+a_{i p} \bar{a}_{i p}+a_{q i} \bar{a}_{q i}+a_{i q} \bar{a}_{i q}\right)(1-\cosh 2 y)\right. \\
-i \sinh 2 y\left[e^{i \beta}\left(a_{i p} \bar{a}_{i q} \bar{a}_{p i} a_{q i}\right)\right. \\
\left.\left.\quad-e^{-i \beta}\left(\bar{a}_{i p} a_{i q}-a_{p i} \bar{a}_{q i}\right)\right]\right\} \\
=\sum_{i \neq p, q}\left(\left|a_{p i}\right|^{2}+\left|a_{i p}\right|^{2}+\left|a_{q i}\right|^{2}+\left|a_{i q}\right|^{2}\right)(1-\cosh 2 y) \\
\quad-i \sinh 2 y\left(e^{i \beta} K-e^{-i \beta} \bar{K}\right)
\end{gathered}
$$

$$
\begin{equation*}
=G(1-\cosh 2 y)-H \sinh 2 y \tag{17.30}
\end{equation*}
$$

where we define

$$
\begin{align*}
K & =\sum_{i \neq p, q}\left(a_{i p} \bar{a}_{i q}-\bar{a}_{p i}{ }_{q i}\right)  \tag{17.31}\\
H & =i\left(e^{i \beta_{K}}-e^{-i \beta} \bar{K}\right) \\
& =-2 \operatorname{Im}\left(e^{i \beta} K\right)  \tag{17.32}\\
G & =\sum_{i \neq p, q}\left(\left|a_{p i}\right|^{2}+\left|a_{i p}\right|^{2}+\left|a_{q i}\right|^{2}+\left|a_{i q}\right|^{2}\right) \tag{17.33}
\end{align*}
$$

Now let

$$
\begin{equation*}
\Delta_{2} \equiv\left|a_{p p}\right|^{2}+\left|a_{q q}\right|^{2}-\left|a_{p p}^{\prime}\right|^{2}-\left|a_{q q}^{\prime}\right|^{2} \tag{17.34}
\end{equation*}
$$

Then

$$
\begin{aligned}
\Delta_{2}= & a_{p p} \bar{a}_{p p}+a_{q q} \overline{\bar{q}}_{q q}-\frac{1}{2}\left[\left(a_{p p}+a_{q q}\right)\left(\bar{a}_{p p}+\bar{a}_{q q}\right)+D \bar{D}_{c o s h}{ }^{2} 2 y\right. \\
& \left.-i B \bar{D} \sinh 2 y \cosh 2 y+i \bar{B} D \sinh 2 y \cosh 2 y+B \bar{B} \sinh ^{2} 2 y\right]
\end{aligned}
$$

$$
\begin{align*}
= & \frac{1}{2}\left[a_{p p} \bar{a}_{p p}+a_{q q^{2}} \bar{a}_{q q^{-a}} p_{p} \bar{a}_{q q^{-}} \bar{a}_{p p}{ }^{a} q q\right. \\
& -|D|^{2} \cosh ^{2} 2 y-|B|^{2} \sinh ^{2} 2 y \\
& +i(B \bar{D}-\bar{B} D) \sinh 2 y \cosh 2 y] \\
= & \frac{1}{2}\left[\left(a_{p p}-a_{q q}\right)\left(\bar{a}_{p p}-\bar{a}_{q q}\right)-|D|^{2} \cosh ^{2} 2 y\right. \\
& \left.-|B|^{2} \sinh ^{2} 2 y+\frac{1}{2} i(B \bar{D}-\bar{B} D) \sinh 4 y\right] \\
= & \frac{1}{2}\left[-|D|^{2} \sinh ^{2} 2 y-|B|^{2} \sinh ^{2} 2 y+\frac{1}{2} i(B \bar{D}-\bar{B} D) \sinh 4 y\right] \\
= & -\frac{1}{2}\left(|B|^{2}+|D|^{2}\right) \sinh ^{2} 2 y+\frac{i}{4}(B \bar{D}-\bar{B} D) \sinh 4 y . \tag{17.35}
\end{align*}
$$

Finally we define

$$
\begin{equation*}
\Delta_{3} \equiv\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}-\left|a_{p q}^{\prime}\right|^{2}-\left|a_{q p}^{\prime}\right|^{2} \tag{17.36}
\end{equation*}
$$

Then

$$
\begin{aligned}
\Delta_{3}= & \left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}-\frac{1}{2}\left[C \bar{C}+B \bar{B} \cosh { }^{2} 2 y\right. \\
& \left.-i B \bar{D} \sinh 2 y \cosh 2 y+i \bar{B} D \sinh 2 y \cosh 2 y+D \bar{D} \sinh 2{ }^{2} 2 \bar{y}\right] \\
= & \left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}-\frac{1}{2}\left[\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}\right. \\
& -a_{p q} \bar{a}_{q p} e^{-2 i \beta}-a_{q p} \bar{a}_{p q} e^{2 i \beta}+|B|^{2} \cosh ^{2} 2 y \\
& \left.+|D|^{2} \sinh ^{2} 2 y+i(\bar{B} D-B \bar{D}) \sinh 2 y \cosh 2 y\right] \\
= & \frac{1}{2}\left[\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}+2 \operatorname{Re}\left(\bar{a}_{p q}{ }^{2} q p\right) e^{2 i \beta}\right. \\
& -|B|^{2} \cosh ^{2} 2 y-|D|^{2} \sinh ^{2} 2 y \\
& -i(\bar{B} D-B \bar{D}) \sinh 2 y \cosh 2 y] \\
= & \frac{1}{2}\left(|B|^{2}(1-\cosh 22 y)-|D|^{2} \sinh ^{2} 2 y\right. \\
& \left.-\frac{1}{2} i(\bar{B} D-B \bar{D}) \sinh 4 y\right)
\end{aligned}
$$

$$
\begin{equation*}
=\frac{1}{2}\left[-\left(|B|^{2}+|D|^{2}\right) \sinh ^{2} 2 y-\frac{1}{2} i(\overline{B D}-B \bar{D}) \sinh 4 y\right] . \tag{17.38}
\end{equation*}
$$

Combining the results for $\Delta_{2}$ and $\Delta_{3}$ we have

$$
\begin{align*}
\Delta_{2}+\Delta_{3} & =-\left(|B|^{2}+|D|^{2}\right) \sinh ^{2} 2 y-\frac{1}{2} i(\bar{B} D-B \bar{D}) \sinh 4 y \\
& =\frac{1}{2}\left(|B|^{2}+|D|^{2}\right)(1-\cosh 4 y)+\operatorname{Im}(\bar{B} D) \sinh 4 y \tag{17.39}
\end{align*}
$$

Hence we finally obtain

$$
\begin{align*}
\Delta= & \Delta_{1}+\Delta_{2}+\Delta_{3} \\
= & G(1-\cosh 2 y)-H \sinh 2 y+\frac{1}{2}\left(|B|^{2}+|D|^{2}\right)(1-\cosh 4 y) \\
& +\operatorname{Im}(\bar{B} D) \sinh 4 y . \tag{17.40}
\end{align*}
$$

## 18. OPTIMAL SHFAR PARAMETERS

With the definition of the commutator matrix C given by equation (17.21) and the expression for $\Delta$ we obtained in (17.40) we are now in a position to prove the following.

Theorem 18.1 Setting the two.first derivatives of $\Delta$ to zero for the maximum is equivalent to annihilating $c_{p q}^{\prime}$. In fact we have the identity:

$$
\begin{equation*}
c_{p q}^{\prime}=\frac{e^{i \beta}}{2}\left[\frac{i}{2} \cdot \frac{\partial \Delta}{\partial y}-\frac{1}{\sinh 2 y} \cdot \frac{\partial \Delta}{\partial \beta}\right] \tag{18.1}
\end{equation*}
$$

Proof: We recall the formulae of the last section

$$
\begin{align*}
\Delta= & G(1-\cosh 2 y)-H \sinh 2 y+\frac{1}{2}\left(|B|^{2}+|D|^{2}\right)(1-\cosh 4 y) \\
& +\operatorname{Im}(\bar{B} D) \sinh 4 y  \tag{18.2}\\
G= & \sum_{i \neq p, q}\left(\left|a_{p i}\right|^{2}+\left|a_{i p}\right|^{2}+\left|a_{q i}\right|^{2}+\left|a_{i q}\right|^{2}\right) \tag{18.3}
\end{align*}
$$

$$
\begin{align*}
& H=i\left(e^{i \beta} K-e^{-i \beta} \bar{K}\right)  \tag{18.4}\\
& K=\sum_{i \neq p, q}\left(a_{i p} \bar{a}_{i q}-\bar{a}_{p i} a_{q i}\right)  \tag{18.5}\\
& B=a_{p q} e^{-i \beta}+a_{q p} e^{i \beta}  \tag{18.6}\\
& C=a_{p q} e^{-i \beta}-a_{q p} e^{i \beta}  \tag{18.7}\\
& D=a_{p p}-a_{q q}  \tag{18.8}\\
& E=a_{p q}+a_{q p}  \tag{18.9}\\
& F=a_{q p}-a_{p q} \tag{18.10}
\end{align*}
$$

We note also that

$$
\begin{equation*}
c_{p q}=\left(A A^{H}-A^{H}\right)_{p q}=\sum_{i=1}^{n}\left(a_{p i} \bar{a}_{q i}-\bar{a}_{i p} a_{i q}\right) . \tag{18.11}
\end{equation*}
$$

From (18.2) we have

$$
\begin{align*}
\frac{\partial \Delta}{\partial y}=-2 G \sinh 2 y & -2 H \cosh 2 y-2\left(|B|^{2}+|D|^{2}\right) \sinh 4 y \\
& +4 \operatorname{Im}(\overline{B D}) \cosh 4 y . \tag{18.12}
\end{align*}
$$

Also, we have

$$
\begin{equation*}
\frac{\partial H}{\partial \beta}=-e^{i \beta} K-e^{-i \beta} \bar{K} . \tag{18.13}
\end{equation*}
$$

Now

$$
\begin{equation*}
|B|^{2}=\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}+2 \operatorname{Re}\left(\bar{a}_{p q}{ }^{2}{ }_{q p} e^{2 i \beta}\right) \tag{18.14}
\end{equation*}
$$

Thus

$$
\begin{align*}
\frac{\partial|B|^{2}}{\partial \beta} & =4 \operatorname{Re}\left(\bar{a}_{p q}{ }^{2}{ }_{q p}{ }^{i e^{2 i \beta}}\right) \\
& =-4 \operatorname{Im}\left(\bar{a}_{p q}{ }^{a}{ }_{q p} e^{2 i \beta}\right) . \tag{18.15}
\end{align*}
$$

Also

$$
\begin{equation*}
\operatorname{Im}(\overline{B D})=\operatorname{Im}\left[\left(\bar{a}_{p q} e^{i \beta}+\bar{a}_{q p} e^{-i \beta}\right) D\right] \tag{18.16}
\end{equation*}
$$

$$
\begin{align*}
\frac{\partial}{\partial \beta}[\operatorname{Im}(\overline{B D})] & =\operatorname{Im}\left[i D\left(\bar{a}_{p q} e^{i_{\beta}}-\bar{a}_{q p} e^{-i \beta}\right)\right] \\
& =\operatorname{Re}\left[D\left(\bar{a}_{p q} e^{i_{\beta}}-\bar{a}_{q p} e^{-i_{\beta}}\right)\right] \tag{18.17}
\end{align*}
$$

Hence

$$
\begin{aligned}
\frac{\partial \Delta}{\partial \beta}= & \left(e^{i \beta_{\beta}}+e^{-i \beta} \bar{K}\right) \sinh 2 y+4 \operatorname{Im}\left(\bar{a}_{p q}{ }^{2} q_{p} e^{2 i \beta}\right) \sinh ^{2} 2 y \\
& +2 \sinh 2 y \cosh 2 y R e\left[D\left(\bar{a}_{p q} e^{i \beta}-\bar{a}_{q p} e^{-i \beta}\right)\right] \cdot(18.18)
\end{aligned}
$$

We now consider $c_{p q}^{\prime}$. From (18.11) we have

$$
\begin{aligned}
& c_{p q}^{\prime}=\sum_{i=1}^{n}\left(a_{p i}^{\prime} \bar{a}_{q i}^{\prime}-\bar{a}_{i p}^{\prime} a_{i q}^{\prime}\right) \\
& =\sum_{i=1}^{n}\left(a_{p i, q}^{\prime} \bar{a}_{q i}^{\prime}-\bar{a}_{i p}^{\prime} a_{i q}^{\prime}\right) \\
& +a_{p p}^{\prime} \bar{a}_{q p}^{\prime}-\bar{a}_{q p}^{\prime} a_{q q}^{\prime}+a_{p q}^{\prime} \bar{a}_{q q}^{\prime}-\bar{a}_{p p}^{\prime} a_{p q}^{\prime} \\
& =\sum_{i \neq, \mathcal{L}}\left[\left(a_{p i} \operatorname{coshy-ia_{qi}} e^{i \beta} \operatorname{sinhy}\right)\right. \\
& *\left(\bar{a}_{q i} \text { coshy-i } \bar{a}_{p i} e^{i \beta} \operatorname{sinhy}\right) \\
& -\left(\bar{a}_{i p} \operatorname{coshy}+i \bar{a}_{i q} e^{i \beta} \operatorname{sinhy}\right) \\
& \left.*\left(a_{i q} \text { coshy }+i a_{i p} e^{i \beta} \operatorname{sinhy}\right)\right] \\
& +\frac{1}{2} e^{i \beta}\left(-\overline{\mathrm{C}}+\overline{\mathrm{B}} \cosh 2 \mathrm{y}-\mathrm{i} \overline{\mathrm{D}}_{\sinh } 2 \mathrm{y}\right) \\
& \text { *(Dcosh2y-iBsinh2y) } \\
& +\frac{1}{2} e^{i \beta}(C+B \cosh 2 y+i D \sinh 2 y) \\
& \text { * (- } \overline{\mathrm{D}} \cosh 2 \mathrm{y}-\mathrm{i} \overline{\mathrm{~B}} \sinh 2 \mathrm{y}) \\
& =\sum_{i \neq p, q}\left[a_{p i} \bar{a}_{q i} \cosh ^{2} y-a_{q i} \bar{a}_{p i} e^{2 i \beta} \sinh ^{2} y\right. \\
& \left.-\bar{a}_{i p}{ }_{i q} \cosh ^{2} y+\bar{a}_{i q} a_{i p} e^{2 i \beta_{i n h}}{ }^{2} y\right] \\
& -i \sum_{i \neq \beta, \xi}\left[a_{p i} \bar{a}_{p i} e^{i \beta} \text { sinhycoshy+a}{ }_{q i} \bar{a}_{q i} e^{i \beta_{\text {sinhycoshy }}}\right.
\end{aligned}
$$

$$
\begin{align*}
& \left.+a_{i p} \bar{a}_{i p} e^{i \beta_{\text {sinhycoshy }}+a_{i q}} \bar{a}_{i q} e^{i_{\beta}} \text { sinhycoshy }\right] \\
& +\frac{1}{2} e^{i \beta}\left[-\bar{C} D \cosh 2 y+\bar{B} D \cosh ^{2} 2 y-i D \bar{D} \sinh 2 y \cosh 2 y\right. \\
& +i \bar{C} B \sinh 2 y-i B \bar{B} \sinh 2 y \cosh 2 y-\bar{D} B \sinh { }^{2} 2 y \\
& -C \bar{D} \cosh 2 y-B \bar{D} \cosh ^{2} 2 y-i D \bar{D} \sinh 2 y \cosh 2 y \\
& \left.-i C \bar{B} \sinh 2 y-i B \bar{B} \sinh 2 y \cosh 2 y+D \bar{B} \sinh ^{2} 2 y\right] \\
& =\sum_{i \neq p, 2}\left[\cosh ^{2} y\left(a_{p i} \bar{a}_{q i}-\bar{a}_{i p} a_{i q}\right)\right. \\
& \left.+e^{2 i \beta_{s i n h}}{ }^{2} y\left(a_{i p} \bar{a}_{i q} \bar{a}_{p i}{ }^{a_{q i}}\right)\right] \\
& -i e^{i \beta_{\text {sinhycoshy }}} \sum_{i \neq q, q}\left(\left|a_{p i}\right|^{2}+\left|a_{i p}\right|^{2}+\left|a_{q i}\right|^{2}+\left|a_{i q}\right|^{2}\right) \\
& +\frac{1}{2} e^{\mathrm{i} \beta}[\|"\|] \\
& =f_{1}+f_{2} \text { say. }  \tag{18.19}\\
& f_{1}=\left(-\bar{K} \cosh ^{2} y+e^{2 i \beta} \sinh ^{2} y \cdot K\right)-\frac{1}{2} i e^{i \beta} \sinh 2 y \cdot G \\
& =e^{i \beta}\left[-\overline{\mathrm{K}} \frac{1}{2} \mathrm{e}^{-\mathrm{i} \beta}(\cosh 2 \mathrm{y}+1)+\frac{1}{2} \mathrm{e}^{\mathrm{i} \beta} \mathrm{~K}(\cosh 2 \mathrm{y}-1)\right] \\
& -\frac{1}{2} i e^{i \beta} \sinh 2 y . G \\
& =\frac{1}{2} e^{i \beta}\left[\cosh 2 y\left(e^{i \beta} K-e^{-i \beta} \bar{K}\right)-\left(e^{i \beta} K+e^{-i \beta} \bar{K}\right)\right. \\
& \text { - iGsinh2y] } \\
& =\frac{1}{2} e^{i \boldsymbol{\beta}}\left[-i H \cosh 2 y-\left(e^{i \boldsymbol{\beta}} \mathrm{~K}+e^{-\mathrm{i} \boldsymbol{\beta}} \bar{K}\right)-i G \sinh 2 y\right] . \\
& f_{2}=\frac{1}{2} e^{i \beta}\left[-\cosh 2 y(\bar{C} D+C \bar{D})+\cosh ^{2} 2 y(\bar{B} D-B \bar{D})\right.  \tag{18.20}\\
& -2 i D \bar{D} \sinh 2 y \cosh 2 y+i \sinh 2 y(\overline{C B}-C \bar{B}) \\
& \left.-2 i B \bar{B} \sinh 2 y \cosh 2 y+\sinh ^{2} 2 y(D \bar{B}-\bar{D} B)\right]
\end{align*}
$$

$$
\begin{aligned}
=\frac{1}{2} e^{i \beta} & {[-2 \cosh 2 y \cdot \operatorname{Re}(\overline{C D})+2 \sinh 2 y \cdot \operatorname{Im}(C \bar{B})} \\
& +\frac{1}{2}(1+\cosh 4 y)(\overline{\mathrm{B}} D-B \bar{D})-i \sinh 4 y(D \bar{D}+\bar{B} B) \\
& \left.+\frac{1}{2}(\cosh 4 y-1)(D \bar{B}-\bar{D} B)\right]
\end{aligned}
$$

$$
=\frac{1}{2} e^{i \beta}[-2 \cosh 2 y \cdot \operatorname{Re}(\bar{C} D)+2 \sinh 2 y \cdot \operatorname{Im}(C \bar{B})
$$

$$
\left.+\cosh 4 y(\bar{B} D-B \bar{D})-i \sinh 4 y\left(|D|^{2}+|B|^{2}\right)\right]
$$

$$
=\frac{1}{2} e^{i \beta}[-2 \cosh 2 y \cdot \operatorname{Re}(\overline{C D})+2 \sinh 2 y \cdot \operatorname{Im}(C \bar{B})
$$

$$
\begin{equation*}
\left.+2 i \cosh 4 y \cdot \operatorname{Im}(\bar{B} D)-i \sinh 4 y\left(|D|^{2}+|B|^{2}\right)\right] . \tag{18.21}
\end{equation*}
$$

However

$$
\operatorname{Re}(\bar{C} D)=\operatorname{Re}\left(D\left(\bar{a}_{p q} e^{i_{\beta}}-\bar{a}_{q p} e^{-i_{\beta}}\right)\right)
$$

and

$$
\begin{align*}
\operatorname{Im}(\bar{C} \bar{B}) & =\operatorname{Im}\left[\left(a_{p q} e^{-i \beta}-a_{q p} e^{i \beta}\right)\left(\bar{a}_{p q} e^{i \beta}+\bar{a}_{q p} e^{-i \beta}\right)\right] \\
& =\operatorname{Im}\left(a_{p q} \bar{a}_{q p} e^{-2 i \beta}-\bar{a}_{p q} a_{q p} e^{2 i \beta}\right) \\
& =-2 \operatorname{Im}\left(\bar{a}_{p q}{ }^{a} q p e^{2 i_{\beta}}\right) \tag{18.23}
\end{align*}
$$

Hence we obtain

$$
\begin{align*}
c_{p q}^{\prime}=\frac{1}{2} e^{i \beta} & {[-i G \sinh 2 y-i H \cosh 2 y} \\
& -i \sinh 4 y\left(|B|^{2}+|D|^{2}\right)+2 i \cosh 4 y \operatorname{Im}(\bar{B} D) \\
& -\left(e^{i_{\beta} K}+e^{-i \beta} \bar{K}\right) \\
& -4 \sinh 2 y \cdot \operatorname{Im}\left(\bar{a}_{p q} a_{q p} e^{2 i \beta}\right) \\
& -2 \cosh 2 y \cdot \operatorname{Re}\left[D\left(\bar{a}_{p q} e^{i \beta}-\bar{a}_{q p} e^{-i \boldsymbol{i}}\right)\right] \tag{18.24}
\end{align*}
$$

Comparing equations (18.12), (18.18) and (18.24) we see that

$$
\begin{equation*}
c_{p q}^{\prime}=\frac{e^{i \beta}}{2}\left[\frac{i}{2} \cdot \frac{\partial \Delta}{\partial y}-\frac{1}{\sinh 2 y} \cdot \frac{\partial \Delta}{\partial \beta}\right] \tag{18.25}
\end{equation*}
$$

and the theorem is proved.
19. CONDITIONS FOR CONVERGENCE

Before the main theorem we prove some lemmata.
Lemma 19.1

$$
\begin{equation*}
H-2 \operatorname{Im}(\bar{B} D)=-2 \operatorname{Im}\left(c_{p q} e^{-i_{\hat{\beta}}}\right) \tag{19.1}
\end{equation*}
$$

Proof: From (18.4) we have

$$
\begin{align*}
H & =i\left(e^{i \boldsymbol{\beta}} K-e^{-i \boldsymbol{\beta}} \bar{K}\right) \\
& =2 \operatorname{Im}\left(\bar{K} e^{-i \boldsymbol{\beta}}\right) \tag{19.2}
\end{align*}
$$

From (18.6) and (18.8) we have

$$
\begin{align*}
2 \operatorname{Im}(\overline{\mathrm{~B}} \mathrm{D})= & 2 \operatorname{Im}\left[\left(\bar{a}_{p q} e^{i \beta}+\bar{a}_{q p} e^{-i \beta}\right)\left(a_{p p}-a_{q q}\right)\right] \\
= & 2 \operatorname{Im}\left(a_{p p} \bar{a}_{p q} e^{i \beta}-\bar{a}_{p q} a_{q q} e^{i \beta}\right. \\
& \left.+a_{p p} \bar{a}_{q p} e^{-i \beta}-\bar{a}_{q p} a_{q q} e^{-i \beta}\right) \\
= & 2 \operatorname{Im}\left[\left(a_{p p} \bar{a}_{q p}-\bar{a}_{p p} a_{p q}\right) e^{-i \beta}\right. \\
& \left.+\left(a_{p q} \bar{a}_{q q}-\bar{a}_{q p} a_{q q}\right) e^{-i \beta}\right] \tag{19.3}
\end{align*}
$$

using $\operatorname{Im}\left(z e^{i \theta}\right)=-\operatorname{Im}\left(\bar{z} e^{-i \theta}\right)$. From (18.5) and (18.11) we note that

$$
\begin{align*}
\overline{\mathrm{K}}+\left(\bar{a}_{p p} a_{p q}-a_{p p} \bar{a}_{q p}\right) & +\left(\bar{a}_{q p} a_{q q}-a_{p q} \bar{a}_{q q}\right) \\
& =-c_{p q} \tag{19.4}
\end{align*}
$$

Hence

$$
\begin{equation*}
H-2 \operatorname{Im}(\bar{B} D)=-2 \operatorname{Im}\left(c_{p q} e^{-i \beta}\right) \tag{19.5}
\end{equation*}
$$

Lemma 19.2

$$
\begin{equation*}
|H-2 \operatorname{Im}(\bar{B} D)| \leqslant G+|B|^{2}+|D|^{2} \text {. } \tag{19.6}
\end{equation*}
$$

Proof:

$$
\begin{equation*}
|H-2 \operatorname{Im}(\bar{B} D)| \leqslant|H|+2|\operatorname{Im}(\bar{B} D)| . \tag{19.7}
\end{equation*}
$$

Now

$$
\begin{align*}
2|\operatorname{Im}(\bar{B} D)| & \leqslant 2|\bar{B} D| \\
& \leqslant|B|^{2}+|D|^{2} \tag{19.8}
\end{align*}
$$

We therefore wish to show

$$
\begin{equation*}
|H| \leqslant G . \tag{19.9}
\end{equation*}
$$

From (18.4)

$$
\begin{equation*}
H=i\left(e^{i \boldsymbol{\beta}} K-e^{-i \beta} \bar{K}\right)=-2 \operatorname{Im}\left(e^{i \beta} K\right) \tag{19.10}
\end{equation*}
$$

As

$$
\begin{equation*}
K=\sum_{i \neq p-2}\left(a_{i p} \bar{a}_{i q}-\bar{a}_{p i} a_{q i}\right) \tag{19.11}
\end{equation*}
$$

we obtain

$$
\begin{align*}
|H| & \leqslant 2\left|\sum_{i \neq p, q}\left(a_{i p} \bar{a}_{i q}-\bar{a}_{p i} a_{q i}\right)\right|  \tag{19.12}\\
& \leqslant 2 \sum_{i \neq p, q}\left|a_{i p} \bar{a}_{i q}-\bar{a}_{p i} a_{q i}\right| \tag{19.13}
\end{align*}
$$

Now, for any complex numbers $a, b, c, d$ we have

$$
\begin{align*}
2|a \bar{b}-\bar{c} \bar{d}| & \leqslant 2|a \bar{b}|+2|\bar{c} \bar{c}| \\
& \leqslant|a|^{2}+|b|^{2}+|c|^{2}+|\bar{a}|^{2} . \tag{19.14}
\end{align*}
$$

Hence

$$
\begin{align*}
& 2 \sum_{i \neq p, \varepsilon}\left|a_{i p} \bar{a}_{i q}-\bar{a}_{p i} a_{q i}\right| \\
& \quad \leqslant \sum_{i \neq p,}\left[\left|a_{p i}\right|^{2}+\left|a_{i p}\right|^{2}+\left|a_{q i}\right|^{2}+\left|a_{i q}\right|^{2}\right] \\
& \quad=G \tag{19.15}
\end{align*}
$$

Therefore

$$
\begin{equation*}
|H| \leqslant G \tag{19.16}
\end{equation*}
$$

and we obtain

$$
\begin{equation*}
|H-2 \operatorname{Im}(\bar{B} D)| \leqslant G+|B|^{2}+|D|^{2} . \tag{19.17}
\end{equation*}
$$

It follows that, certainly

$$
\begin{align*}
|H-2 \operatorname{Im}(\bar{B} D)| & \leqslant G+|B|^{2}+|D|^{2} \\
& \leqslant G+2\left(|B|^{2}+|D|^{2}\right) \tag{19.18}
\end{align*}
$$

Lemma 19.3

$$
\begin{align*}
G+2\left(|B|^{2}+|D|^{2}\right) & \leqslant 4\|A\|_{E}^{2} \\
& =4 \sum_{i} \sum_{j}\left|a_{i j}\right|^{2} \tag{19.19}
\end{align*}
$$

Now from the definition of $G$ in (18.3) it remains to show

$$
|B|^{2}+|D|^{2} \leqslant 2\left(\left|a_{p p}\right|^{2}+\left|a_{q q}\right|^{2}+\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}\right)
$$

(19.20)

Now

$$
\begin{align*}
|B|^{2} & =\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}+2 \operatorname{Re}\left(\bar{a}_{p q} a_{q p} e^{2 i_{\beta}}\right) \\
& \leqslant\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}+2\left|\bar{a}_{p q} a_{q p}\right| \\
& \leqslant\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}+\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2} \\
& =2\left(\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}\right) . \tag{19.21}
\end{align*}
$$

Also

$$
\begin{aligned}
|D|^{2} & =\left(a_{p p}-a_{q q}\right)\left(\bar{a}_{p p} \bar{a}_{q q}\right) \\
& =\left|a_{p p}\right|^{2}+\left|a_{q q}\right|^{2}-a_{p p} \bar{a}_{q q}-\bar{a}_{p p} a_{q q} \\
& \leqslant\left|a_{p p}\right|^{2}+\left|a_{q q}\right|^{2}-2 \operatorname{Re}\left(a_{p p} \bar{a}_{q q}\right)
\end{aligned}
$$

$$
\begin{align*}
& \leqslant\left|a_{p p}\right|^{2}+\left|a_{q q}\right|^{2}+2\left|a_{p p} \bar{a}_{q q}\right| \\
& \leqslant 2\left(\left|a_{p p}\right|^{2}+\left|a_{q q}\right|^{2}\right) \tag{19.22}
\end{align*}
$$

From (19.21) and (19.22) we have

$$
|B|^{2}+|D|^{2} \leqslant 2\left(\left|a_{p p}\right|^{2}+\left|a_{q q}\right|^{2}+\left|a_{p q}\right|^{2}+\left|a_{q p}\right|^{2}\right)
$$

(19.23)
and hence

$$
\begin{equation*}
G+2\left(|B|^{2}+|D|^{2}\right) \leqslant 4\|A\|_{E}^{2} \tag{19.24}
\end{equation*}
$$

which proves the lemma.
Lemma 19.4 If

$$
\begin{equation*}
\tan \beta=-\frac{\operatorname{Re}\left(c_{p q}\right)}{\operatorname{Im}\left(c_{p q}\right)} \tag{19.25}
\end{equation*}
$$

then

$$
\begin{equation*}
\left|\operatorname{Im}\left(c_{p q} e^{-i \beta}\right)\right|^{2}-\left|c_{p q}\right|^{2}=0 \tag{19.26}
\end{equation*}
$$

Proof: If

$$
\begin{equation*}
\operatorname{Im}\left(c_{p q}\right) \sin \beta+\operatorname{Re}\left(c_{p q}\right) \cos \beta=0 \tag{19.27}
\end{equation*}
$$

then

$$
\begin{equation*}
\operatorname{Re}\left(c_{p q} e^{-i \beta}\right)=0 \tag{19.28}
\end{equation*}
$$

This implies $c_{p q} e^{-i \beta}$ is purely imaginary. Therefore

$$
\begin{align*}
c_{p q} e^{-i \beta} & = \pm i\left|c_{p q} e^{-i \beta}\right| \\
& = \pm i\left|c_{p q}\right| \tag{19.29}
\end{align*}
$$

Thus

$$
\begin{equation*}
\left|\operatorname{Im}\left(c_{p q} e^{-i \beta}\right)\right|^{2}=\left|c_{p q}\right|^{2} \tag{19.30}
\end{equation*}
$$

and the result is proved.

We now prove
Theorem 19.1 Let $\Delta$ denote $\Delta(y)$ where $y$ is defined by

$$
\begin{align*}
-\operatorname{tanhy} & =\frac{H-2 \operatorname{Im}(\bar{B} D)}{2\left[G+2\left(|B|^{2}+|D|^{2}\right)\right]} \\
& =\frac{-\operatorname{Im}\left(c_{p q} e^{-i \beta}\right)}{G+2\left(|B|^{2}+|D|^{2}\right)} \tag{19.31}
\end{align*}
$$

then

$$
\begin{equation*}
\Delta \geqslant \frac{1}{3} \cdot \frac{\left|c_{p q}\right|^{2}}{\|A\|_{E}^{2}} \tag{19.32}
\end{equation*}
$$

Proof: Recalling (17.40)

$$
\begin{align*}
\Delta=G(1-\cosh 2 y) & -H \sinh 2 y+\frac{1}{2}\left(|B|^{2}+|D|^{2}\right)(1-\cosh 4 y) \\
& +\operatorname{Im}(\bar{B} D) \sinh 4 y . \tag{19.33}
\end{align*}
$$

Thus

$$
\begin{aligned}
\Delta= & -2 G \sinh ^{2} y-2 H \operatorname{sinhycoshy} \\
& +\frac{1}{2}\left(|B|^{2}+|D|^{2}\right)\left(-2 \sinh ^{2} 2 y\right) \\
& +4 \operatorname{Im}(\bar{B} D) \operatorname{sinhycoshycosh} 2 y \\
= & -2 G \sinh ^{2} y-4 \sinh ^{2} y \cosh ^{2} y\left(|B|^{2}+|D|^{2}\right) \\
& -2 \sinh y \cosh y[H-2 \operatorname{Im}(\bar{B} D) \cosh 2 y] \\
= & -2 \sinh ^{2} y\left[G+2 \cosh ^{2} y\left(|B|^{2}+|D|^{2}\right)\right] \\
& -2{\sinh y \operatorname{coshy}\left[H-2 I m(\bar{B} D)\left(1+2 \sinh ^{2} y\right)\right]}_{=}-2 \sinh ^{2} y\left[G: 2\left(|B|^{2}+|D|^{2}\right)+2 \sinh ^{2} y\left(|B|^{2}+|D|^{2}\right)\right. \\
& -4 \sinh y \cosh y I m(\bar{B} D)] \begin{aligned}
-2 \sinh ^{2} y \operatorname{coshy}[H-2 \operatorname{Im}(\bar{B} D)]
\end{aligned}
\end{aligned}
$$

$$
\begin{align*}
=- & 2 \sinh ^{2} y\left[G+2\left(|B|^{2}+|D|^{2}\right)+2 \sinh ^{2} y\left(|B|^{2}+|D|^{2}\right)\right. \\
& -4 \operatorname{sinhycoshyIm}(\bar{B} D)] \\
& +4 \operatorname{sinhycoshy} \operatorname{Im}\left(c_{p q} e^{-i \beta}\right) \tag{19.34}
\end{align*}
$$

Therefore

$$
\begin{align*}
\frac{1}{2} \Delta= & 2 \cosh ^{2} y \tanh y \cdot \operatorname{Im}\left(c_{p q} e^{i \beta}\right) \\
& -\cosh ^{2} y \tanh ^{2} y\left[G+2\left(|B|^{2}+|D|^{2}\right)\right. \\
& +2 \sinh ^{2} y\left(|B|^{2}+|D|^{2}\right) \\
& -4 \sinh y \cosh y \operatorname{Im}(\bar{B} D)] . \tag{19.35}
\end{align*}
$$

From (19.1) and (19.31) we obtain

$$
\begin{aligned}
{ }^{\frac{1}{2} \mathbf{A}=}= & \frac{\cosh ^{2} y}{G+2\left(|B|^{2}+|D|^{2}\right)}\left\{2\left|\operatorname{Im}\left(c_{p q} e^{i \boldsymbol{\beta}}\right)\right|^{2}\right. \\
- & \left\{[ \operatorname { I m } ( c _ { p q } e ^ { i \beta } ) ] ^ { 2 } \cdot \left[G+2\left(|B|^{2}+|D|^{2}\right)\right.\right. \\
& +2 \sinh ^{2} y\left(|B|^{2}+|D|^{2}\right)-4 \operatorname{sinhycoshy\operatorname {Im}(\overline {B}D)]\} } \\
& \left./\left[G+2\left(|B|^{2}+|D|^{2}\right)\right]\right\} \\
= & \frac{\cosh ^{2} y\left|c p_{p q}\right|^{2}}{} \begin{aligned}
G+2\left(|B|^{2}+|D|^{2}\right)
\end{aligned} \\
& \left.+2 \sinh ^{2} y\left(|B|^{2}+|D|^{2}\right)-4 \operatorname{sinhycoshyIm}(B D)\right] / \\
& \left./\left[G+2\left(|B|^{2}+|D|^{2}\right)\right]\right\}
\end{aligned}
$$

(from lemma 19.4)

$$
\begin{aligned}
&= \frac{\cosh ^{2} y\left|c_{p q}\right|^{2}}{G+2\left(|B|^{2}+|D|^{2}\right)}\left\{\left[G+2\left(|B|^{2}+|D|^{2}\right)\right.\right. \\
&-2 \sinh ^{2} y\left(|B|^{2}+|D|^{2}\right)+4 \operatorname{sinhycoshy\operatorname {Im}(\overline {B}D)]/} \\
&\left./\left[G+2\left(|B|^{2}+|D|^{2}\right)\right]\right\} \\
&= \frac{\cosh ^{2} y\left|c_{p q}\right|^{2}}{G+2\left(|B|^{2}+|D|^{2}\right)}\{1- \\
&\left.\frac{\left[2 \sinh ^{2} y\left(|B|^{2}+|D|^{2}\right)-4 \operatorname{sinhycoshy\operatorname {Im}(\overline {B}D)]}\right.}{G+2\left(|B|^{2}+|D|^{2}\right)}\right\} .
\end{aligned}
$$

(19.36)

We now consider the expression inside the brackets

$$
\begin{aligned}
&\{1-\left.\frac{\left[2 \sinh ^{2} y\left(|B|^{2}+|D|^{2}\right)-4 \operatorname{sinhycoshy\operatorname {Im}(\overline {B}D)]}\right.}{G+2\left(|B|^{2}+|D|^{2}\right)}\right\} \\
&=1+\sinh ^{2} y\left[-\frac{2\left(|B|^{2}+|D|^{2}\right)}{G+2\left(|B|^{2}+|D|^{2}\right)}\right. \\
&\left.+\frac{4(\operatorname{coshy} / \sinh y) \operatorname{Im}(\bar{B} D)}{G+2\left(|B|^{2}+|D|^{2}\right)}\right] \\
& \geqslant 1+\sinh ^{2} y\left[-1+\frac{4 \operatorname{Im}(\bar{B} D) \cdot \operatorname{coth} y}{G+2\left(|B|^{2}+|D|^{2}\right)}\right] \\
&= {\left[\begin{array}{r}
\sinh { }^{2} y\left[-1+\frac{4 \operatorname{Im}(\bar{B} D)}{\frac{1}{2}(2 \operatorname{Im}(\bar{B} D)-H)}\right] \\
=
\end{array}\right] }
\end{aligned}
$$

$$
\begin{align*}
& =1+2 \sinh ^{2} \mathrm{y}\left[\frac{3 \operatorname{Im}(\overline{\mathrm{~B} D})+\frac{1}{2} \mathrm{H}}{2 \operatorname{Im}(\overline{\mathrm{~B} D})-\mathrm{H}}\right] \\
& \left.\geqslant 1-2 \sinh ^{2} \mathrm{y} \cdot \left\lvert\, \frac{3 \operatorname{Im}(\overline{\mathrm{BD}})+\frac{1}{2} \mathrm{H}}{2 \operatorname{Im}(\overline{\mathrm{~B} D})-\mathrm{H}}\right.\right] \tag{19.37}
\end{align*}
$$

Now

$$
\begin{equation*}
\sinh ^{2} y=1 /\left(\operatorname{coth}^{2} y-1\right) \tag{19.38}
\end{equation*}
$$

therefore

$$
\begin{align*}
\sinh ^{2} y & =\frac{[H-2 \operatorname{Im}(\overline{\mathrm{~B}})]^{2}}{4\left[G+2\left(|\mathrm{~B}|^{2}+|D|^{2}\right)\right]^{2}-[H-2 \operatorname{Im}(\overline{\mathrm{~B} D})]^{2}} \\
& \leqslant \frac{[H-2 \operatorname{Im}(\overline{\mathrm{~B} D})]^{2}}{3\left[G+2\left(|\mathrm{~B}|^{2}+|D|^{2}\right)\right]^{2}} \tag{19.39}
\end{align*}
$$

Therefore

$$
\begin{aligned}
& \left\{1-\frac{\left[2 \sinh ^{2} y\left(|B|^{2}+|D|^{2}\right)-4 \operatorname{sinhycoshy} \operatorname{Im}(\bar{B} D)\right]}{G+2\left(|B|^{2}+|D|^{2}\right)}\right\} \\
& \geqslant 1-2-\frac{1}{3\left[G+2\left(|B|^{2}+|D|^{2}\right)\right]^{2}} \cdot\left|\frac{[2 \operatorname{Im}(\bar{B} D)-H]^{2}}{2 \operatorname{Im}(\bar{B} D)-H}\right| \\
& =1-\frac{2}{3}\left|\frac{[2 \operatorname{Im}(\bar{B} D)-H]\left[3 \operatorname{Im}(\bar{B} D)+\frac{1}{2} H\right]}{\left[G+2\left(|B|^{2}+|D|^{2}\right)\right]^{2}}\right| \\
& \geqslant 1-\frac{2\left[G+|B|^{2}+|D|^{2}\right]\left[\frac{1}{2} G+3\left(|B|^{2}+|D|^{2}\right) / 2\right]}{3\left[G+2\left(|B|^{2}+|D|^{2}\right)\right]^{2}} \\
& =1-\frac{1}{3}\left[\frac{G^{2}+4 G\left(|B|^{2}+|D|^{2}\right)+3\left(|B|^{2}+|D|^{2}\right)^{2}}{\left[G+2\left(|B|^{2}+|D|^{2}\right)\right]^{2}}\right] \\
& \geqslant 1-1 / 3
\end{aligned}
$$

$$
\begin{equation*}
=2 / 3 . \tag{19.40}
\end{equation*}
$$

From lemma 19.3 and using

$$
\begin{equation*}
\cosh ^{2} y \geqslant 1 \tag{19.41}
\end{equation*}
$$

we have from (19.36) and (19.40)

$$
\begin{equation*}
\frac{1}{2} \Delta \geqslant \frac{\left|c_{p q}\right|^{2}}{6\|A\|_{E}^{2}} \tag{19.42}
\end{equation*}
$$

Therefore

$$
\begin{equation*}
\Delta \geqslant \frac{\left|c_{p q}\right|^{2}}{3\|A\|_{E}^{2}} \tag{19.43}
\end{equation*}
$$

which proves the theorem.
We have thus obtained a lower bound for $\Delta$.
Eberlein (1962) has proved sufficient conditions for

$$
\begin{equation*}
\lim _{i \rightarrow \infty} \mathbb{N}^{2}\left(C_{i}\right)=0 . \tag{19.44}
\end{equation*}
$$

It then follows from theorem 19.1 that as $\mathbb{N}^{2}\left(A_{i}\right)$ is a decreasing monotone function bounded below by $\sum\left|\lambda_{i}\right|^{2}$

$$
\begin{equation*}
\left\|A_{i} A_{i}^{H}-A_{i}^{H} A_{i}\right\|_{E}^{2} \rightarrow 0 \tag{19.45}
\end{equation*}
$$

or, equivalently, that

$$
\begin{equation*}
\left\|A_{i}\right\|_{E}^{2} \rightarrow \sum_{i=1}^{n}\left|\lambda_{i}\right|^{2} \tag{19.46}
\end{equation*}
$$

as i increases.

## 20. IMPLEMENTATION

We have closely followed the implementation due to Eberlein (1970) but one major change has been made. Eberlein orders the eigenvalues at the end of each sweep so that

$$
\begin{gather*}
\left|\operatorname{Re}\left(\lambda_{i}\right)\right|+\left|\operatorname{Im}\left(\lambda_{i}\right)\right| \geqslant\left|\operatorname{Re}\left(\lambda_{i+1}\right)\right|+\left|\operatorname{Im}\left(\lambda_{i+1}\right)\right|, \\
i=1,2, \ldots, n-1 . \tag{2.1}
\end{gather*}
$$

With this Ruhe (1968) has shown that the process is ultimately quadratically convergent. We carried out two further experiments. In the first the ordering was such that

$$
\begin{equation*}
\left|\lambda_{1}\right| \geqslant\left|\lambda_{2}\right| \geqslant \ldots \geqslant\left|\lambda_{n}\right| \tag{20.2}
\end{equation*}
$$

and in the second no ordering was used. Over a wide range of examples, including many with multiple eigenvalues, ordering was found to have a negligible effect. The number of rotations needed to almost diagonalise the matrix was nearly always the same and never differed by more than a few per cent but always the running time was less without ordering as the permuting of the rows and columns of the matrix was avoided. We are further encouraged to omit the ordering as in our particular application to simultaneous iteration the matrices upon which the generalised Jacobi method is applied are often diagonally dominant with the diagonal elements such that

$$
\begin{equation*}
\left|a_{11}\right| \geqslant\left|a_{22}\right| \geqslant \ldots \geqslant\left|a_{n n}\right| . \tag{20.3}
\end{equation*}
$$

We note that there is no question of the process not converging whether it is performed with or without ordering; it is simply that it has not been proved that ultimate quadratic convergence can be guaranteed to take place if there is no ordering. However, our experience suggests that, in general, ordering is not necessary and some time can be saved by omitting it. A listing of the program is given in appendix 4.

## 21. RUTISHAUSER'S ALGORITHM

Finally in this chapter we mention an algorithm due to Rutishauser (1964). The algorithm is delightfully simple but we show that convergence can never be proved.

Given an arbitrary matrix A Rutishauser forms the commutator matrix $C$

$$
\begin{equation*}
C=A A^{H}-A^{H} A . \tag{21.1}
\end{equation*}
$$

The element $c_{p q}$ is annihilated using Jacobi's
method for normal matrices. The rotation matrices $R$ needed for this are also used to form

$$
\begin{equation*}
A^{\prime}=R^{H} A R . \tag{21.2}
\end{equation*}
$$

We then choose the larger of $c_{p p}$ and $c_{q q}$, say $c_{p p}$,
and perform a shear on $A^{\prime}$ given by

$$
\begin{equation*}
A^{\prime \prime}=S^{-1} A^{\prime} S \tag{21.3}
\end{equation*}
$$

where

$$
\begin{equation*}
s_{i j}=\delta_{i j} \tag{21.4}
\end{equation*}
$$

save that

$$
\begin{equation*}
s_{p p}=x \tag{21.5}
\end{equation*}
$$

The elements of $A^{\prime \prime}$ are then given by

$$
\begin{array}{lr}
a_{i j}^{\prime \prime}=a_{i j} & i, j \neq p \\
a_{i p}^{\prime \prime}=x \cdot a_{i p}^{\prime} & i \neq p \\
a_{p i}^{\prime \prime}=a_{p i}^{\prime} / x & i \neq p \\
a_{p p}^{\prime \prime}=a_{p p}^{\prime} . & \tag{21.6}
\end{array}
$$

Again we attempt to maximise $\Delta$ given by

$$
\begin{align*}
\Delta & =\sum_{i, i}\left|a_{i j}\right|^{2}-\sum_{i, j}\left|a_{i j}^{\prime}\right|^{2}  \tag{21.7}\\
& =\sum_{i, j}\left|a_{i j}^{\prime}\right|^{2}-\sum_{i, j}\left|a_{i j}^{\prime \prime}\right|^{2}  \tag{21.8}\\
& =\left(1-x^{2}\right) \sum_{i \neq p}\left|a_{i p}\right|^{2}+\left(1-1 / x^{2}\right) \sum_{i \neq p}\left|a_{p i}\right|^{2} \tag{21.9}
\end{align*}
$$

From (21.9)

$$
\begin{equation*}
\frac{d \Delta}{d x^{2}}=-\sum_{i \neq p}\left|a_{i p}\right|^{2}+x^{-4} \sum_{i \not p p}\left|a_{p i}\right|^{2} \tag{21.10}
\end{equation*}
$$

If

$$
\begin{equation*}
\frac{d \Delta}{d x^{2}}=0 \tag{21.11}
\end{equation*}
$$

then

$$
\begin{equation*}
x^{4}=\sum_{i \neq p}\left|a_{p i}\right|^{2} / \sum_{i \neq p}\left|a_{i p}\right|^{2} . \tag{21.12}
\end{equation*}
$$

We then form the new commutator matrix and continue annihilating its elements in a serial fashion.

In attempting to prove convergence we looked
at two possible approaches. Firstly after each rotation-shear pair and secondly after a complete sweep. We have counter examples to show that in both cases $A$ is not nearer to diagonal form than before. The overall process is often convergent but is extremely slow and does not appear to be a contender with the Eberlein type algorithm.

ON THE ORTHONORMALISATION AND BIORTHONORMALISATION OF SETS OF VECTORS

## 1. INTRODUCTION

In this chapter we shall consider firstly the problem of orthogonalising a set of p linearly independent real vectors. The orthogonalised vectors will then be normalised to give an orthonormal set. Thus, if we let

$$
\begin{equation*}
\mathrm{x}=\left[\mathrm{x}_{1}, \mathrm{x}_{2}, \ldots, \mathrm{x}_{\mathrm{p}}\right] \tag{1.1}
\end{equation*}
$$

where the $x_{i}$ are vectors of $n$ components we shall obtain

$$
\begin{equation*}
X^{T} X=I_{p} \tag{1.2}
\end{equation*}
$$

or, equivalently,

$$
\begin{equation*}
\left(x_{i}, x_{j}\right)=\delta_{i j} \tag{1.3}
\end{equation*}
$$

This is solved by the Gram-Schmidt process and is well documented by, for example, Rice (1966) and Björck (1967). We then extend the process to permit the $x_{i}$ to have complex elements and orthonormalise such that, instead of equation (1.2), we have

$$
\begin{equation*}
X^{H_{X}}=I_{p} \tag{1.4}
\end{equation*}
$$

Finally we turn to the problem of biorthonormalisation. That is, given two sets of vectors (which may be complex),

$$
x=\left[x_{1}, x_{2}, \ldots, x_{p}\right]
$$

and

$$
\begin{equation*}
Y=\left[y_{1}, y_{2}, \ldots, y_{p}\right] \tag{1.5}
\end{equation*}
$$

we wish to biorthonormalise such that

$$
\begin{equation*}
Y^{H} X=I_{p} \tag{1.6}
\end{equation*}
$$

or, equivalewtly,

$$
\begin{equation*}
\left(y_{i}, x_{j}\right)=\delta_{i j} \tag{1.7}
\end{equation*}
$$

We note that the Gram-Schmidt process is a particular case of biorthonormalisation given by setting

$$
\begin{equation*}
y_{i}=x_{i}, \quad i=1,2, \ldots, p \tag{1.8}
\end{equation*}
$$

The problem of biorthonormalisation does not appear to have been studied although a passing reference to it is made in Clint and Jennings (1971).

Having discussed the theoretical aspects of these problems we look at the implementation of them on a computer. It is well known, for example Rice (1966), that the classical Gram-Schmidt process is not suitable for automatic computation but that a slight variant of it, the modified Gram-Schmidt process, is well constructed for an electronic computer. Analogously we introduce a modified biorthonormalisation process. For our application to simultaneous iteration we require great accuracy on two points; firstly that the vectors are orthogonal, that is, for a specified $\varepsilon$,

$$
\begin{equation*}
\left(x_{i}, x_{j}\right)<\varepsilon \quad i \neq j \tag{1.9}
\end{equation*}
$$

and secondly the invariance of the original subspace defined by

$$
\begin{equation*}
x=\left[x_{1}, x_{2}, \ldots, x_{p}\right] \tag{1.10}
\end{equation*}
$$

In order to ensure the greatest possible accuracy we introduce reinforcement into our algorithm. This is a device to reorthogonalise any vector
which may be thought to be not strictly orthogonal to its predecessors.

## 2. GRAM-SCHMIDT ORTHONORMALISATION

Suppose we have a set of $p$ linearly independent real vectors, each of $n$ (non-infinite) components, $\left[f_{1}, f_{2}, \ldots, f_{p}\right]$. From these we wish to construct an orthonormal set $\left[\phi_{1}, \phi_{2}, \ldots, \phi_{p}\right]$ such that

$$
\begin{equation*}
\left(\phi_{i}, \phi_{j}\right) \equiv\left(\phi_{i}\right)^{T}\left(\phi_{j}\right)=\delta_{i j} . \tag{2.1}
\end{equation*}
$$

From the set $\left\{f_{i} \mid i=1, \ldots, p\right\}$ we first of all construct an orthogonal set $\left\{\psi_{i} \mid i=1, \ldots, p\right\}$ where

$$
\begin{align*}
\left(\psi_{i}, \psi_{j}\right) & =0 & & i \neq j \\
& \neq 0 & & i=j \tag{2.2}
\end{align*}
$$

and

$$
\begin{align*}
& \psi_{1}=f_{1} \\
& \psi_{2}=a_{21} f_{1}+f_{2} \\
& \cdots \cdots \cdots \cdots  \tag{2.3}\\
& \psi_{k}=\sum_{i=1}^{k-1} a_{k i} f_{i}+f_{k} \quad k=2,3, \ldots, p,
\end{align*}
$$

where the $a_{i j}$ are constants appropriately determined. Consider now the reciprocal system

$$
\begin{align*}
& f_{1}=\psi_{1} \\
& f_{2}=c_{21} \psi_{1}+\psi_{2} \\
& \cdots \cdots \cdot \cdots  \tag{2.4}\\
& f_{k}=\sum_{i=1}^{k-1} c_{k i} \psi_{i}+\psi_{k} \quad k=2,3, \ldots, p .
\end{align*}
$$

We require the $\psi_{i}$ to be orthogonal thus, on taking inner products with $\psi_{i}$, we obtain

$$
\begin{align*}
\left(\psi_{i}, f_{k}\right) & =\sum_{j=1}^{k-1} c_{k j}\left(\psi_{i}, \psi_{j}\right)+\left(\psi_{i}, \psi_{k}\right) \\
& =c_{k i}\left(\psi_{i}, \psi_{i}\right) \tag{2.5}
\end{align*}
$$

Equation (2.5) immediately gives

$$
\begin{equation*}
c_{k i}=\frac{\left(\psi_{i}, f_{k}\right)}{\left(\psi_{i}, \psi_{i}\right)} \tag{2.6}
\end{equation*}
$$

From equation (2.4) we obtain

$$
\begin{align*}
\psi_{k} & =f_{k}-\sum_{i=1}^{k-1} c_{k i} \psi_{i} \\
& =f_{k}-\sum_{i=1}^{k-1} \frac{\left(\psi_{i}, f_{k}\right)}{\left(\psi_{i}, \psi_{i}\right)} \cdot \psi_{i} \quad k=2, \ldots, p \tag{2.7}
\end{align*}
$$

The set $\left\{\psi_{k} \mid k=1, \ldots, p\right\}$ is now orthogonal. If we further demana that it be orthonormal, that is, that

$$
\begin{equation*}
\left(\psi_{i}, \psi_{i}\right)=1 \tag{2.8}
\end{equation*}
$$

we form

$$
\begin{align*}
\phi_{k} & =\psi_{k} /\left\|\psi_{k}\right\| \\
& =\frac{\psi_{k}}{\left(\psi_{k}, \psi_{k}\right)^{\frac{1}{2}}} \tag{2.9}
\end{align*}
$$

and the set $\left\{\phi_{k} \mid k=1, \ldots, p\right\}$ is now an orthonormal
set. (Throughout this chapter \|.\| denotes the 2-norm.)
We may modify equation (2.7) to give

$$
\begin{align*}
\psi_{k}= & f_{k}=\sum_{i=1}^{k-1}\left(\phi_{i}, f_{k}\right) \phi_{i} \quad k=2, \ldots, p \\
& : \phi_{k}=\psi_{k} /\left\|\psi_{k}\right\| \quad k=1,2, \ldots, p . \tag{2.10}
\end{align*}
$$

The above, the classical Gram-Schmidt process, holds for real vectors in which case we note that

$$
\begin{equation*}
(f, g)=(g, f) \tag{2.11}
\end{equation*}
$$

and, for vectors of finite dimension, we take

$$
\begin{equation*}
(f, g)=f^{T} g \tag{2.12}
\end{equation*}
$$

With only slight modification the process holds for complex vectors. However, in this case

$$
\begin{equation*}
(f, g)=\overline{(g, f)} \tag{2.13}
\end{equation*}
$$

where $\bar{z}$ denotes the complex conjugate of $z . ~ A l s o$, analogously to (2.12) we take

$$
\begin{equation*}
(f, g)=f^{H} g . \tag{2.14}
\end{equation*}
$$

We may thus summarise the classical GramSchmidt process as

$$
\begin{align*}
\phi_{1} & =f_{1} /\left\|f_{1}\right\| \\
\phi_{k}^{\prime}=f_{k} & -\sum_{i=1}^{k-1}\left(\phi_{i}, f_{k}\right) \phi_{i} \quad k=2, \ldots, p \\
\phi_{k} & =\phi_{k}^{\prime} /\left\|\phi_{k}^{\prime}\right\| \tag{2.15}
\end{align*}
$$

## 3. MODIFIED GRAM-SCHMIDT

It is well known, see for example Rice (1966), that the classical Gram-Schmidt process is often computationally disastrous. This has led to the introduction of the modified Gram-Schmidt process which we explain below.

In the classical Gram-Schmidt process we
remove, at the $k-t h$ stage, all components of the now orthonormal $f_{1}, f_{2}, \ldots, f_{k-1}$ from $f_{k}$. In the modified process we remove the relevant component of the k-th vector from each of the remaining ( $p-k$ ) vectors. We may summarise the process as follows

$$
\left.\begin{array}{c}
\phi_{1}=f_{1} /\left\|f_{1}\right\| \\
f_{k}^{(i)}=f_{k}^{(i-1)}-\left(\phi_{i}, f_{k}^{(i-1)}\right) \phi_{i}  \tag{3.1}\\
i=1,2, \ldots, k-1 \\
\phi_{k}=f_{k}^{(k-1)} /\left\|f_{k}^{(k-1)}\right\|
\end{array}\right\} k=2, \ldots, p
$$

where we define $f_{k}^{(0)}=f_{k}$.
By comparing equations (2.15) with (3.1) the similarity of the two processes will be seen. It is also apparent that the modified process is easier to implement than the classical one. We now prove the following theorem.

Theorem 3.1 The classical and modified Gram-Schmidt processes are theoretically identical.

Proof: We rewrite the second equation of (2.15) as

$$
\begin{align*}
f_{k}^{(k-1)}= & f_{k}^{(0)}-\left(\phi_{1}, f_{k}^{(0)}\right) \phi_{1}-\left(\phi_{2}, f_{k}^{(0)}\right) \phi_{2}- \\
& -\ldots-\left(\phi_{k-1}, f_{k}^{(0)}\right) \phi_{k-1} \tag{3.2}
\end{align*}
$$

and rewrite (3.1) as

$$
\begin{align*}
f_{k}^{(k-1)}= & f_{k}^{(0)}-\left(\phi_{1}, f_{k}^{(0)}\right) \phi_{1}-\left(\phi_{2}, f_{k}^{(1)}\right) \phi_{2}- \\
& -\ldots-\left(\phi_{k-1}, f_{k}^{(k-2)}\right) \phi_{k-1} \tag{3.3}
\end{align*}
$$

We see that for $p=1$ or 2 the computations involved in the two processes are identical but for $p \geqslant 3$ they are performed in a different order.

To prove that the processes are theoretically the same we need to show that

$$
\left(\phi_{i}, f_{k}^{(0)}\right) \phi_{i}=\left(\phi_{i}, f_{k}^{(i-1)}\right) \phi_{i} \quad 1 \leqslant i \leqslant k-1
$$

Consider

$$
\begin{aligned}
& \left(\phi_{i}, \mathrm{f}_{\mathrm{k}}^{(\mathrm{i}-1)}\right) \phi_{i} \\
& =\left\{\phi_{i},\left[\mathrm{f}_{\mathrm{k}}^{(\mathrm{i}-2)}-\left(\phi_{i-1}, \mathrm{f}_{\mathrm{k}}^{(i-2)}\right) \phi_{i-1}\right]\right\} \phi_{i}
\end{aligned}
$$

(by (3.1))

$$
\begin{equation*}
=\left(\phi_{i}, f_{k}^{(i-2)}\right) \phi_{i}, \tag{3.5}
\end{equation*}
$$

as $\left(\phi_{i}, \phi_{i-1}\right)=0$. Similarly we may show

$$
\begin{equation*}
\left(\phi_{i}, f_{k}^{(i-2)}\right) \phi_{i}=\left(\phi_{i}, f_{k}^{(i-3)}\right) \phi_{i} \tag{3.6}
\end{equation*}
$$

Repeated application gives

$$
\begin{equation*}
\left(\phi_{i}, f_{k}^{(i-1)}\right) \phi_{i}=\left(\phi_{i}, f_{k}^{(0)}\right) \phi_{i} \tag{3.7}
\end{equation*}
$$

Since equation (3.7) holds for all

$$
\begin{equation*}
1 \leqslant i \leqslant k-1 \tag{3.8}
\end{equation*}
$$

it follows that equations (3.2) and (3.3) are identical and the theorem is proved.

Rice (1966) has given a simple error analysis
to show why the classical Gram-Schmidt process may be computationally poor and this we outline.

Suppose that for some value $k$ we have

$$
\begin{equation*}
\left(\phi_{i}, \phi_{j}\right)=\varepsilon_{i j} \quad i, j \leqslant k-1 \tag{3.9}
\end{equation*}
$$

Let

$$
\begin{equation*}
f_{k}=\sum_{i=1}^{k-1} \beta_{i} \phi_{i}+\eta \tag{3.10}
\end{equation*}
$$

where

$$
\begin{equation*}
\left(\eta, \phi_{i}\right)=0 \quad \text { for } \quad 1 \leqslant i \leqslant k-1 . \tag{3.11}
\end{equation*}
$$

Then

$$
\begin{align*}
\phi_{k}^{\prime} & =f_{k}-\sum_{j=1}^{k-1}\left(\phi_{j}, f_{k}\right) \phi_{j} \\
& =\sum_{i=1}^{k-1} \beta_{i} \phi_{i}+\eta-\sum_{j=1}^{k-1}\left[\phi_{j},\left(\sum_{i=1}^{k-1} \beta_{i} \phi_{i}+\eta\right)\right] \phi_{j} \\
& =\eta-\sum_{j=1}^{k-1}\left(\sum_{i \neq j} \beta_{i} \varepsilon_{i j}\right) \phi_{j} . \tag{3.12}
\end{align*}
$$

From equations (3.9) and (3.12)

$$
\begin{align*}
\varepsilon_{k l} & =\left(\phi_{k}, \phi_{l}\right) \\
& =\left(\phi_{k}^{\prime} /\left\|\phi_{k}^{\prime}\right\|, \phi_{l}\right) \\
& =\frac{-\sum_{j=1}^{k-1}\left(\sum_{i \neq j} \beta_{i} \varepsilon_{i j}\right) \varepsilon_{j l}}{\left\|\phi_{k}^{\prime}\right\|} . \tag{3.13}
\end{align*}
$$

Hence non-orthogonality effects are magnified by the factor $1 /\left\|\phi_{k}^{\prime}\right\|$ in the classical Gram-Schmidt process. If, as may quite often happen, $\|\eta\|$ becomes small then $\left\|\phi_{k}^{\prime}\right\|$ becomes small. This increases the $\varepsilon_{i j}$ which makes $\phi_{k}^{\prime}$ tend to become a linear combination of the $\left\{\phi_{i} \mid i=1, \ldots, k-1\right\}$. Thus $\varepsilon_{k, k-1}$ approaches unity and the vectors, instead of being orthogonal, become parallel!

However, the modified Gram-Schmidt process always has $\varepsilon_{k, k-1}=0$ (to machine accuracy). For we have

$$
\begin{align*}
\left(\phi_{i}, f_{k}^{(i)}\right) & =\left(\phi_{i}, f_{k}^{(i-1)}\right)-\left(\phi_{i}, f_{k}^{(i-1)}\right)\left(\phi_{i}, \phi_{i}\right) \\
& =0 . \tag{3.14}
\end{align*}
$$

Rice (1966) has carried out a large number of experiments and all his results support the theoretical findings given above. It is also apparent from the above analysis that if the classical process once loses orthogonality it then always produces almost identical vectors.

However the modified process always generates distinct vectors (even if they are not orthogonal) as we know that $\phi_{k}$ is always orthogonal (to machine accuracy) to $\phi_{\mathrm{k}-1}$.

In addition to the simple analysis given above Björck (1967) has given a complete rounding error analysis of the Gram-Schmidt process. In order to illustrate the difference between the classical and modified processes he gives the following example. Suppose

$$
\left[f_{1}, f_{2}, f_{3}\right]=\left[\begin{array}{lll}
1 & 1 & 1  \tag{3.15}\\
\varepsilon & 0 & 0 \\
0 & \varepsilon & 0 \\
0 & 0 & \varepsilon
\end{array}\right]
$$

where $\varepsilon$ is a small number such that due to the machine round-off error $1+\varepsilon^{2}$ is everywhere put equal to 1. It is easily verified that, if no other rounding errors are made, then the maximum deviation from orthogonality of the
computed $\left\{\emptyset_{i}\right\}$ is given by

$$
\begin{equation*}
\frac{\left|\left(\phi_{3}, \phi_{2}\right)\right|}{\left\|\phi_{3}\right\|_{2}\left\|\phi_{2}\right\|_{2}}=\frac{1}{2} \tag{3.16}
\end{equation*}
$$

for the classical process and

$$
\begin{equation*}
\frac{\left|\left(\phi_{3}, \phi_{1}\right)\right|}{\left\|\phi_{3}\right\|_{2}\left\|\phi_{1}\right\|_{2}}=\sqrt{\frac{2}{3}} \frac{1}{2} \varepsilon \tag{3.17}
\end{equation*}
$$

for the modified process.
4. REINFORCEMENT

By reinforcement we mean reorthogonalising one of the (supposedly orthogonal). $\phi_{k}$ against $\left\{\phi_{i} \mid i=1, \ldots, k-1\right\}$. In general there should be no need to reinforce but if a particular $f_{k}$ is almost parallel to one of the preceding $\phi_{i}$ or if $f_{k}^{(k-1)}$ is a vector all of whose components are small it may well be advisable to take the precaution of reorthogonalising. We have no proof of the validity of the strategy we describe, which was first suggested by Rutishauser (1970), but over a large number of experiments it has been seen to be satisfactory.

At the $k-t h$ stage of the modified Gram-Schmidt process we form successively the inner-products

$$
\begin{equation*}
\left(\phi_{i}, f_{k}^{(i-1)}\right) \quad i=1, \ldots, k-1 \tag{4.1}
\end{equation*}
$$

and finally

$$
\begin{equation*}
\left\|f_{k}^{(k-1)}\right\|=\left(f_{k}^{(k-1)}, f_{k}^{(k-1)}\right)^{\frac{1}{2}} . \tag{4.2}
\end{equation*}
$$

If any of the products (4.1) were large this would be an indication that $\phi_{i}$ and $f_{k}^{(i-1)}$ were nearly parallel and that a large component of $f_{k}$ existed in the $\varnothing_{i}$ direction. The existence and removal of such a large component might well suggest the desirability of reorthogonalising. We might also expect ( $f_{k}^{(k-1)}, f_{k}^{(k-1)}$ ) not to be pathologically small. If this were the case the resulting error in $\phi_{\mathrm{k}}$ defined by (3.1) might be magnified. With these points in mind we form at.the $k$-th step the total t given by

$$
\begin{equation*}
t=\sum_{i=1}^{k-1}\left(\phi_{i}, f_{k}^{(i-1)}\right)^{2} \tag{4.3}
\end{equation*}
$$

and let

$$
\begin{equation*}
s=\left(f_{k}^{(k-1)}, f_{k}^{(k-1)}\right) . \tag{4.4}
\end{equation*}
$$

The possibly undesirable situations we have outlined above correspond to either

$$
\begin{equation*}
t \gg s \tag{4.5}
\end{equation*}
$$

or

$$
\begin{equation*}
s \cdot \varepsilon=0 \tag{4.6}
\end{equation*}
$$

where $\varepsilon$ is the machine precision. As a typical value for $\varepsilon$ is $0\left(10^{-12}\right)$ if equation (4.6) is true it is clear that every component of $f_{k}^{(k-1)}$ must be very small. In this case we assume $f_{k}$ to be linearly dependent upon $\left\{\phi_{i} \mid i=1, \ldots, k-1\right\}$ and set

$$
\begin{equation*}
\phi_{k} \equiv 0 . \tag{4.7}
\end{equation*}
$$

If however relation (4.5) is true but (4.6) is not we reorthogonalise $f_{k}^{(k-1)}$. It is a relatively arbitrary choice but we replace (4.5) by the test Is $t \geqslant 100.5 ?$

If so, we reịnforce $f_{k}$; otherwise we accept $\phi_{k}$ and proceed to $f_{k+1^{\prime}}$. The factor of 100 appears to err on the side of caution but does not cause many unnecessary reinforcements to be performed. As a high degree of orthogonality is required in our application this is the factor we have used throughout.

## 5. COMPUTATIONAL FORMULATION

The modified Gram-Schmidt process is delightfully easy to program and follows exactly the theoretical formulation given in equations (3.1). The tests for reinforcement are as given in section
4. Two versions of the program are needed; one is for the case of real vectors, the other for the complex case. The latter is similar to the real case with all the complex arithmetic performed using only real variables. Both routines use a separate subprogram to calculate the inner-products and, for the complex case, three additional subprograms are required. Full details of the programming are to be found in chapter 5 and
listings of the orthonormalisation routines are included in appendix 5 (real case) and appendix 6 (complex case).

## 6. BIORTHONORMALISATION

We have just discussed the problem of orthonormalisation and we now turn to that of biorthonormalisation. Thus given two sets of $p$ vectors with $n$ components ( $p \leqslant n$ ), $\left\{f_{i} \mid i=1, \ldots, p\right\}$ and $\left\{g_{i} \mid i=1, \ldots, p\right\}$ it is possible, subject to certain conditions (in this case rather more stringent than those of the Gram-Schmidt process), to biorthogonalise the vectors to give two new $\operatorname{set}\left\{\psi_{i}^{\prime} \mid i=1, \ldots, p\right\}$ and $\left\{\phi_{i}^{\prime} \mid i=1, \ldots, p\right\}$ such that

$$
\begin{align*}
\left(\psi_{i}^{\prime}, \not \phi_{j}^{\prime}\right) & =0 & & i \neq j \\
& \neq 0 & & i=j . \tag{6.1}
\end{align*}
$$

We may further demand biorthonormalisation of the sets $\left\{\psi_{i}\right\}$ and $\left\{\phi_{i}\right\} ;$

$$
\begin{align*}
\left(\psi_{i}, \phi_{j}\right) & =0 & & i \neq j \\
& =1 & & i=j . \tag{6.2}
\end{align*}
$$

We assume from the outset that $\left\{f_{i}\right\}$ and $\left\{g_{i}\right\}$
may be complex and express $\psi_{i}$ and $\phi_{i}$ in terms of
our original sets $\{f\}$ and $\{g\}$. Thus

$$
\begin{aligned}
& \psi_{1}=f_{1} \\
& \psi_{2}=a_{21} f_{1}+f_{2}
\end{aligned}
$$

$$
\begin{equation*}
\psi_{k}=\sum_{i=1}^{k-1} a_{k i} f_{i}+f_{k} \quad k=2, \ldots, p \tag{6.3}
\end{equation*}
$$

and

$$
\begin{align*}
& \phi_{1}=g_{1} \\
& \phi_{2}=b_{21} g_{1}+g_{2} \\
& \cdots \cdot \cdots  \tag{6.4}\\
& \phi_{k}=\sum_{i=1}^{k-1} b_{k i} g_{i}+g_{k} \quad k=2, \ldots, p
\end{align*}
$$

where the $a_{i j}$ and $b_{i j}$ are appropriately determined. Consider now the reciprocal systems

$$
\begin{align*}
& f_{1}=\psi_{1} \\
& f_{2}=c_{21} \psi_{1}+\psi_{2} \\
& \cdots \cdot \cdots  \tag{6.5}\\
& f_{k}=\sum_{i=1}^{k-1} c_{k i} \psi_{i}+\psi_{k} \quad k=2, \ldots, p
\end{align*}
$$

and

$$
\begin{align*}
& \mathrm{g}_{1}=\phi_{1} \\
& \mathrm{~g}_{2}=\mathrm{d}_{21} \phi_{1}+\phi_{2} \\
& \cdots \cdot \cdot \cdot \cdots  \tag{6.6}\\
& \mathrm{~g}_{\mathrm{k}}=\sum_{i=1}^{k-1} \mathrm{~d}_{\mathrm{ki}} \phi_{i}+\phi_{\mathrm{k}} \quad \mathrm{k}=2, \ldots, \mathrm{p} .
\end{align*}
$$

We require the $\psi_{i}$ and $\phi_{i}$ to be biorthogonal thus, on taking inner-products of (6.5) with $\phi_{i}$ and of (6.6) with $\psi_{i}$, we obtain

$$
\begin{equation*}
\left(\phi_{i}, f_{k}\right)=c_{k i}\left(\phi_{i}, \psi_{i}\right) \tag{6.7}
\end{equation*}
$$

and

$$
\begin{equation*}
\left(\psi_{i}, g_{k}\right)=d_{k i}\left(\psi_{i}, \phi_{i}\right) . \tag{6.8}
\end{equation*}
$$

These equations immediately give

$$
\begin{equation*}
c_{k i}=\frac{\left(\phi_{i}, f_{k}\right)}{\left(\phi_{i}, \psi_{i}\right)} \tag{6.9}
\end{equation*}
$$

and

$$
\begin{equation*}
d_{k i}=\frac{\left(\psi_{i}, g_{k}\right)}{\left(\psi_{i}, \phi_{i}\right)} \tag{6.10}
\end{equation*}
$$

Where we define the inner-products exactly as before in section 2. From equations (6.5) and (6.6) we obtain

$$
\begin{align*}
\psi_{k} & =f_{k}-\sum_{i=1}^{k-1} c_{k i} \psi_{i} \\
& =f_{k}-\sum_{i=1}^{k-1} \frac{\left(\phi_{i}, f_{k}\right)}{\left(\phi_{i}, \psi_{i}\right)} \cdot \psi_{i} \tag{6.11}
\end{align*}
$$

and

$$
\begin{align*}
\phi_{k} & =g_{k}-\sum_{i=1}^{k-1} d_{k i} \phi_{i} \\
& =g_{k}-\sum_{i=1}^{k-1} \frac{\left(\psi_{i}, g_{k}\right)}{\left(\psi_{i}, \phi_{i}\right)} \cdot \phi_{i} . \tag{6.12}
\end{align*}
$$

The sets $\left\{\psi_{i} \mid i=1, \ldots, p\right\}$ and $\left\{\phi_{i} \mid i=1, \ldots, p\right\}$ are now biorthogonal. If we further demand that they be biorthonormal, that is, that

$$
\begin{equation*}
\left(\psi_{i}, \phi_{i}\right)=1=\left(\phi_{i}, \psi_{i}\right) \tag{6.13}
\end{equation*}
$$

we may modify equations (6.11) and (6.12) to give

$$
\begin{equation*}
\psi_{k}^{\prime}=f_{k}-\sum_{i=1}^{k-1}\left(\phi_{i}, f_{k}\right) \psi_{i} \tag{6.14}
\end{equation*}
$$

and

$$
\begin{equation*}
\phi_{\mathrm{k}}^{\prime}=\mathrm{g}_{\mathrm{k}}-\sum_{i=1}^{k-1}\left(\psi_{i}, g_{k}\right) \phi_{i} . \tag{6.15}
\end{equation*}
$$

The question of how to calculate the normalising factor is much more complicated than in the GramSchmidt process and we leave a full discussion to section 8. However the obvious approach, by analogy with the previous sections, would be to form

$$
\begin{equation*}
\left(\phi_{k}, \psi_{k}\right)=\overline{\left(\psi_{k}, \phi_{k}\right)} \tag{6.16}
\end{equation*}
$$

and then to take

$$
\begin{align*}
& \psi_{\mathrm{k}}^{\prime}=\frac{\psi_{\mathrm{k}}}{\left(\phi_{\mathrm{k}}, \psi_{\mathrm{k}}\right)^{\frac{1}{2}}}  \tag{6.17}\\
& \phi_{\mathrm{k}}^{\prime}=\frac{\phi_{\mathrm{k}}}{\left(\phi_{\mathrm{k}}, \psi_{\mathrm{k}}\right)^{\frac{1}{2}}} \tag{6.18}
\end{align*}
$$

Whilst this is theoretically acceptable in practice it may not be satisfactory as we see in section 8 .

## 7. MODIFIED BIORTHONORMALISATION

We summarise the biorthonormalisation process
as:
Biorthonormalise $f_{1}$ and $g_{1}$ to give $\psi_{1}$ and $\phi_{1}$ such that $\left(\psi_{1}, \phi_{1}\right)=1$,

$$
\left.\begin{array}{c}
\psi_{k}^{\prime}=f_{k}-\sum_{i=1}^{k-1}\left(\phi_{i}, f_{k}\right) \psi_{i} \\
\phi_{k}^{\prime}=g_{k}-\sum_{i=1}^{k-1}\left(\psi_{i}, g_{k}\right) \phi_{i} \\
\text { biorthonormalise } \psi_{k}^{\prime} \text { and } \phi_{k}^{\prime} \text { to give } \\
\psi_{k} \text { and } \phi_{k} \text { such that }\left(\psi_{k}, \phi_{k}\right)=1
\end{array}\right\} k=2, \ldots, p
$$

Following section 3 it seems natural to introduce
the modified biorthonormalisation process in which, at the k-th stage, we remove the relevant components of the $k$-th vector from each of the remaining (p-k-) vectors. This contrasts with equations (7.1) in which we remove all components of the first (k-1) biorthonormal vectors from the k-th one. We may summarise the modified process as follows:

Biorthonormalise $f_{1}$ and $g_{1}$ to give $\psi_{1}$ and $\phi_{1}$ such that $\left(\psi_{1}, \phi_{1}\right)=1$,

$$
\left.\begin{array}{l}
f_{k}^{(i)}=f_{k}^{(i-1)}-\left(\phi_{i}, f_{k}^{(i-1)}\right) \psi_{i} \\
g_{k}^{(i)}=g_{k}^{(i-1)}-\left(\psi_{i}, g_{k}^{(i-1)}\right) \phi_{i}
\end{array}\right\} \quad i=1, \ldots, k-1
$$

biorthonormalise $\mathrm{f}_{\mathrm{k}}^{(\mathrm{k}-1)}$ and $\mathrm{g}_{\mathrm{k}}^{(\mathrm{k}-1)}$ to
give $\psi_{k}$ and $\phi_{k}$ such that $\left(\psi_{k}, \phi_{k}\right)=1$

$$
\begin{equation*}
k=2, \ldots, p \tag{7.2}
\end{equation*}
$$

where we define $f_{k}^{(0)}=f_{k}$ and $g_{k}^{(0)}=g_{k}$.
Comparison between equations (7.1) and (7.2)
shows the similarity of the processes and again reveals that the modified one is easier to implement. We now prove the following theorem. Theorem 7.1 The classical and modified biorthonormalisation processes are theoretically identical.

Proof: We consider firstly equations (7.1)
rewritten as

$$
\begin{align*}
f_{k}^{(k-1)}= & f_{k}^{(0)}-\left(\phi_{1}, f_{k}^{(0)}\right) \psi_{1}-\left(\phi_{2}, f_{k}^{(0)}\right) \psi_{2}- \\
& -\ldots-\left(\phi_{k-1}, f_{k}^{(0)}\right) \psi_{k-1}  \tag{7.3}\\
g_{k}^{(k-1)}= & g_{k}^{(0)}-\left(\psi_{1}, g_{k}^{(0)}\right) \phi_{1}-\left(\psi_{2}, g_{k}^{(0)}\right) \phi_{2}- \\
& -\ldots-\left(\psi_{k-1}, g_{k}^{(0)}\right) \phi_{k-1} \tag{7.4}
\end{align*}
$$

and equations (7.2) we write as

$$
\begin{align*}
f_{k}^{(k-1)}= & f_{k}^{(0)}-\left(\phi_{1}, f_{k}^{(0)}\right) \psi_{1}-\left(\phi_{2}, f_{k}^{(1)}\right) \psi_{2}- \\
& -\ldots-\left(\phi_{k-1}, f_{k}^{(k-2)}\right) \psi_{k-1}  \tag{7.5}\\
g_{k}^{(k-1)}= & g_{k}^{(0)}-\left(\psi_{1}, g_{k}^{(0)}\right) \phi_{1}-\left(\psi_{2}, \mathrm{~g}_{k}^{(1)}\right) \phi_{2}- \\
& -\ldots-\left(\psi_{k-1}, \mathrm{~g}_{\mathrm{k}}^{(\mathrm{k}-2)}\right) \phi_{\mathrm{k}-1} . \tag{7.6}
\end{align*}
$$

Again we can see that for $p=1$ or 2 the computations involved in the processes are identical but for $p \geqslant 3$ they are performed in a different order.

To prove the two schemes are identical we need to show that
and

$$
\left.\begin{array}{l}
\left(\phi_{i}, f_{k}^{(0)}\right) \psi_{i}=\left(\phi_{i}, f_{k}^{(i-1)}\right) \psi_{i}  \tag{7.7}\\
\left(\psi_{i}, g_{k}^{(0)}\right) \phi_{i}=\left(\psi_{i}, g_{k}^{(i-1)}\right) \phi_{i}
\end{array}\right\} 1 \leqslant i \leqslant k-1
$$

Consider

$$
\begin{align*}
& \left(\phi_{i}, f_{k}^{(i-1)}\right) \psi_{i} \\
& \quad=\left\{\phi_{i},\left[f_{k}^{(i-2)}-\left(\phi_{i-1}, f_{k}^{(i-2)}\right) \psi_{i-1}\right]\right\} \psi_{i} \\
& \quad=\left(\phi_{i}, f_{k}^{(i-2)}\right) \psi_{i},
\end{align*}
$$

as $\left(\phi_{i}, \psi_{i-1}\right)=0$. Similarly we may show

$$
\begin{equation*}
\left(\phi_{i}, f_{k}^{(i-2)}\right) \psi_{i}=\left(\phi_{i}, f_{k}^{(i-3)}\right) \psi_{i} \tag{7.10}
\end{equation*}
$$

and, by repeated application of (7.2), that

$$
\begin{equation*}
\left(\phi_{i}, f_{k}^{(i-1)}\right) \psi_{i}=\left(\phi_{i}, f_{k}^{(0)}\right) \psi_{i} . \tag{7.11}
\end{equation*}
$$

A similar argument shows that

$$
\begin{equation*}
\left(\psi_{i}, \mathrm{~g}_{\mathrm{k}}^{(\mathrm{i}-1)}\right) \phi_{\mathrm{i}}=\left(\psi_{\mathrm{i}}, \mathrm{~g}_{\mathrm{k}}^{(0)}\right) \phi_{\mathrm{i}} . \tag{7.12}
\end{equation*}
$$

Since equations (7.11) and (7.12) hold for all

$$
\begin{equation*}
1 \leqslant i \leqslant k-1 \tag{7.13}
\end{equation*}
$$

it follows that the theorem is proved.
Identical analysis to that used in section 3 shows the inherent instability of the classical biorthonormalisation process and for the modified biorthonormalisation process shows a stability similar to that for the modified Gram-Schmidt process. We have carried out extensive tests of both the classical and modified biorthonormalisation programs and the experimental evidence strongly supports the theoretical analysis. Indeed there would seem to be no reason whatever to implement either the classical Gram-Schmidt or the classical biorthonormalisation as, in both cases, the modified schemes are easier to program and give better results.

We included reinforcement in our biorthonormalisation scheme utilising the technique of section 4 and applying it to both sets of vectors.

Thus we form

$$
t_{L}=\sum_{i=1}^{k-1}\left|\left(\phi_{i}, f_{k}^{(i-1)}\right)\right|^{2}
$$

and

$$
\begin{equation*}
t_{R}=\sum_{i=1}^{k-1}\left|\left(\psi_{i}, g_{k}^{(i-1)}\right)\right|^{2} \tag{7.14}
\end{equation*}
$$

in place of equation (4.3). We replace equation (4.4) by

$$
\begin{equation*}
s=\left|\left(g_{k}^{(k-1)}, f_{k}^{(k-1)}\right)\right| \tag{7.15}
\end{equation*}
$$

We now perform the tests given in section. 4 independently to both $t_{I}$ and $t_{R}$ and reinforce if either result suggests that it is necessary.

## 8. NORMALISATION

There is one very important difference between orthogonalisation and biorthogonalisation. In the Gram-Schmidt process the inner-product ( $\varnothing_{\mathrm{k}}, \varnothing_{\mathrm{k}}$ ) is always real and positive irrespective of whether the vectors are real or complex. Hence

$$
\begin{equation*}
\left\|\phi_{k}\right\|=\left(\phi_{k}, \phi_{k}\right)^{\frac{1}{2}} \tag{8.1}
\end{equation*}
$$

is always real. However, in the case of biorthonormalisation, there is no reason why, for real vectors, $\left(\phi_{\mathrm{k}}, \psi_{\mathrm{k}}\right)$ should be positive and hence $\left(\phi_{k}, \psi_{k}\right)^{\frac{1}{2}}$ may be complex. If it is desired to remain wholly within the real plane then the sign of each of the components of one of the vectors $\phi_{k}$ or $\psi_{k}$ should be changed.

This leads us to consider how the normalisation should be performed. We saw at the end of section 6 that theoretically we may take, for an unnormalised $\psi_{k}$ and $\phi_{k}$,

$$
\begin{align*}
& \psi_{k}^{\prime}=\frac{\psi_{k}}{\left(\phi_{k}, \psi_{k}\right)^{\frac{1}{2}}}  \tag{8.2}\\
& \phi_{k}^{\prime}=\frac{\phi_{k}}{\left(\phi_{k}, \psi_{k}\right)^{\frac{1}{2}}} . \tag{8.3}
\end{align*}
$$

Unfortunately there is no reason why this should give us

$$
\begin{equation*}
\left\|\psi_{k}^{\prime}\right\|=O\left(\left\|\phi_{\mathrm{k}}^{\prime}\right\|\right) \tag{8.4}
\end{equation*}
$$

and in practice the two norms are often wildly different. We therefore propose the following. We wish to determine

$$
\begin{equation*}
\psi_{k}^{\prime}=\psi_{k} / \lambda \quad \text { and } \quad \phi_{k}^{\prime}=\phi_{k} / \mu . \tag{8.5}
\end{equation*}
$$

such that

$$
\begin{equation*}
\left(\psi_{k}^{\prime}, \phi_{k}^{\prime}\right)=\frac{\left(\psi_{k}, \phi_{k}\right)}{\bar{\lambda} \mu}=1 \tag{8.6}
\end{equation*}
$$

together with

$$
\begin{equation*}
\left\|\psi_{\mathrm{k}}^{\prime}\right\|=\left\|\phi_{\mathrm{k}}^{\prime}\right\| . \tag{8.7}
\end{equation*}
$$

Equations (8.5) give

$$
\begin{equation*}
\left\|\psi_{k}^{\prime}\right\|=\frac{\left\|\psi_{k}\right\|}{|\lambda|} \quad \text { and } \quad\left\|\phi_{k}^{\prime}\right\|=\frac{\left\|\phi_{k}\right\|}{|\mu|} \tag{8.8}
\end{equation*}
$$

Thus, dropping the subscript $k$,

$$
\begin{equation*}
\frac{\|\boldsymbol{\psi}\|}{|\lambda|}=\frac{\|\phi\|}{|\mu|} \tag{8.9}
\end{equation*}
$$

giving

$$
\begin{equation*}
\frac{|\lambda|}{|\mu|}=\frac{\|\psi\|}{\|\phi\|} . \tag{8.10}
\end{equation*}
$$

Equation (8.6) gives

$$
\begin{equation*}
\bar{\lambda}_{\mu}=(\psi, \phi) \tag{8.11}
\end{equation*}
$$

thus (8.10) yields

$$
\begin{equation*}
|\lambda|^{2}=\frac{\|\psi\|}{\|\phi\|} \cdot|(\psi, \phi)| . \tag{8.12}
\end{equation*}
$$

Similarly we may obtain

$$
\begin{equation*}
|\mu|^{2}=\frac{\|\phi\|}{\|\psi\|} \cdot|(\psi, \phi)| . \tag{8.13}
\end{equation*}
$$

Hence $(8.11),(8.12),(8: 13)$ are satisfied by

$$
\begin{equation*}
\bar{\lambda}=\|\psi\|\left[\frac{(\psi, \phi)}{\|\phi\| \cdot\|\psi\|}\right]^{\frac{1}{2}} \tag{8.14}
\end{equation*}
$$

and

$$
\begin{equation*}
\mu=\|\phi\|\left[\frac{(\psi, \phi)}{\|\phi\| \cdot\|\psi\|}\right]^{\frac{1}{2}} \tag{8.15}
\end{equation*}
$$

Hence equations (8.5) and (8.15) give us a method for normalising such that

$$
\begin{equation*}
\left\|\psi_{k}^{\prime}\right\|=\left\|\phi_{k}^{\prime}\right\| \tag{8.16}
\end{equation*}
$$

We have implanented the above in our program and found it most satisfactory. The implementation is straightforward, as is the rest of the biorthonormalisation process, and a complete listing is included in appendix 7 .

## 9. APPLICABIIITY

We know that in order to be able to orthogonalise a pair of vectors using the Gram-Schmidt process they must be linearly independent. In order to be able to biorthogonalise two sets of vectors we must have that, at each stage,

$$
\begin{equation*}
\left(\phi_{i}, \psi_{i}\right) \neq 0 \quad i=1, \ldots, p . \tag{9.1}
\end{equation*}
$$

Some rather long and tedious manipulation of equations (6.11) and (6.12) shows that this is equivalent to demanding. that at the k-th stage

$$
\operatorname{det}\left[\begin{array}{cccc}
\left(f_{1}, g_{1}\right) & \left(f_{1}, g_{2}\right) & \ldots . & \left(f_{1}, g_{k}\right)  \tag{9.2}\\
\left(f_{2}, g_{1}\right) & \left(f_{2}, g_{2}\right) & \ldots . & \left(f_{2}, g_{k}\right) \\
\cdots & \ldots & \ldots . & \ldots . . . . \\
\left(f_{k}, g_{1}\right) & \left(f_{k}, g_{2}\right) & \ldots & \left(f_{k}, g_{k}\right)
\end{array}\right] \neq 0
$$

Conversely if equation (9.2) is true for all $k$ then it is possible to biorthonormalise the two sets of vectors.

## 1. INTRODUCTION

In this chapter we give an account of some of the more commonly used iterative methods for solving the eigenvalue problem. Most methods are essentially iterative in nature but here we confine ourselves to those which are concerned with the determination of no more than a few eigensolutions.

We restrict ourselves for the moment to
matrices having linear elementary divisors. For any such matrix A we have

$$
\begin{align*}
A & =X \cdot \operatorname{diag}\left(\lambda_{i}\right) X^{-1} \\
& =X \Delta Y^{H} \\
& =\sum_{i=1}^{n} \lambda_{i} X_{i} y_{i}^{H} \tag{1.1}
\end{align*}
$$

where the rows $y_{i}^{H}$ of $Y^{H}$ and the columns $x_{i}$ of $X$ are the left-hand and right-hand eigenvectors of A normalised such that

$$
\begin{equation*}
y_{i}^{H} x_{i}=1 \tag{1.2}
\end{equation*}
$$

Hence

$$
\begin{align*}
A^{S} & =X \cdot \operatorname{diag}\left(\lambda_{i}^{S}\right) Y^{H} \\
& =\sum_{i=1}^{n} \lambda_{i}^{S} x_{i} y_{i}^{H} \quad s=1,2,3, \ldots \tag{1.3}
\end{align*}
$$

and if

$$
\begin{equation*}
\left|\lambda_{1}\right| \geqslant\left|\lambda_{2}\right| \geqslant \ldots \geqslant\left|\lambda_{r}\right|>\left|\lambda_{r+1}\right| \geqslant \ldots \geqslant\left|\lambda_{n}\right| \tag{1.4}
\end{equation*}
$$

the expression on the right of (1.3) is ultimately dominated by the terms $\sum_{i=1}^{r} \lambda_{i}^{s} x_{i} y_{i}^{H}$. This is the
fundamental result on which the methods of this chapter are based. We note also that it is the basis of both the LR and $Q R$ algorithms and we begin by looking briefly at these.

## 2. THE LR ALGORITHM

Before continuing with the discussion of methods leading up to simultaneous iteration we look at the LR algorithm due to Rutishauser (1958) and the $Q R$ algorithm of Francis (1961). We shall show that there is a close theoretical similarity between simultaneous iteration and the $L R$ and $Q R$ algorithms.

Rutishauser's algorithm is based on the triangular decomposition of a matrix and we write

$$
\begin{equation*}
A=L R \tag{2.1}
\end{equation*}
$$

where $L$ is unit lower triangular and $R$ is upper triangular. We now consider

$$
\begin{equation*}
\mathrm{I}^{-1} \mathrm{AL}=\mathrm{I}^{-1}(\mathrm{LR}) \mathrm{L}=\mathrm{RL} \tag{2.2}
\end{equation*}
$$

Hence if we perform a triangular decomposition of
A and then multiply the factors in the reverse order we obtain a matrix similar to $A$. In the $I R$ algorithm this process is repeated indefinitely and, renaming the original matrix $A_{1}$, the algorithm is defined by the equations

$$
\begin{equation*}
A_{s-1}=I_{s-1} R_{s-1} ; \quad R_{s-1} L_{s-1}=A_{s} \quad s=2,3, \ldots \tag{2.3}
\end{equation*}
$$

We know $A_{S}$ is similar to $A_{s-1}$ and hence, by induction, to $A_{1}$. Rutishauser showed that under certain restrictions

$$
L_{s} \longrightarrow I
$$

and

$$
R_{s} \rightarrow A_{s} \rightarrow\left[\begin{array}{cccc}
\lambda_{1} & & &  \tag{2.4}\\
& \lambda_{2} & & x \\
& & & \\
& & & \\
& & & \lambda_{n}
\end{array}\right] \text { as } s \rightarrow \infty
$$

We now derive some relations between the successive iterates which we shall•find of use later. From equations (2.3) we have

$$
\begin{equation*}
A_{S}=L_{S-1}^{-1} A_{S-1} I_{S-1} \tag{2.5}
\end{equation*}
$$

and, by repeated application, it follows that

$$
\begin{equation*}
A_{s}=\left(I_{s-1}^{-1} L_{s-2}^{-1} \cdots \cdots L_{1}^{-1}\right) A_{1}\left(I_{1} L_{2} \ldots . L_{s-1}\right) \tag{2.6}
\end{equation*}
$$

c.r

$$
\begin{equation*}
L_{1} I_{2} \ldots . I_{s-1} A_{s}=A_{1} I_{1} L_{2} \ldots I_{s-1} \tag{2.7}
\end{equation*}
$$

The matrices $T_{S}$ and $U_{S}$ defined by

$$
\begin{equation*}
T_{s}=I_{1} L_{2} \ldots L_{s} \text { and } U_{s}=R_{s} R_{s-1} \ldots R_{1} \tag{2.8}
\end{equation*}
$$

are unit lower triangular and upper triangular respectively. We now consider their product.

$$
\begin{aligned}
& T_{S} U_{S}=I_{1} L_{2} \ldots L_{S-1}\left(L_{s} R_{s}\right) R_{s-1} \ldots R_{2} R_{1} \\
& =I_{1} L_{2} \ldots I_{s-1} A_{s} R_{s-1} \ldots R_{2} R_{1} \\
& =A_{1} L_{1} I_{2} \quad \cdots \cdot I_{s-1} R_{s-1} \cdots \cdots R_{2} R_{1}
\end{aligned}
$$

$$
\begin{equation*}
=A_{1} T_{S-1} U_{S-1} \tag{2.9}
\end{equation*}
$$

Repeated application of this result gives us that

$$
\begin{equation*}
T_{S} U_{S}=A_{1}^{S} \tag{2.10}
\end{equation*}
$$

Thus $T_{S} U_{S}$ is the triangular decomposition of $A_{1}^{S}$.

## 3. CONVERGENCE OF THE IR ALGORITHM

We assume initially that the eigenvalues of
$A_{1}$ satisfy

$$
\begin{equation*}
\left|\lambda_{1}\right|>\left|\lambda_{2}\right|>\ldots>\left|\lambda_{n}\right| \tag{3.1}
\end{equation*}
$$

Since $A_{1}$ must then have linear divisors we may write

$$
\begin{equation*}
A_{1}^{S}=\operatorname{Xdiag}\left(\lambda_{i}^{S}\right) X^{-1}=X D^{S} Y \tag{3.2}
\end{equation*}
$$

We define the matrices $\mathrm{I}_{\mathrm{X}}, \mathrm{U}_{\mathrm{X}}, \mathrm{I}_{\mathrm{Y}}$ and $\mathrm{U}_{\mathrm{Y}}$ by the relations

$$
\begin{equation*}
X=L_{X} U_{X} \quad ; \quad Y=I_{Y} U_{Y} \tag{3.3}
\end{equation*}
$$

where the U's are upper triangular and the L's unit lower triangular. All four matrices are independent of $s$ and the triangular decompositions exist only if all the leading principal minors of $X$ and. $Y$ are non-zero. From equations (3.3) we have

$$
\begin{align*}
A_{1}^{S} & =X D^{S} Y \\
& =L_{X} U_{X} D^{S} I_{Y} U_{Y} \\
& =I_{X} U_{X}\left(D^{S_{S}} I_{Y} D^{-S}\right) D^{S} U_{Y} \tag{3.4}
\end{align*}
$$

Clearly $D^{s} L_{Y} D^{-S}$ is a unit lower triangular matrix and its (i,j) element is given by

$$
\begin{equation*}
l_{i j}\left(\lambda_{i} / \lambda_{j}\right)^{s} \quad \text { when.i> } j \tag{3.5}
\end{equation*}
$$

and hence we may write

$$
\begin{equation*}
D^{s} L_{\mathrm{Y}} \mathrm{D}^{-\mathrm{s}}=I+\mathrm{E}_{\mathrm{s}} \quad \text { where } E_{\mathrm{s}} \rightarrow 0 \text { as } \mathrm{s} \rightarrow \infty \text {. } \tag{3.6}
\end{equation*}
$$

Equation (3.4) therefore gives

$$
\begin{align*}
A_{1}^{S} & =I_{X} U_{X}\left(D^{s} L_{Y} D^{-s}\right) D^{S} U_{Y} \\
& =I_{X} U_{X}\left(I+E_{S}\right) D^{s} U_{Y} \\
& =I_{X}\left(I+U_{X} E_{S} U_{X}^{-1}\right) U_{X} D^{s} U_{Y} \\
& =I_{X}\left(I+F_{s}\right) U_{X} D^{D_{S_{U}}} \\
& \quad \text { where } F_{S} \rightarrow 0 \text { as } s \rightarrow \infty . \tag{3.7}
\end{align*}
$$

The matrix ( $I+F_{s}$ ) has a triangular decomposition for all sufficiently large $s$ and, since $F_{s} \rightarrow 0$, both the factors of the decomposition tend to I. For small values of $s$ this decomposition may not exist corresponding to the case which arises when a principal minor of some $A_{S}$ is zero. Ignoring this possibility we see that, in the notation of the previous section,

$$
\begin{equation*}
\mathrm{T}_{\mathrm{s}} \longrightarrow \mathrm{I}_{\mathrm{X}} . \tag{3.8}
\end{equation*}
$$

From this it follows that $A_{s}$ tends to upper triangular form with the $\lambda_{i}$ in the correct order on the diagonal.

If one or more of the leading principal
minors of $Y$ vanishes Wilkinson (1965) has shown
that there is nevertheless a permutation matrix $P$ such that $P Y$ has a triangular decomposition. Denoting this by $I_{Y} U_{Y}$ we have

$$
\begin{equation*}
A_{1}^{S}=X D^{S} P^{T} L_{Y} U_{Y}=\left(X P^{T}\right)\left(P D^{S_{S}} P^{T}\right) I_{Y} U_{Y} \tag{3.9}
\end{equation*}
$$

If $X P^{T}$ has a triangular decomposition $I_{X} U_{X}$, that is if all its leading principal minors are nonzero, then we can show as before that

$$
\begin{equation*}
\mathrm{T}_{\mathrm{s}} \longrightarrow \mathrm{I}_{\mathrm{X}} \tag{3.10}
\end{equation*}
$$

and $A_{S}$ tends to a triangular matrix with $D P^{T}$ as its diagonal.

## 4. EIGENVALUES OF EQUAL MODULUS

We now consider the case when $A_{1}$ has some eigenvalues of equal modulus but all its elementary divisors are linear. We assume that all the leading principal minors of $X$ and $Y$ are non-zero as we have just considered the case when they are not. We have

$$
\begin{equation*}
A_{1}^{S}=X D^{S} L_{Y} U_{Y} \tag{4.1}
\end{equation*}
$$

Suppose

$$
\begin{equation*}
\left|\lambda_{r}\right|=\left|\lambda_{r+1}\right|=\ldots=\left|\lambda_{t}\right| \tag{4.2}
\end{equation*}
$$

and all the other eigenvalues have distinct moduli. The elements of $D^{s} L_{Y^{D}} D^{-s}$ in the ( $i, j$ ) position below the diagonal therefore tend to zero unless

$$
\begin{equation*}
t \geqslant i>j \geqslant r \tag{4.3}
\end{equation*}
$$

in which case they remain equal in modulus to $I_{i j}$.

When all the eigenvalues of equal modulus are in fact equal we may write

$$
D^{S} I_{Y} D^{-S}=I+E_{S} \quad \text { where } E_{S} \rightarrow 0 \text { as } s \rightarrow \infty
$$

where $I$ is a fixed unit lower triangular matrix which is equal to $I$, except for the elements in position (i,j) which satisfy (4.3) where they are equal to $l_{i j}$. If we write

$$
\begin{equation*}
X I=I_{X} U_{X} \tag{4.5}
\end{equation*}
$$

then we have

$$
\begin{aligned}
A_{1}^{S} & =X\left(D^{S} I_{Y} D^{-S}\right) D^{S} U_{Y} \\
& =X\left(I+E_{S}\right) D^{S} U_{Y} \\
& =I_{X} U_{X}\left(I+I^{-1} E_{S}\right) D^{S} U_{Y} \\
& =I_{X}\left(I+U_{X} I^{-1} E_{S} U_{X}^{-1}\right) U_{X} D^{S} U_{Y} \\
& =I_{X}\left(I+F_{S}\right) U_{X} D^{S} U_{Y} \quad \text { where } F_{S} \rightarrow 0 \text { as } s \rightarrow \infty .(4.6)
\end{aligned}
$$

The matrix $\left(I+F_{S}\right)$ has, as before, a triangular decomposition for all sufficiently large $s$ and, since $F_{s} \rightarrow 0$, both the factors of the decomposition tend to I. Hence we see again that

$$
\begin{equation*}
T_{S} \longrightarrow I_{X} \tag{4.7}
\end{equation*}
$$

where $I_{X}$ is the matrix obtained by factorising XL.
We notice that the columns of XI are a set of linearly independent eigenvectors of $A_{1}$ since $X L$ differs from $X$ only in that columns $r$ to $t$ are
replaced by combinations of themselves. Thus
multiple eigenvalues corresponding to linear divisors do not prevent convergence.

If the eigenvalues are of equal modulus but are not actually equal then the matrix $L$ is of a similar form as before but the non-zero subdiagonal elements are not now fixed. If

$$
\begin{equation*}
\lambda_{i}=\left|\lambda_{i}\right| \exp \left(i \theta_{i}\right) \tag{4.8}
\end{equation*}
$$

we have

$$
\begin{equation*}
I_{i j}=I_{i j} \exp \left[i s\left(\theta_{i}-\theta_{j}\right)\right] . \tag{4.9}
\end{equation*}
$$

The matrix $X L$ is fixed apart from columns r to t. For each value of $s$ these columns consist of a linear combination of the corresponding columns of $X$. Thus in the $I_{X} U_{X}$ decomposition of $X I$ all columns of $I_{X}$ are fixed except for columns $r$ to $t$ and hence, apart from these columns, $T_{s}$ is convergent.

We also mention for the sake of completeness that if $A_{1}$ is symmetric and positive definite the process is always convargent, irrespective of the multiplicities of the eigenvalues. Further details may be found in Wilkinson (1965).

## 5. THE QR ALGORITHM

We now turn to the QR algorithm of Francis
(1951). In place of the triangular decomposition used in the LR algorithm Francis uses a
factorisation into the product of a unitary matrix $Q$ and an upper triangular matrix $R$.

The algorithm is defined by the equations

$$
\begin{align*}
A_{S} & =Q_{S} R_{S} \\
A_{S+1} & =Q_{S}^{H} A_{S} Q_{S} \\
& =Q_{S}^{H} Q_{S} R_{S} Q_{S} \\
& =R_{S} Q_{S} \tag{5.1}
\end{align*}
$$

and at each stage we see that we are now using a unitary transformation in place of the general similarity transformation of the LR algorithm given by equations (2.3). The factorisation of $A_{S}$ is essentially unique and indeed it is unique if we take the diagonal elements of $R_{s}$ to be real and positive. The advantage of this factorisation is that the vanishing of a principal minor of $A_{S}$ does not cause a breakdown of the process as it does in the $L R$ decomposition. We note that if $A_{S}$ is real both $Q_{S}$ and $R_{S}$ are real.

The successive iterates satisfy relations similar to those for the LR algorithm which we derived in section 2. We have

$$
\left.\begin{array}{rl}
A_{s+1} & =Q_{s}^{H} A_{s} Q_{s} \\
& =Q_{s}^{H}\left(Q_{s-1}^{H} A_{s-1} Q_{s-1}\right) Q_{s} \\
& =\left(Q_{s}^{H} Q_{s-1}^{H} \cdots \cdots\right. \tag{5.2}
\end{array} Q_{1}^{H}\right) A_{1}\left(Q_{1} Q_{2} \ldots Q_{s}\right),
$$

[^0]which gives us
\[

$$
\begin{equation*}
Q_{1} Q_{2} \ldots \cdot Q_{s} A_{s+1}=A_{1} Q_{1} Q_{2} \ldots Q_{s} . \tag{5.3}
\end{equation*}
$$

\]

All $A_{s}$ are therefore unitarily similar to $A_{1}$ and if we define $P_{S}$ and $U_{S}$ by

$$
\begin{equation*}
P_{S}=Q_{1} Q_{2} \ldots Q_{S} ; \quad U_{S}=R_{s} R_{s-1} \ldots . R_{1} \tag{5.4}
\end{equation*}
$$

and consider their product we obtain

$$
\begin{align*}
P_{S} U_{S} & =Q_{1} Q_{2} \cdots \cdots Q_{S-1}\left(Q_{S} R_{S}\right) R_{S-1} \cdots \cdots R_{1} \\
& =Q_{1} Q_{2} \cdots \cdots Q_{S-1} A_{s} R_{S-1} \cdots \cdots R_{1} \\
& =A_{1} Q_{1} Q_{2} \cdots \cdot Q_{s-1} R_{S-1} \cdots \cdots R_{1} \\
& =A_{1} P_{s-1} U_{S-1} \cdots \tag{5.5}
\end{align*}
$$

Hence

$$
\begin{equation*}
P_{S} U_{S}=A_{1}^{S} \tag{5.6}
\end{equation*}
$$

Thus $P_{S} U_{S}$ is the factorisation of $A_{1}^{s}$.

## 6. CONVERGENCE OF THE QR ALGORITHM

In general the matrix $A_{s}$ tends to upper
triangular form under similar, but less stringent, conditions than were necessary for convergence of the LR algorithm. We note firstly one small difference between the two algorithms.

If $A_{1}$ is already an upper triangular matrix
the LR algorithm gives us

$$
\begin{equation*}
L_{1}=I ; \quad R_{1}=A_{1} \tag{6.1}
\end{equation*}
$$

and hence

$$
\begin{equation*}
A_{S}=A_{1} \quad \text { for all } \mathrm{s} \tag{6.2}
\end{equation*}
$$

This is not true however for the $Q R$ algorithm if we insist that $R_{s}$ should have positive diagonal elements. Writing

$$
\begin{equation*}
a_{i i}=\left|a_{i i}\right| \exp \left(i \theta_{i}\right), \quad D=\operatorname{diag}\left(\exp \left(i \theta_{i}\right)\right) \tag{6.3}
\end{equation*}
$$

we have

$$
\begin{equation*}
A_{1}=D\left(D^{-1} A_{1}\right), \quad A_{2}=D^{-1} A_{1} D \tag{6.4}
\end{equation*}
$$

Hence, although $A_{2}$ has the same diagonal elements as $A_{1}$ the super diagonal elements are multiplied by complex factors of modulus unity. Obviously we cannot have $A_{S}$ tending to a strict limit unless all the eigenvalues are real and positive. However, the factors of modulus unity are of little importance and we say that $A_{S}$ is essentially convergent if

$$
\begin{equation*}
A_{S+1} \longrightarrow D^{-1} A_{S} D \tag{6.5}
\end{equation*}
$$

asymptotically for some unitary diagonal matrix D.
The proof of convergence is very similar to that given for the LR algorithm. We assume initially that the eigenvalues of $A_{1}$ satisfy

$$
\begin{equation*}
\left|\lambda_{1}\right|>\left|\lambda_{2}\right|>\ldots>\left|\lambda_{n}\right| . \tag{6.6}
\end{equation*}
$$

As before we may write

$$
\begin{equation*}
A_{1}^{S}=X D^{S} \tag{6.7}
\end{equation*}
$$

but we now define $Q, R, L$ and $U$ by

$$
\begin{equation*}
X=Q R, \quad Y=L U \tag{6.8}
\end{equation*}
$$

where $R$ and $U$ are upper triangular, $L$ is unit lower
triangular and $Q$ is unitary. The $Q R$ decomposition always exists but, as before, the triangular decomposition of $Y$ exists only if all its leading principal minors are non-zero. The non-singularity of $R$ follows from that of $X$. An analysis similar to that in section 3 gives us

$$
\begin{equation*}
A_{1}^{S}=Q\left(I+F_{S}\right) R D^{S} U \tag{6.9}
\end{equation*}
$$

where

$$
\begin{equation*}
F_{S}=R E_{S} R^{-1} \tag{6.10}
\end{equation*}
$$

and

$$
\begin{equation*}
\mathrm{F}_{\mathrm{s}} \longrightarrow 0 \quad \text { as } \mathrm{s} \longrightarrow \infty \tag{6.11}
\end{equation*}
$$

The matrix ( $I+F_{s}$ ) may be factorised into the product of a unitary matrix $Q_{S}$ and an upper triangular $\operatorname{matrix} R_{S}$ and, since $F_{S} \rightarrow 0, Q_{S}$ and $R_{S}$ both tend to I. Hence we have

$$
\begin{equation*}
A_{1}^{S}=\left(Q Q_{S}\right)\left(R_{S} R D_{U}^{S}\right) . \tag{6.12}
\end{equation*}
$$

The first factor of (6.12) is unitary and the second is upper triangular. Provided $A_{1}^{S}$ is non-singular its factorisation into this product is unique and hence

$$
\begin{equation*}
P_{S}=Q Q_{S} \tag{6.13}
\end{equation*}
$$

except possibly for a multiplying diagonal unitary matrix. Hence $P_{S}$ converges essentially to $Q$. If we insist additionally that all $\mathrm{R}_{\mathrm{s}}$ have positive
diagonal elements then it is possible to calculate the unitary diagonal factor from equation (6.12).

The proof shows that provided all leading principal minors of $Y$ are non-zero we not only have convergence but that the eigenvalues are correctly ordered on the diagonal. Although $Y$ will not have a triangular decomposition when one of its principal minors vanishes there is always a permutation matrix $P$ so that PY has such a decomposition. The reasoning is the same as that for the LR algorithm given in section 3 .

## 7. EIGENVALUES OF EQUAI MODULUS

We again assume that $A_{1}$ has linear elementary divisors but that some of its eigenvalues are of equal modulus. The analysis is similar to that of section 4 except that we replace equation (4.5) by

$$
\begin{equation*}
X L=Q R \tag{7.1}
\end{equation*}
$$

which gives us

$$
\begin{align*}
A_{1}^{S} & =Q R\left(I+L^{-1} E_{S}\right) D^{S} U \\
& =Q\left(I+R L^{-1} E_{S} R^{-1}\right) R D^{S} U \\
& =Q\left(I+F_{S}\right) R D^{S_{U}} \\
& =\left(Q Q_{S}\right)\left(R_{S} R D^{S} U\right) \quad \text { where } F_{S} \rightarrow 0 \text { as } s \rightarrow \infty \tag{7.2}
\end{align*}
$$

where $Q_{S} R_{S}$ is the factorisation of $\left(I+F_{S}\right)$. Hence $P_{S}$ tends to $Q$ which is the matrix obtained by
factorising XL. The rest of the discussion is as for the LR algorithm given in section 4.

## 8. THE POWER METHOD

The simplest application of the idea of section 1 is to the power method for determining the dominant eigensolution. Let $u_{0}$ be an arbitrary vector and let the sequences $v_{s}$ and $u_{s}$ be defined by the equations

$$
\begin{align*}
& v_{s+1}=A u_{s} \\
& u_{s+1}=v_{s+1} / \max \left(v_{s+1}\right) \tag{8.1}
\end{align*}
$$

where we use the notation $\max (x)$ to denote the element of maximum modulus of the vector $x$. Clearly we have

$$
\begin{equation*}
u_{s}=A^{s} u_{0} / \max \left(A^{s} u_{0}\right) \tag{8.2}
\end{equation*}
$$

and if we write

$$
\begin{equation*}
u_{0}=\sum_{i}^{n} a_{i} x_{i} \tag{8.3}
\end{equation*}
$$

then, apart from the normalising factor, $u_{s}$ is given by

$$
\begin{equation*}
\sum_{1}^{n} a_{i} \lambda_{i}^{s} x_{i}=\lambda_{1}^{s}\left[a_{1} x_{1}+\sum_{2}^{n} a_{i}\left(\lambda_{i} / \lambda_{1}\right)^{s} x_{i}\right] \tag{8.4}
\end{equation*}
$$

If $\left|\lambda_{1}\right|>\left|\lambda_{2}\right| \geqslant\left|\lambda_{3}\right| \geqslant \ldots \geqslant\left|\lambda_{n}\right|$ then, provided $a_{1} \neq 0$,
we have

$$
\begin{equation*}
u_{s} \longrightarrow x_{1} / \max \left(x_{1}\right) \text { and } \max \left(v_{s}\right) \longrightarrow \lambda_{1} \cdot \tag{8.5}
\end{equation*}
$$

Hence this process provides simultaneously the
dominant eigenvalue and the corresponding eigenvector. If $\left|\lambda_{1} / \lambda_{2}\right|$ is close to unity the
convergence is very slow.
If there are a number of independent eigenvectors corresponding to the dominant eigenvalue this does not affect the convergence. Thus if

$$
\lambda_{1}=\lambda_{2}=\cdots=\lambda_{r}
$$

and

$$
\begin{equation*}
\left|\lambda_{1}\right|>\left|\lambda_{r+1}\right| \geqslant \ldots \geqslant\left|\lambda_{n}\right| \tag{8.6}
\end{equation*}
$$

we have

$$
\begin{align*}
A^{S} u_{0} & =\lambda_{1}^{S}\left[\sum_{i}^{r} a_{i} x_{i}+\sum_{r+1}^{n} a_{i}\left(\lambda_{i} / \lambda_{1}\right)^{S} x_{i}\right] \\
& \longrightarrow \lambda_{1}^{S} \sum_{i}^{r} a_{i} x_{i} \tag{8.7}
\end{align*}
$$

The iterates therefore tend to some vector lying in the subspace spanned by the eigenvectors ( $\mathrm{x}_{1}, \ldots . \mathrm{x}_{\mathrm{r}}$ ), the limit depending upon the initial vector $u_{0}$.

## 9. COMPLEX CONJUGATE EIGENVALUES

If the dominant eigenvalues of a real matrix are a complex conjugate pair $\lambda_{1}$ and $\bar{\lambda}_{1}$ the iterated vectors will not converge. In fact if $x_{1}$ and $\bar{x}_{1}$ are the corresponding eigenvectors an arbitrary real vector $u_{0}$ is expressible in the form

$$
\begin{equation*}
u_{o}=a_{1} x_{1}+\bar{a}_{1} \bar{x}_{1}+\sum_{i=3}^{n} a_{i} x_{i} . \tag{9.1}
\end{equation*}
$$

Hence we have

$$
\begin{align*}
A^{s} u_{0}= & r_{1}^{s}\left[\rho_{1} e^{i(a+s \theta)} x_{1}+\rho_{1} e^{-i(a+s \theta)} \bar{x}_{1}\right. \\
& \left.+\sum_{3}^{n} a_{i}\left(\lambda_{i} / r_{1}\right) x_{x_{i}}\right] \tag{9.2}
\end{align*}
$$

where

$$
\begin{equation*}
\lambda_{1}=r_{1} e^{i \theta} ; \quad a_{1}=\rho_{1} e^{i a} \tag{9.3}
\end{equation*}
$$

The components of $x_{3}, \ldots, x_{n}$ ultimately die out, but if we write

$$
\begin{equation*}
v_{s+1}=A u_{s}, \quad \max \left(v_{s+1}\right)=k_{s+1}, \quad u_{s+1}=v_{s+1} / k_{s+1} \tag{9.4}
\end{equation*}
$$

it is clear from (9.2) that neither $k_{s+1}$ nor $u_{s+1}$ tend to a limit. If we denote the j-th component of $x_{1}$ by $\xi_{j} \exp \left(i \phi_{j}\right)$ equation (9.2) gives

$$
\begin{equation*}
\left(A^{s} u_{o}\right)_{j} \longrightarrow 2 \rho_{1} r_{1}^{s} \xi_{j} \cos \left(a+\phi_{j}+s \theta\right) \tag{9.5}
\end{equation*}
$$

and hence the components of $u_{s}$ oscillate in sign.
If $\lambda_{1}$ and $\bar{\lambda}_{1}$ are the roots of

$$
\begin{equation*}
\lambda^{2}-p \lambda-q=0 \tag{9.6}
\end{equation*}
$$

we have

$$
\begin{equation*}
\left(A^{s+2}-p A^{s+1}-q A^{s}\right) u_{0} \longrightarrow 0, s \rightarrow \infty \tag{9.7}
\end{equation*}
$$

or

$$
\begin{equation*}
k_{s+1} k_{s+2} u_{s+2}-p k_{s+1} u_{s+1}-q u_{s} \longrightarrow 0 \tag{9.8}
\end{equation*}
$$

and hence ultimately any three successive iterates are linearly dependent. By the method of least squares we can determine successive approximations $p_{s}$ and $q_{S}$ to $p$ and $q$. We have

$$
\begin{align*}
k_{s+1} k_{s+2} & {\left[\begin{array}{c}
u_{s+1}^{T} u_{s+2} \\
u_{s}^{T} u_{s+2}
\end{array}\right] } \\
& =\left[\begin{array}{cc}
u_{s+1}^{T} u_{s+1} & u_{s+1}^{T} u_{s} \\
u_{s}^{T} u_{s+1} & u_{s}^{T} u_{s}
\end{array}\right]\left[\begin{array}{c}
p_{s} k_{s+1} \\
q_{s}
\end{array}\right] \tag{9.9}
\end{align*}
$$

When $p_{s}$ and $q_{s}$ have tended to limits $p$ and $q$, $\lambda_{1}$ and $\bar{\lambda}_{1}$ may be computed from the relations

$$
\begin{equation*}
\operatorname{Re}\left(\lambda_{1}\right)=\frac{1}{2} p, \quad \operatorname{Im}\left(\lambda_{1}\right)=\frac{1}{2}\left(p^{2}+4 q\right)^{\frac{1}{2}} . \tag{9.10}
\end{equation*}
$$

## 10. SIMULTANEOUS DETERMINAMION OF SEVERAL EIGENVALUES

The essential feature of the previous section is the determination of two eigenvalues from a single sequence of iterates. The fact that the eigenvalues were complex conjugate is really not pertinent and the method may be extended to cover the determination of several real or complex eigenvalues. Suppose for example that

$$
\begin{equation*}
\left|\lambda_{1}\right| \geqslant\left|\lambda_{2}\right| \geqslant\left|\lambda_{3}\right|>\left|\lambda_{4}\right| \geqslant \ldots \geqslant\left|\lambda_{n}\right| . \tag{10.1}
\end{equation*}
$$

The components of $x_{4}$ to $x_{n}$ will die out rapidly in the iterated vectors and we shall soon reach a stage at which $u_{s}$ is effectively given by $a_{1} x_{1}+a_{2} x_{2}+a_{3} x_{3}$. If we define quantities $p_{2}, p_{1}$ and $p_{0}$ by the equation

$$
\begin{equation*}
\left(\lambda-\lambda_{1}\right)\left(\lambda-\lambda_{2}\right)\left(\lambda-\lambda_{3}\right) \equiv \lambda^{3}+p_{2} \lambda^{2}+p_{1} \lambda+p_{0} \tag{10.2}
\end{equation*}
$$

then

$$
\begin{equation*}
\left(A^{3}+p_{2} A^{2}+p_{1} A+p_{0} I\right) u_{s}=0 \tag{10.3}
\end{equation*}
$$

giving

$$
-\left(A^{3} u_{s}\right)=\left(A^{2} u_{s}, A u_{s}, u_{s}\right)\left[\begin{array}{l}
p_{2}  \tag{10.4}\\
p_{1} \\
p_{0}
\end{array}\right]
$$

The coefficients $p_{i}$ may therefore be obtained by least squares from any four consecutive iterates following $u_{s}$.

The use of such a technique would have most to recommend it when $\left|\lambda_{1}\right|,\left|\lambda_{2}\right|$ and $\left|\lambda_{3}\right|$ were close, since it is in such circumstances that the iterates are slow to converge to the dominant eigenvector. Unfortunately if $\lambda_{1}, \lambda_{2}$ and $\lambda_{3}$ are of the same sign and close together the equations determining the $p_{i}$ are ill-conditioned. For these reasons the method is of little practical value. In general to determine $r$ eigenvalues in a wellconditioned manner we require $r$ independent sets of iterated vectors. Such methods we discuss later.

## 11. DEFLATION

If $A$ is real and has real eigenvalues it is possible to employ shifts of origin to give
convergence either to $\lambda_{1}$ or to $\lambda_{n}$. In the case of complex matrices, by using appropriate shifts of origin, we could in principle make a number of the eigenvalues dominant in turn but in practice this device would usually be prohibitively difficult to use.

It is natural to ask whether we can make use of our knowledge of $\lambda_{1}$ and $x_{1}$ in such a way that another eigenvector may be found without danger of again converging to $x_{1}$. One class of such methods depends essentially on replacing A by a matrix which possesses only the remaining eigenvalues. We shall refer to such methods as methods of deflation.

Probably the simplest is that due to Hotelling (1933) which can be applied when an eigenvalue $\lambda_{1}$ and vector $x_{1}$ of a symmetric matrix $A_{1}$ are known. If we define $A_{2}$ by the relation

$$
\begin{equation*}
A_{2}=A_{1}-\lambda_{1} x_{1} x_{1}^{T} \quad \text { where } x_{1}^{T} x_{1}=1 \tag{11.1}
\end{equation*}
$$

then from the orthogonality of the $x_{i}$ we have

$$
\begin{array}{rlrl}
A_{2} x_{i}=A_{1} x_{i}-\lambda_{1} x_{1} x_{1}^{T} x_{i} & =0, \quad i=1 \\
& =\lambda_{i} x_{i}, & i \neq 1 . \tag{11.2}
\end{array}
$$

Hence the eigenvalues of $A_{2}$ are $0, \lambda_{2}, \ldots, \lambda_{n}$ corresponding to eigenvectors $x_{1}, x_{2}, \ldots, x_{n}$ and the dominant eigenvalue $\lambda_{1}$ has been reduced to

## zero.

When $A_{1}$ is unsymmetric there is a corresponding
deflation technique also due to Hotelling (1933) but it requires the determination of the left-hand eigenvector $y_{1}$ as well as $\mathrm{x}_{1}$. If both are determined and normalised so that $\mathrm{y}_{1}^{\mathrm{H}} \mathrm{x}_{1}=1$ then, defining $\mathrm{A}_{2}$ by

$$
\begin{equation*}
A_{2}=A_{1}-\dot{\lambda}_{1} x_{1} y_{1}^{H}, \tag{11.3}
\end{equation*}
$$

we have from the biorthogonality of the $x_{i}$ and $y_{i}$

$$
\begin{align*}
A_{2} x_{i}=A_{1} x_{i}-\lambda_{1} x_{1} y y_{1}^{H} x_{i} & =0, \quad i=1 \\
& =\lambda_{i} x_{i}, \quad i \neq 1 \tag{11.4}
\end{align*}
$$

We have found in practice that these two methods of deflation have rather poor numerical stability and their use is not to be recommended.

## 12. TREPPEN-ITERATION

One problem in using iteration and deflation is that in general we do not know at each stage whether the current dominant eigenvalue is real or complex, repeated, or whether it belongs to a non-linear divisor. It is possible to avoid this difficulty by working simultaneously with a complete set of $n$ vectors and ensuring that they are independent by taking these $n$ vectors to be the columns of a unit lower triangular matrix. If at each stage we denote the matrix formed by
the set of $n$ vectors by $L_{s}$ the process can be summarised as

$$
\begin{equation*}
X_{S+1}=A L_{s} ; \quad X_{S+1}=L_{S+1} R_{S+1} \tag{12.1}
\end{equation*}
$$

where each $\mathrm{L}_{\mathrm{s}}$ is unit lower triangular and each $R_{S}$ is upper triangular. If we take

$$
\begin{equation*}
L_{0}=I \tag{12.2}
\end{equation*}
$$

then we have

$$
\begin{equation*}
L_{s} R_{s}=X_{s}=A L_{s-1} \tag{12.3}
\end{equation*}
$$

Thus

$$
\begin{align*}
L_{s} R_{s} R_{s-1} & =A L_{s-1} R_{s-1} \\
& =A A L_{s-2} \\
& =A^{2} L_{s-2} \tag{12.4}
\end{align*}
$$

therefore

$$
\begin{equation*}
L_{s}\left(R_{s} R_{s-1} \cdots R_{1}\right)=A^{s} L_{0}=A^{s} . \tag{12.5}
\end{equation*}
$$

Hence $I_{s}$ and ( $R_{s} R_{s-1} \ldots R_{1}$ ) are the matrices obtained by the triangular decomposition of $A^{s}$ and, by comparison with the LR algorithm of section 2, $I_{s}$ is equal to the product of the first $s$ lower triangular matrices obtained in the LR algorithm while the $R_{s}$ are identical with the individual
upper triangular matrices in the same algorithm. Although the LR and treppen-iteration algorithms are theoretically similar it does not follow that in practice their behaviour will be even approximately alike.

There is no need to use a complete set of $n$ vectors and it is possible to work with a set of $p$ vectors in unit lower trapezoidal form. Denoting these by $T_{S}$ the process becomes:

$$
\begin{equation*}
\mathrm{AT}_{s}=X_{s+1} \quad ; \quad X_{s+1}=T_{s+1} R_{s+1} \tag{12.6}
\end{equation*}
$$

where $R_{s}$ is a $p * p$ upper triangular matrix. If the $p$ dominant eigenvalues of $A$ have distinct moduli then

$$
\begin{equation*}
\mathrm{T}_{\mathrm{S}} \longrightarrow \mathrm{~T} \tag{12.7}
\end{equation*}
$$

where $T$ is obtained by trapezoidal decomposition of the matrix of $p$ eigenvectors. In general if

$$
\begin{equation*}
\left|\lambda_{1}\right| \geqslant\left|\lambda_{2}\right| \geqslant \ldots \geqslant\left|\lambda_{p}\right|>\left|\lambda_{p+1}\right| \geqslant \ldots \geqslant\left|\lambda_{n}\right| \tag{12.8}
\end{equation*}
$$

$T_{S}$ does not tend to a limit but it does tend to an invariant subspace. This process was first described by Bauer (1957) and was called treppeniteration.

If

$$
\begin{equation*}
\left|\lambda_{1}\right| \gg\left|\lambda_{2}\right| \tag{12.9}
\end{equation*}
$$

the first column of $T_{S}$ will converge to $x_{1}$ in a few iterations and at this stage there is little point in including $x_{1}$ in the matrix $T_{S}$ when computing $X_{s+1}$. In general if the first $k$ vectors of $T_{S}$ have converged we need not multiply these vectors by $A$ in subsequent steps. We may write

$$
\begin{equation*}
T_{S}=\left[T_{S}^{(1)}, T_{S}^{(2)}\right] \tag{12.10}
\end{equation*}
$$

where $T_{s}^{(1)}$ consists of the first $k$ vectors, which have converged, and $T_{S}^{(2)}$ consists of the remaining ( $p-k$ ) vectors which have not. We now define $X_{s+1}$ by

$$
\begin{equation*}
\mathrm{X}_{\mathrm{S}+1}=\left[\mathrm{T}_{\mathrm{s}}^{(1)}, \mathrm{AT}_{\mathrm{S}}^{(2)}\right] \tag{12.11}
\end{equation*}
$$

where $T_{S}^{(1)}$ is already in trapezoidal form but $A T_{S}^{(2)}$ consists, in general, of ( $p-k$ ) full vectors. $X_{s+1}$ is then reduced to trapezoidal form in the obvious way.

## 13. ORTHOGONALISATION TECHNIQUES

We now turn to an alternative technique for suppressing the dominant eigenvector (or eigenvectors). The simplest application is to real symmetric matrices and these we now consider.

Suppose $\lambda_{1}$ and $x_{1}$ have been determined so that

$$
\begin{equation*}
A x_{1}=\lambda_{1} x_{1} \tag{13.1}
\end{equation*}
$$

where $A$ is real and symmetric. We know that the remaining eigenvectors are orthogonal to $\mathrm{x}_{1}$ and hence we may suppress the component of $x_{1}$ in any of the other vectors by orthogonalising them with respect to $\mathrm{x}_{1}$. This leads to the iterative procedure defined by the equations:

$$
\begin{gather*}
v_{s+1}=A u_{s}, \quad w_{s+1}=v_{s+1}-\left(v_{s+1}^{T} x_{1}\right) x_{1} \\
u_{s+1}=w_{s+1} / \max \left(w_{s+1}\right) \tag{13.2}
\end{gather*}
$$

where we assume that

$$
\begin{equation*}
\left\|x_{1}\right\|_{2}=1 \tag{13.3}
\end{equation*}
$$

Clearly $u_{s}$ tends to the subdominant eigenvector or, if $A$ has a second eigenvalue equal to $\lambda_{1}$, it tends to an eigenvector corresponding to $\lambda_{1}$ which is orthogonal to $\mathrm{x}_{1}$.

Unless

$$
\begin{equation*}
\left|\lambda_{1}\right| \gg\left|\lambda_{2}\right| \tag{13.4}
\end{equation*}
$$

it is not strictly necessary to orthogonalise with respect to $\mathrm{X}_{1}$ at each iteration but if A is of high order the work involved in the orthogonalisation is in any case relatively small.

This process may be generalised to find $\mathrm{X}_{\mathrm{r}+1}$
when $x_{1}, x_{2}, \ldots, x_{r}$ have already been determined. The corresponding iteration is defined by

$$
\begin{gather*}
v_{s+1}=A u_{s}, \quad w_{s+1}=v_{s+1}-\sum_{i=1}^{r}\left(v_{s+1}^{T} x_{i}\right) x_{i} \\
u_{s+1}=w_{s+1} / \max \left(w_{s+1}\right) \tag{13.5}
\end{gather*}
$$

We note that, apart from rounding errors, this method gives results identical with those of Hotelling described in section 11 , for, from ( 13.2 ) we have,

$$
w_{s+1}=v_{s+1}-\left(v_{s+1}^{T} x_{1}\right) x_{1}
$$

$$
\begin{align*}
\because & =A u_{s}-x_{1}\left(u_{s}^{T} A x_{1}\right) \\
& =A u_{s}-\lambda_{1} x_{1}\left(u_{s}^{T} x_{1}\right) \\
& =A u_{s}-\lambda_{1} x_{1}\left(x_{1}^{T} u_{s}\right) \\
& =\left(A-\lambda_{1} x_{1} x_{1}^{T}\right) u_{s} \tag{13.6}
\end{align*}
$$

The analogous process for an unsymmetric matrix A requires the computation of both the lefthand eigenvector $y_{1}$ and the right-hand eigenvector
$\mathrm{x}_{1}$. If these are normalised so that

$$
\begin{equation*}
x_{1} \mathrm{H}_{1}=1 \tag{13.7}
\end{equation*}
$$

we may use the iterative procedure

$$
\begin{gather*}
v_{s+1}=A u_{s}, \quad w_{s+1}=v_{s+1}-\left(v_{s+1}^{H} y_{1}\right) x_{1}, \\
u_{s+1}=w_{s+1} / \max \left(w_{s+1}\right) . \tag{13.8}
\end{gather*}
$$

Because of the biorthogonality of the left-hand and right-hand eigenvectors the component of $x_{1}$ in $w_{s+1}$ is suppressed. Apain, there is the generalisation when $r$ eigenvectors have been determined:

$$
\begin{gather*}
v_{s+1}=A u_{s}, \quad w_{s+1}=v_{s+1}-\sum_{i=1}^{r}\left(v_{s+1}^{H} y_{i}\right) x_{i} \\
u_{s+1}=w_{s+1} / \max \left(w_{s+1}\right) \tag{13.9}
\end{gather*}
$$

14. TREPPEN-ITERATION USING ORTHOGONALISATIOIN

In treppen-iteration we iterate simultaneously with a number of vectors whose independence is
maintained by reducing them to standard trapezoidal form at each step. There is an analogous procedure in which the independence of the vectors is maintained by using the Gram-Schmidt orthogonalisation process. Consider firstly the case when we iterate simultaneously with $n$ vectors. Denoting the matrix formed by these vectors at each stage by $Q_{S}$ the process may be summarised as

$$
\begin{equation*}
A Q_{S}=V_{S+1}, \quad V_{S+1}=Q_{S+1} R_{S+1} \tag{14.1}
\end{equation*}
$$

where the columns of $Q_{S+1}$ are orthogonal and $R_{S+1}$ is upper triangular. Hence

$$
\begin{equation*}
A Q_{S}=Q_{S+1} R_{S+1} \tag{14.2}
\end{equation*}
$$

and if we take

$$
\begin{equation*}
Q_{0}=I, \tag{14.3}
\end{equation*}
$$

we have

$$
\begin{equation*}
A^{s}=Q_{s}\left(R_{s} R_{s-1} \ldots R_{1}\right) \tag{14.4}
\end{equation*}
$$

by reasoning similar to that of section 12.
Equation (14.4) implies that $Q_{s}$ and $\left(R_{s} R_{s-1} \ldots R_{1}\right)$
are the matrices obtained by orthogonal
triangularisation of $A^{S}$. Comparison with the $Q R$
algorithm of section 5 shows that $Q_{S}$ is equal to
the product of the first $s$ orthogonal matrices determined by the $Q R$ process. Thus, if all the $\left|\lambda_{i}\right|$ are different, $Q_{S}$ essentially tends to a limit, this being that matrix obtained from the
triangular orthogonalisation of $X$, the matrix of eigenvectors. The diagonal elements of $R_{s}$ tend to $\left|\lambda_{i}\right|$. In the general case, where some of the eigenvalues are of the same modulus, the corresponding columns of $Q_{S}$ may not tend to a limit but they ultimately span the appropriate subspaces. We note, as in section 6, that theoretical equivalence of this. method with the QR algorithm does not imply that in practice they will produce even similar results.

## 15. BI-ITERATION

Bauer (1957) suggested a generalisation of the methods which we have so far discussed and this he called bi-iteration. At each stage two systems of $n$ vectors, $\left\{x_{i}\right\}$ and $\left\{y_{i}\right\}$, are used and these comprise the columns of two matrices $X_{S}$ and $Y_{S}$. The two matrices $P_{s+1}$ and $Q_{s+1}$ defined by

$$
\begin{equation*}
P_{S+1}=A X_{S}, \quad Q_{S+1}=A^{T} Y_{S} \tag{15.1}
\end{equation*}
$$

are formed and from them the two matrices $X_{S+1}$ and $Y_{S+1}$ are derived. The columns of these matrices are chosen to be biorthogonal and the equations defining the i-th columns of $X_{S+1}$ and $Y_{S+1}$ are therefore

$$
\begin{align*}
x_{i}^{(s+1)}= & p_{i}^{(s+1)}-r_{1 i} x_{1}^{(s+1)}-r_{2 i} x_{2}^{(s+1)}- \\
& -\ldots-r_{i-1, i^{x_{i-1}}}^{(s+1)} \\
y_{i}^{(s+1)}= & q_{i}^{(s+1)}-u_{1 i} y_{1}^{(s+1)}-u_{2 i} y_{2}^{(s+1)}- \\
& -\ldots-u_{i-1, i} y_{i-1}^{(s+1)} \tag{15.2}
\end{align*}
$$

where the $r_{k i}$ and $u_{k i}$ are chosen such that

$$
\begin{gather*}
\left(y_{k}^{(s+1)}\right)^{T_{x}} x_{i}^{(s+1)}=0,\left(x_{k}^{(s+1)}\right)_{y_{i}}(s+1)=0 \\
k=1, \ldots, i-1 . \tag{15.3}
\end{gather*}
$$

Clearly we have

$$
\begin{equation*}
P_{s+1}=X_{s+1} R_{s+1}, \quad Q_{s+1}=Y_{s+1}^{U} S_{s+1} \tag{15.4}
\end{equation*}
$$

where $R_{S+1}$ and $U_{S+1}$ are the unit upper triangular matrices formed from the $r_{k i}$ and $u_{k i}$. From the biorthogonality we have

$$
\begin{equation*}
Y_{S+1}^{\dot{T}} X_{S+1}=D_{S+1} \tag{15.5}
\end{equation*}
$$

where $D_{S+1}$ is a diagonal matrix. If we take

$$
\begin{equation*}
X_{0}=Y_{0}=I \tag{15.6}
\end{equation*}
$$

we have

$$
\begin{align*}
& A=X_{1} R_{1}, \quad A X_{S}=X_{S+1} R_{S+1} \\
& A^{T}=Y_{1} U_{1}, \quad A^{T} Y_{S}=Y_{S+1} U_{S+1} \tag{15.7}
\end{align*}
$$

giving

$$
\begin{equation*}
A^{S}=X_{S} R_{S} R_{S-1} \cdots \cdot R_{1} \quad\left(A^{T}\right)^{S}=Y_{S} U_{S} U_{S-1} \cdots U_{1} \tag{15.8}
\end{equation*}
$$

Hence

$$
\left.\left.\begin{array}{rl}
A^{2 s} & =\left(Y_{s} U_{s} U_{s-1}\right.
\end{array} \cdots \cdot U_{1}\right)^{T_{X_{s}} R_{s} R_{s-1}} \cdots \cdots R_{1}\right)
$$

showing that the unit lower-triangular matrix $\left(U_{1}^{T} U_{2}^{T} \ldots U_{s}^{T}\right)$ is that corresponding to the triangular decomposition of $A^{2 s}$. In the $I R$ algorithm $\left(L_{1} L_{2} \ldots I_{2 s}\right)$ is the matrix obtained by the triangular decomposition of $A^{2 s}$ and hence

$$
\begin{equation*}
U_{s}^{T}=I_{2 s-1} I_{2 s} \tag{15.10}
\end{equation*}
$$

Results from the LR algorithn carry over immediately to bi-iteration. If the $\left|\lambda_{i}\right|$ are distinct $\left(U_{1}^{T} U_{2}^{T} \cdots U_{s}^{T}\right)$ tends to the matrix given by the triangular decomposition of $X_{S}$ and hence

$$
\mathrm{U}_{\mathrm{S}} \longrightarrow I
$$

and

$$
\begin{equation*}
\mathrm{R}_{\mathrm{s}} \longrightarrow I \tag{15.11}
\end{equation*}
$$

In practice the columns of $X_{S}$ and $Y_{S}$ are norinalised at each stage, usually so that

$$
\begin{equation*}
\max \left(x_{i}^{(s)}\right)=\max \left(y_{i}^{(s)}\right)=1 \tag{15.12}
\end{equation*}
$$

Hence in the case of distinct $\left|\lambda_{i}\right|$

$$
\begin{equation*}
X_{S} \longrightarrow X \quad \text { and } \quad Y_{S} \longrightarrow Y \tag{15.13}
\end{equation*}
$$

where $X$ and $Y$ are the matrices formed by the righthand and left-hand eigenvectors respectively. When some of the $\left|\lambda_{i}\right|$ are equal the subspaces formed
by the corresponding columns of $X_{S}$ and $Y_{S}$ tend to the relevant invariant subspaces. If $A$ is symmetric the two systems $X_{S}$ and $Y_{S}$ are identical and the method becomes essentially that of section 13 as the columns of $X_{S}$ are made orthogonal at each stage.

In order to facilitate comparison with the IR algorithm we have considered the case when $X_{S}$ and $Y_{S}$ consist of complete systems of $n$ vectors but the process can still be used when they have any number of columns, p.say, from 1 to n. Exactly the same equations apply but now $R_{S}$ and $U_{S}$ are $\mathrm{p} * \mathrm{p}$ matrices. In general the process will provide the $p$ dominant left-hand and right-hand eigenvectors or invariant subspaces.

It is against this background that we proceed to consider simultaneous iteration and its developments.

## 16. SIMULTANEOUS ITERATION

The particular case of bi-iteration for symmetric positive definite matrices was discussed by Rutishauser (1969) who later (1970) published an algol program for this method. We have also discussed the symmetric case, Gudgin (1971), and here we simply recall the main points. The basic idea of bi-iteration was that two
sets of iteration vectors $\left(x_{1}, x_{2}, \ldots, x_{p}\right)$ and $\left(y_{1}, y_{2}, \ldots, y_{p}\right)$ are iterated simultaneously with $A$ and $A^{T}$ respectively. The iteration is then combined with linear iterations such that at any time the systems $x_{i}$ and $y_{j}$ are biorthogonal. It is assumed that

$$
\begin{equation*}
1 \leqslant p \leqslant n \tag{16.1}
\end{equation*}
$$

although usually

$$
\begin{equation*}
1<p \ll n \tag{16.2}
\end{equation*}
$$

If $A$ is symmetric the two sets of iteration vectors can be chosen to be identical and they then form a system of orthonormal vectors $\left(x_{1}, x_{2}, \ldots, x_{p}\right)$ which are the columns of an $n * p$ matrix $X$ such that

$$
\begin{equation*}
X^{T} X=I_{p} \tag{16.3}
\end{equation*}
$$

Denoting the matrix $X$ after $k$ iteration steps by $X_{k}$ the method is given by
i) Choose $X_{O}$ such that $X_{O}^{T} X_{0}=I$

$$
\left.\begin{array}{l}
\text { ii) } Z_{k}=A X_{k-1}  \tag{16.4}\\
\text { iii) } X_{k}=Z_{k} R_{k}^{-1}
\end{array}\right\} \quad k=1,2, \ldots
$$

where $R_{k}$ is an upper triangular matrix with positive diagonal elements chosen such that $X_{k}$ has its columns orthogonal. This implies that

$$
\begin{equation*}
\mathrm{z}_{\mathrm{k}}^{\mathrm{T}} \mathrm{Z}_{\mathrm{k}}=\left(\mathrm{X}_{\mathrm{k}} \mathrm{R}_{\mathrm{k}}\right)^{\mathrm{T}}\left(\mathrm{X}_{\mathrm{k}} \mathrm{R}_{\mathrm{k}}\right)=\mathrm{R}_{\mathrm{k}}^{\mathrm{T}} \mathrm{R}_{\mathrm{k}} \tag{16.5}
\end{equation*}
$$

and we compute $R_{k}$ by Gram-Schmidt orthogonalisation
of the columns of $Z_{k}$. Provided $A$ is positive definite it will be shown that with equations (16.4)

$$
\begin{align*}
& \lim _{k \rightarrow \infty} X_{k}=V \\
& \lim _{k \rightarrow \infty}=D, \text { a } p * p \text { diagonal matrix } \tag{16.6}
\end{align*}
$$

where both limits exist and

$$
\begin{equation*}
\mathrm{V}^{\mathrm{T}} \mathrm{AV}=\mathrm{D} . \tag{16.7}
\end{equation*}
$$

Thus the columns of $X_{k}$ converge to eigenvectors and the diagonal elements of $R_{k}$ to eigenvalues of the matrix $A$.

This result can be established by showing that (16.4) is equivalent to the LRCH transformation (by which we mean the LR transformation with Cholesky decomposition into two transposed factors - see for example Wilkinson (1965).) if the latter is applied to the matrix

$$
\begin{equation*}
G_{1}=x_{0}^{T} A^{T} \mathrm{~T}_{\mathrm{A}}=X_{0}^{T_{A}} A^{2} x_{0} \tag{16.8}
\end{equation*}
$$

where $X_{0}$ is an $n * n$ orthogonal matrix obtained by appending ( $n-p$ ) further columns to $X_{O}$. If we use (16.4) with the initial matrix $X_{0}$ then the $k$-th iterate $\mathrm{X}_{\mathrm{k}}$ is related to the k-th LRCH transformation $G_{k+1}$ of $G_{1}$ by

$$
\begin{equation*}
G_{k+1}=X_{k}^{T} A^{2} X_{k} \tag{16.9}
\end{equation*}
$$

where $X_{k}$ is contained in the first $p$ columns of $X_{k}$.

This also enables us to estimate the convergence rate, for letting A have eigenvalues

$$
\lambda_{1} \geqslant \lambda_{2} \geqslant \ldots \geqslant \lambda_{p}>\lambda_{p+1} \geqslant \ldots \geqslant \lambda_{n}>0(16.10)
$$

and if $v_{j}$ is the eigenvector corresponding to $\lambda_{j}$ then, denoting the $j$-th column of $X_{k}$ by $x_{j}^{(k)}$, we have

$$
\begin{equation*}
\left\|v_{j}-x_{j}^{(k)}\right\|=O\left(q^{k}\right) \tag{16.11}
\end{equation*}
$$

where $q=\max \left(\lambda_{j+1} / \lambda_{j}, \lambda_{j} / \lambda_{j-1}\right)$. A proof of this theorem is to be found in Bauer (1957).

The scheme given in (16.4) conceals the fact that we are actually performing an iteration with p-dimensional spaces. Letting $\mathrm{E}_{\mathrm{k}}$ denote the linear space spanned by the columns of $X_{k}$ we have

$$
\begin{equation*}
E_{k}=\left\{x \mid x=A y, \quad y \in E_{k-1}\right\} \tag{16.12}
\end{equation*}
$$

We know that if A is symmetric and positive definite, then $\lim _{k \rightarrow \infty}$ exists and is an invariant subspace of $A$. We note that the $X_{k}$ given by (16.4) appear simply as a means for spanning $E_{k}$ but that, for example,

$$
\begin{equation*}
X_{k}=A X_{k-1} \tag{16.13}
\end{equation*}
$$

also defines the sequence $E_{k}$. However the $X_{k}$ produced by (16.13) are of little practical use since they are not in general numerically stable while those produced by (16.4) are.

In the case of stable convergence the angle $\phi_{j}^{(k)}$ between the $j$-th eigenvector $v_{j}$ and $E_{k}$ is asymptotically for $k \rightarrow \infty$

$$
\begin{equation*}
o\left(q_{j}^{k}\right) \quad \text { where } q_{j}=\lambda_{p+1} / \lambda_{j} \tag{16.14}
\end{equation*}
$$

To establish this we note that (16.4) and (16.13) are both orthogonally invariant. By this we mean that if $U$ is an $n * n$ orthogonal matrix then replacing $A$ by $U^{T} A U$ and $X_{O}$ by $U^{T} X_{O}$ has the effect that all $X_{k}$ are replaced by $U^{T} X_{k}$ and the $R_{k}$ are unchanged. Thus we can assume without loss of generality that

$$
\begin{equation*}
A=\operatorname{diag}\left(\lambda_{1}, \lambda_{2}, \ldots, \lambda_{n}\right) \tag{16.15}
\end{equation*}
$$

Now $E_{O}$ can be spanned by the $p$ vectors
and hence from (16.12) $\mathrm{E}_{\mathrm{k}}$ is spanned by the vectors


From (16.17) it follows immediately that the angle $\phi_{j}^{(k)}$ is at most $O\left(\lambda_{p+1}^{k} / \lambda_{j}^{k}\right)$.

This result also shows the interesting and important fact that there are directions in $E_{k}$ which are closer to the eigenvectors $v_{j}$ than the columns of the matrices $\mathrm{X}_{\mathrm{k}}$ as generated by (16.4).

Improved convergence may be obtained by a modified iteration procedure for which the convergence rate is the same as given in (16.14). In his paper of 1969 Rutishauser gives such a scheme and this we now describe; the algorithm we have implemented is explained in the next section.

Rutishauser defines the "projected eigenvalue equation"

$$
\begin{equation*}
Y^{T} A^{-2} Y=D_{k}^{-2} \tag{16.18}
\end{equation*}
$$

where $Y^{T} Y=I_{p}$ and $D_{k}^{-2}$ is a $p * p$ diagonal matrix. The matrix $Y$ is the matrix whose columns are the projection of the columns of $A^{-2}$ onto $E_{k}$. The solution of (16.18) is

$$
\begin{equation*}
Y=A X_{k-1} Q_{k} D_{k}^{-1} \tag{16.19}
\end{equation*}
$$

where $Q_{k}$ is a $p * p$ orthogonal matrix which transforms

$$
\begin{equation*}
G_{k}=X_{k-1}^{T} A^{2} X_{k-1} \text { into } Q_{k}^{T} G_{k} Q_{k}=D_{k}^{2} \tag{16.20}
\end{equation*}
$$

and $X_{k-1}$ is the previous iteration matrix, the columns of which are assumed to be orthogonal. Assuming the diagonal elements of $D_{k}$ are in decreasing order such that

$$
\begin{equation*}
d_{11} \geqslant d_{22} \geqslant \ldots \geqslant a_{p p}>0 \tag{16.21}
\end{equation*}
$$

Rutishauser (1969) suggests the following scheme for obtaining $X_{k}$ from $X_{k-1}$ :
i) $Z_{k}=A X_{k-1}$
ii) $G_{k}=Z_{k}^{T} Z_{k}$
iii) Solve the eigenvalue problem for $G_{k}$.

That is, compute $Q_{k}$ and $D_{k}$ as in (16.20)

$$
\begin{equation*}
\text { iv) } X_{k}=Z_{k} Q_{k} D_{k}^{-1} \tag{16.22}
\end{equation*}
$$

Using equations (16.22) the convergence is given, not by (16.11), but by

$$
\begin{equation*}
\left\|v_{j}-x_{j}^{(k)}\right\|=O\left(q_{j}^{k}\right) \tag{16.23}
\end{equation*}
$$

where $q_{j}=\lambda_{p+1} / \lambda_{j}$.
This scheme has been tried in practice and found to suffer from the disadvantage that there is no guarantee that the computed $\mathrm{X}_{\mathrm{k}}$ will be orthogonal. Additionally, large errors may be introduced in step (iv) of (16.22) if any of the $\mathrm{d}_{\text {ii }}$ are small.
17. AN ALTERNATIVE APPROACH TO SIMULTANEOUS ITERATION

We now return to the ideas of section 13 for an alternative and simpler approach to simultaneous iteration. This also leads directly to our implementation of the method.

Previously we saw that if we had determined $\lambda_{1}$ and $\mathrm{x}_{1}$, where we assume the eigenvalues to be in non-increasing order, it was possible to determine $\lambda_{2}$ and $x_{2}$ by iterating with an arbitrary vector which had been orthogonalised with respect to $\mathrm{x}_{1}$. In general when $\mathrm{x}_{1}, \mathrm{x}_{2}, \ldots, \mathrm{x}_{\mathrm{r}-1}$ had been determined it was possible to obtain $\lambda_{r}$ and $x_{r}$ by iterating with an arbitrary vector which had been orthogonalised with respect to the already determined $x_{i}$.

This leads naturally to a scheme in which the iterations are performed, not serially, but in parallel or simultaneously. Thus we let

$$
\begin{equation*}
x=\left[x_{1}, x_{2}, \ldots ., x_{p}\right] \tag{17.1}
\end{equation*}
$$

and ensure that

$$
\begin{equation*}
\mathrm{X}^{\mathrm{T}} \mathrm{X}=\mathrm{I}_{\mathrm{p}} . \tag{17.2}
\end{equation*}
$$

We then form the product

$$
\begin{equation*}
X^{\prime}=A X, \tag{17.3}
\end{equation*}
$$

reorthogonalise $X^{\prime}$ and repeat (17.3).
This is repeated until the process has converged.
We note that if

$$
\begin{gather*}
\left|\lambda_{1}\right|>\left|\lambda_{2}\right|>\ldots>\left|\lambda_{p}\right|>\left|\lambda_{p+1}\right| \geqslant\left|\lambda_{p+2}\right| \geqslant \ldots \\
\ldots \ldots \geqslant\left|\lambda_{n}\right| \tag{17.4}
\end{gather*}
$$

then convergence is guaranteed. Hence we may summarise the basic process as:
i) Choose $X_{0}$ such that $X_{0}^{T} X_{0}=I$

| ii) $Y_{k}:=A X_{k-1}$ |
| :--- | :--- | :--- |
| iii) $X_{k}:=Y_{k} R_{k}^{-1}$ where $X_{k}^{T} X_{k}=I$ |$| k=1,2, \ldots$ (17.5)

In order to accelerate the convergence of this
method we consider the projected eigenvalue equation:

$$
\begin{equation*}
\mathrm{B}_{\mathrm{k}}=\mathrm{X}_{\mathrm{k}}^{\mathrm{T}} \mathrm{AX}_{\mathrm{k}} \tag{17.6}
\end{equation*}
$$

We note that $B_{k}$ is a matrix of order $p$ and we
denote the eigensolution by

$$
\mathrm{V}_{\mathrm{k}}^{\mathrm{T}} \mathrm{~B}_{\mathrm{k}} \mathrm{~V}_{\mathrm{k}}=\mathrm{D}_{\mathrm{k}}
$$

If the first $r$ columns of $X_{k}$ are eigenvectors of A then the first $r$ rows and $r$ columns of $B_{k}$ will
be zero except for the diagonal elements which will be equal to the first $r$ eigenvalues of $A$. This leads to the following scheme for obtaining $X_{k+1}$ from $X_{k}$ :
i) Choose $X_{O}$ such that $X_{O}^{T} X_{O}=I$
ii) $Y:=A X_{k}$
iii) $B_{k}:=X_{k}^{T} Y=X_{k}^{T} A X_{k}$
iv) Solve the eigenproblem for $B_{k}$. Thus, we compute $V_{k}$ and $D_{k}$ such that $\mathrm{V}_{\mathrm{k}}^{\mathrm{T}} \mathrm{B}_{\mathrm{k}} \mathrm{V}_{\mathrm{k}}=\mathrm{D}_{\mathrm{k}}$
v) $Y_{k}:=X_{k} V_{k}$
vi) $X_{k+1}:=Y_{k} R_{k}^{-1}$ where $X_{k+1}^{T} X_{k+1}=I$
and steps ii) to vi) are repeated for $k=0,1,2, \ldots$.

## 18. THE INTERMEDIATE STEPS

The iteration rule defined by (17.8) is extremely powerful but it is important to realise that, as we saw in section 16 , the final space $E_{m}$ produced by $m$ steps of (17.8) is the same (apart from rounding errors) as that produced by $m$ steps of (17.5). Hence there is nothing to be lost by using (17.5) m-1 times followed by one step of (17.8). A further saving in time is possible by replacing (17.5) with the even simpler rule

$$
\begin{equation*}
X_{k}=A X_{k-1} \quad k=1,2, \ldots \tag{18.1}
\end{equation*}
$$

However, in this case, two further precautions are necessary. We have seen earlier that continued iteration using (18.1) makes the columns of $\mathrm{X}_{\mathrm{k}}$ become more and more parallel. Thus we must always orthonormalise $X_{k+m-1}$ after using (18.1) m-1 times and also we must limit m so that the columns of $X_{k}$ can never start to become parallel.

In order to choose the correct value of $m$ we note that if

$$
\begin{equation*}
\left(\left|\lambda_{1}\right| /\left|\lambda_{p}\right|\right)^{m-1}<10 \tag{18.2}
\end{equation*}
$$

then the parallelisation of the columns of $X_{k+m-1}$
will not have gone further than to cause the loss of at most one decimal digit when the columns are next orthonormalised. Obviously as $\lambda_{1}$ and $\lambda_{p}$ are not known we take the current values of $d_{11}$ and $d_{p p}$ as approximations. At the begining of the iteration $d_{11}$ and $d_{p p}$ are not known and in the first few steps they are still far from $\lambda_{1}$ and $\lambda_{p}$. In order to prevent $m$ being too large we start therefore with $\mathrm{m}=2$ and allow it to increase by one at each stage of the iteration. Thus we have the following computational scheme:
i) Let $\mathrm{k}=0, \mathrm{~m}=2$
ii) Choose $X_{0}$ such that $X_{0}^{T} X_{0}=I$

$$
\begin{align*}
& \text { iii) Perform } m-1 \text { steps of (18.1) on } X_{k} \\
& \text { iv) Orthonormalise the columns of } X_{k+m-1} \\
& \text { v) Let } Y=A X_{k+m-1} \\
& \text { vi) Let } B=X_{k+m-1}^{T} Y \\
& \text { vii) Compute } V \text { and } D \text { such that } V^{T} B V=D \\
& \text { viii) Let } X_{k+m}=X_{k+m-1} V \\
& \text { ix) Orthonormalise the columns of } X_{k+m} \\
& \text { x) Let } k=k+m \\
& \text { xi) Test for termination } \\
& \text { xii) If (|di1/|d } d_{p p} \mid \text { m } 10 \text { let } m=m+1 \\
& \text { xiii) Go to (iii) }  \tag{18.3}\\
& \text { In practice we have found it advantageous to } \\
& \text { perform step (iii) between steps (viii) and (ix), } \\
& \text { omitting step (iv). This saves one orthonormal- } \\
& \text { isation at each stage and our experience is that } \\
& \text { it does not impair accuracy or convergence. }
\end{align*}
$$

## 19. TESTS FOR CONVERGENCE

Rutishauser (1969) has stated that "the most efficient computing process becomes doubtful, if it is not possible to determine the proper time for termination automatically".

In this algorithm it is relatively easy to determine the proper time for termination of the process. The diagonal elements of $D$ in (18.3) (vii) will be changing throughout the iteration process.

Thus, as soon as the first diagonal element does not appear to change between successive stages of (18.3) it is determined to machine accuracy. We may then test for the second diagonal element and thence for the later ones.

This test is not sufficient for the eigenvectors. It is true to say however that if the eigenvalues have not converged to a given precision the eigenvectors will not have converged either. Thus we do not start testing for convergence of an eigenvector until after the corresponding eigenvalue has converged. We base our test for convergence of the vectors on examining the $\infty$-norm of each vector and testing whether this has altered between successive stages of (18.3).

In practice it is unlikely that we shall need to determine the eigensolutions to full machine accuracy and the tests are ammended to take this into account. Thus for the eigenvalues we test whether

$$
\begin{equation*}
\left|\frac{d_{i i}-d_{i i}}{d_{i i}^{\prime}}\right| \leqslant \varepsilon \quad \text { for } i=1,2, \ldots, p \tag{19.1}
\end{equation*}
$$

where $d_{i j}$ is the current value of $D_{i i}, d_{i i}$ was the value of $D_{i i}$ at the previous stage and $\varepsilon$ is the desired tolerance. Similarly for the eigenvectors we test whether

$$
\left|\frac{\left\|x_{i}^{\prime}\right\|_{\infty}-\left\|x_{i}\right\|_{\infty}}{\left\|x_{i}^{\prime}\right\|_{\infty}}\right| \leqslant \varepsilon \quad \text { for } i=1,2, \ldots \ldots, p
$$

where $x_{i}$ is the i-th column of $X$. The $p$
quantities on the left of inequality (19.2) form the components of the error vector described in chapter 5 , section 15.

Once $g$ eigenvectors have been accepted the active powering steps of (18.3) are no longer applied to these columns but they are retained for orthonormalisation of the columns $g+1$ to $p$.

## 20. THE HERMITIAN CASE

The extensions of the algorithm for the symmetric case needed to cover the Hermitian case are straightforward. We have already discussed the generalisations of the Jacobi and orthonormalisation algorithms and these are used in place of the symmetric and real versions. The only other alteration needed is to work with complex eigenvectors and Hermitian transposes. Thus the steps of (18.3) are replaced by
i) Let $\mathrm{k}=0, \mathrm{~m}=2$
ii) Choose $X_{O}$ such that $X_{O}^{H_{X}}=I$
iii) $\operatorname{Let} Y=A X_{k}$
iv) Let $B=X_{k}^{H}$
v) Compute $V$ and $D$ such that $V^{H} V_{B V}$

$$
\begin{align*}
& \text { vi) Let } X_{k+1}=X_{k} V \\
& \text { vii) Perform } m-1 \text { steps of (18.1) on } X_{k} \\
& \text { viii) Orthonormalise the columns of } X_{k+m} \\
& \text { ix) Let } k=k+m \\
& \text { x) Test for termination } \\
& \text { xi) If }\left(\left|d_{11}\right| /\left|d_{p p}\right|\right)^{m}<10 \text { let } m=m+1 \\
& \text { xii) Go to (iii). } \tag{20.1}
\end{align*}
$$

## 21. EIGENVALUES OF EQUAL MODULUS

We saw in section 10 that it is not necessary for convergence that all the eigenvalues must be distinct. In fact, for both the real and Hermitian cases, if we are iterating with p vectors the only condition necessary for convergence is that

$$
\begin{equation*}
\left|\lambda_{p}\right|>\left|\lambda_{p+1}\right| . \tag{21.1}
\end{equation*}
$$

It should be noted however that if $\left|\lambda_{p}\right|$ is close to $\left|\lambda_{p+1}\right|$ then convergence may be impracticably slow. In practice p should be chosen as far as possible so that

$$
\begin{equation*}
\left|\lambda_{\mathrm{p}}\right| \ll\left|\lambda_{\mathrm{k}}\right| \tag{21.2}
\end{equation*}
$$

where $k$ is the number of eigensolutions that it is desired to compute.

## 22. THE GENERAL CASE

We now turn our attention to the case of a
general matrix and as for the symmetric algorithm we return to the ideas of section 13. We shall assume initially that

$$
\begin{equation*}
\left|\lambda_{1}\right|>\left|\lambda_{2}\right|>\ldots>\left|\lambda_{p}\right|>\left|\lambda_{p+1}\right| \geqslant \ldots \geqslant\left|\lambda_{n}\right| \tag{22.1}
\end{equation*}
$$

and hence that there are $p$ left-hand and $p$ righthand eigenvectors corresponding to the p dominant eigenvalues.

Having calculated the first $r$ eigenvalues and eigenvectors we saw how to suppress the appropriate components of these in order to calculate the (r+1)-th eigensolution. Applying the process simultaneously to two sets of $p$ vectors we may write the algorithm as
i) Choose $\mathrm{Y}_{\mathrm{O}}$ and $\mathrm{X}_{\mathrm{O}}$, both $\mathrm{n} * \mathrm{p}$, such that $Y_{0}^{H} X_{O}=I$
$\left.\begin{array}{l}\text { ii) Form } Y_{k}=A H_{Y_{k-1}}, X_{k}=A X_{k-1} \\ \text { iii) Biorthonormalise } Y_{k} \text { and } X_{k}\end{array}\right\} k=1,2, \ldots$ (22.2)

To accelerate this method we consider the projected eigenvalue equation

$$
\begin{equation*}
\mathrm{B}=\mathrm{Y}_{\mathrm{k}}^{\mathrm{H}} \mathrm{AX}_{\mathrm{k}} \tag{22.3}
\end{equation*}
$$

We denote the eigensolution of $B$ by

$$
\begin{equation*}
T_{L} \cdot B \cdot T_{R}=D \tag{22.4}
\end{equation*}
$$

where $T_{L}$ and $T_{R}$ are respectively the left-hand and right-hand eigenvectors of $B$ and $D$ is a diagonal matrix of the eigenvalues of $B$. Thus we are led
to the following accelerated scheme for determining $Y_{k+1}$ and $X_{k+1}$ from $Y_{k}$ and $X_{k}$.
i) Choose $Y_{O}$ and $X_{O}$ such that $Y_{O}^{H_{X}}=I$
ii) Form $W=A^{H} Y_{k}, \quad V=A X_{k}$
iii) Form $B=Y_{k}^{H}{ }_{V}$
iv) Solve the eigenproblem for $B$; that is compute $T_{L}, T_{R}$ and $D$ as in (22.4)
v) Form $Y_{k+1}=W \bar{T}_{L}, X_{k+1}=V T_{R}$
vi) Biorthonormalise such that $\mathrm{Y}_{\mathrm{k}+1}^{\mathrm{H}} \mathrm{X}_{\mathrm{k}+1}=\mathrm{I}$ (22.5)
and repeat steps ii) to vi) for $k=0,1, \ldots$. .
Just as it was possible to use powering steps
in the symmetric case so in the general case we may use a similar device to speed up the process. We replace steps (ii) and (iii) of (22.2) by the simpler rule:

$$
\begin{equation*}
Y_{k}=A^{H_{Y_{k-1}}} ; \quad X_{k}=A X_{k-1} \quad \mathrm{k}=1,2, \ldots \tag{22.6}
\end{equation*}
$$

As before we use $m-1$ steps of (22.6) followed by one step of (22.5). For the reasons outlined previously in section 18 it is essential that $m$ is limited in order to prevent the columns of $Y_{k}$ and $X_{k}$ becoming less and less biorthogonal with respect to each other. This leads to a scheme very similar to that for the Hermitian case except that we are now working with two sets of
vectors.
i) Let $k=0, m=2$
ii) Choose $Y_{O}$ and $X_{O}$ such that $Y_{O}^{H_{X}}=I$
iii) Let $W=A^{H} Y_{k}, \quad V=A X_{k}$
iv) Let $B=Y^{H_{V}}$
v) Compute $\mathrm{T}_{\mathrm{L}}, \mathrm{T}_{\mathrm{R}}$ and D such that $\mathrm{T}_{\mathrm{L}} \mathrm{BT}_{\mathrm{R}}=\mathrm{D}$
vi) Let $Y_{k+1}=W \bar{T}_{L}, \quad X_{k+1}=V T_{R}$ vii) Perform $m-1$ steps of (22.6) on $Y_{k}$ and $X_{k}$ viii) Biorthonormalise such that $\mathrm{Y}_{\mathrm{k}}^{\mathrm{H}} \mathrm{X}_{\mathrm{k}}=\mathrm{I}$
ix) Let $k=k+m$
x) Test for termination
xi) If $\left(\left|a_{g+1}\right| /\left|a_{p p}\right|\right)^{m}<10$ let $m=m+1$
( $g$ is the number of eigenvectors accepted thus far)
xii) Go to (iii).

## 23. EQUAL EIGENVALUES

We know that an arbitrary matrix does not necessarily have a complete set of eigenvectors and hence the case of equal eigenvalues is more complicated than for Hermitian matrices. Suppose firstly that the matrix is non-defective but derogatory; we then have a situation similar to that of the Hermitian case and convergence is
possible if

$$
\begin{equation*}
\left|\lambda_{p}\right|>\left|\lambda_{p+1}\right| \tag{23.1}
\end{equation*}
$$

If the matrix is defective (irrespective of whether or not it is derogatory) in as much as one or more of the first $p$ eigenvectors do not exist there is no guarantee that the process will be convergent. However all our experimental results suggest that convergence does normally take place.

COMPUTATIONAL DETAILS

## 1. INTRODUCTION

In this chapter we describe the implementation of the theory that we have discussed in the preceqding chapters. We also explain the operation of the programs and give sufficient details to enable a prospective user to run them.

All the programs have been written in Fortran and developed on an I.C.I. 1904 S machine using the XFAT compiler. They will run on all 1900 series machines but small modifications may be needed to enable them to be used with other compilers on different machines. In the descriptions of the programs that follow we list the non-standard functions and explain their purpose so that any necessary alterations may be made easily.

We begin in the next section by describing the general structure of the programs and then we give details of the Jacobi programs. This is followed by a description of the simultaneous iteration programs and finally we give details of some test runs.

## 2. PROGRAM STRUCTURE

All the programs are written in a similar manner in order to facilitate their use and comparison between them. The basic structure of the programs is as follows:
i) A steering segment.
ii) The main program segment (called the MASTER segment in 1900 Fortran).
iii) The main subroutine (which performs most of the calculation).
iv) Other subroutines
v) A final subroutine, altered by the user, used for the input of data.

The steering segment is used to allocate channel numbers to the peripherals. Following the usual Fortran convention we have used channel 5 as input from the card reader and channel 6 as output to the line printer. Channel 4 is used, if necessary, for additional monitoring information with channel 2 used for both input to and output from an internal array. This enables character conversions from text strings to integers (and vice versa) to be performed. Although machine dependent a facility similar to this is normally provided with most compilers.

The main program segment is used principally to print the headings and output the results; in particular no calculations pertinent to the problem are performed in it. This is because the writer is convinced that a reasonably neat presentation of the results is an important feature of any computer program. Implicit in this is the need to display the name of the program, the date and time when it was run, the example number and a
clear heading to each set of results. The absence of any calculations from the main segment also means that an intending user can see at a glance the form the output will take just from looking at the first segment. We have also assumed that if the line width of the output is 120 characters or more then it is to a line printer and the results are centralised on the page. If however the line width is less than 120 characters the results are all left-justified as this is particularly suitable for output to a teletype if the program is being run on-line.

The first subroutine normally performs the bulk of the calculation and it is here that the theory we have developed is implemented. Often repeated calculations such as the formation of inner-products are not performed here but are left to the following subroutines.

In all the programs the final subroutine is used to input or store information about the matrix. Since this will change from problem to problem it is up to the user to modify this routine for his particular problem.
3. A JACOBI PROGRAM FOR SYMMETRIC MATRICES - JACO

The program takes as data a real symmetric matrix $A$ of order $n$ and calculates its eigenvalues, $\lambda_{i}$, and optionally the eigenvectors, $v_{i}$. Also
printed are the number of rotations needed to diagonalise the matrix to a preset tolerance. Should the total number of sweeps exceed fifty the program is terminated and a warning message is printed. Additionally the program will, if requested, form the matrix $V^{T} A V$ and normalise the vectors such that

$$
\begin{equation*}
\left\|v_{i}\right\|_{\infty}=1 \quad i=1,2, \ldots, n . \tag{3.1}
\end{equation*}
$$

We now describe each routine.

## Master segrnent

At the beginning of this segment the arrays are dimensioned. If it is desired to alter the size of these arrays this is the only point at which a change to the program has to be made. Five arrays are used and as far as possible their names have been chosen with reference to the theoretical discussion of earlier chapters.
$A(n * n)$ - stores the elements $a_{i j}$ of the original matrix A.
$V(n * n)$ - stores if they are required the elements of the matrix $V$, the columns of which approximate the eigenvectors of $A$.

D ( $n$ ) - stores the approximations to the eigenvalues $\lambda_{i}$.

B ( $n$ ) - used as workspace.
Z ( $n$ ) - used as workspace.
The value given to $n$ must be the same for each of
the five arrays.
There is a call to an I.C.I. subroutine TIME( $T$ ). This returns in $T$ the time of day as an eight bit character string. All the other subroutine calls are to segments appearing later in the program.

Subroutine Jaco
The coding follows exactly the computational details given in sections 10 and 11 of chapter 2 and we describe only the additional features not mentioned there. Firstly, as the matrix $A$ is symmetric, only the upper half is used in the computation. This means that the information stored in the lower half can be used to recreate the original matrix. Secondly, in order to ensure the maximum possible accuracy in the eigenvalues the following device is adopted. During each sweep, as well as updating the vector $D$ at each rotation, the updates are accumulated in a separate vector $Z$. At the end of each sweep the value in $Z$ is then used to produce a fresh value of $D$. This is given by updating the value of $D$ as it was at the end of the previous sweep (stored in B) by the current value of $Z$. Although this uses an extra $2 n$ storage locations it does ensure great accuracy in the eigenvalues as very small individual increments in the elements of $D$ are accumulated independently.

Having completed the diagonalisation process to the required tolerance the program uses the exchange sort algorithm to order the eigenvalues (and their corresponding vectors) such that their moduli are in non-increasing order.

Subroutine Normalisation
This subroutine, if called, normalises the eigenvectors as in (3.1). Subroutine Check

As with Normalisation this subroutine is only called if specifically requested by the user. It uses the calculated values of the eigenvectors to form the product $V^{T} A V$ storing the result in $A$. All the summations are performed in double precision. Subroutine Elapse

This subroutine, which is used in all the programs we have written, performs three small calculations needed by other routines. Firstly, it calculates the mill time that the program has used. This involves using the I.C.I. subroutine MTIME(N) which gives $N$ as the number of milliseconds so far used by the program. This is converted to minutes and seconds and output at the end of the program. Secondly, Elapse uses the machine routine $\operatorname{DATE}(D)$ to obtain in $D$ an eight character text string containing the date. In order to print the month as a three letter abbreviationwe call DEFBUF. This routine, combined
with the use of channel 2, enables us to access an internal array called BUFFER and perform the necessary character conversion.

Finally the subroutine calculates the machine constant. That is, the smallest number m such that

$$
\begin{equation*}
1.0+m \neq 1.0 \tag{3.2}
\end{equation*}
$$

This means that there is no need for the user to provide this information for each different machine.

Subroutine Mxop
Mxop has been developed as a general purpose routine for the outputting of matrices. The input parameters for the subroutine are the matrix $A$, its actual dimensions as defined in the Master segment, the size of matrix it is desired to output, the format required for an individual element, the number of printing positions per line, the logical stream number for the output channel and finally a flag. If the flag has a negative value the output is left-justified; if flag is positive the output is centralised on the page. If flag is zero Mxop is not initiallised and the output is then in the same format as on the previons occasion. It is recommended that flag is set to zero if the same format is being used a number of times. This saves reinitiallising Mxop with a consequent saving of time.

The form of the output from Mxop consists of a heading to indicate which columns of the matrix are to be printed followed by those columns. The program automatically prints as many columns as the width of line allows. For example, suppose a ( $20 * 15$ ) matrix is to be output centrally on a 120 character line with each element printed under the format F16.8. The output from Mxop would take the form:

COLUMNS 1 TO 7 ARE:

| $a_{11}$ | $a_{12}$ | $a_{13}$ | $\cdots$ | $\cdot$ | $a_{17}$ |
| :--- | :--- | :--- | :--- | :--- | :--- |
| $\cdots$ | $\cdot$ | $\cdots$ | $\cdots$ | $\cdot$ | $\cdot$ |
| $a_{20,1}$ | $a_{20,2}$ | $a_{20,3}$ | $\cdots$ | $\cdot$ | $\cdot$ |
| $a_{20,7}$ |  |  |  |  |  |

COLUMINS 8 TO 14 ARE:
$a_{18}$
$a_{19}$
$a_{1,10}$
$a_{1,14}$
$a_{20,8} a_{20,9}$
$a_{20,10}$
$a_{20,14}$

COLUMN 15 IS:

$$
\begin{aligned}
& a_{1,15} \\
& \cdot \\
& a_{20,15}
\end{aligned}
$$

There are no restrictions on the size of matrix Mxop can handle including ( $n * 1$ ) and ( $1 * n$ ); in the case of ( $1 * \mathrm{n}$ ) matrices however the column headings are suppressed. This subroutine has proved invaluable in the programs we have written
and also during the development stage of many other routines.

## Subroutine Input

This routine is used to input the data for each example and it/ the user's responsibility to write the appropriate sections of code. A computed GO TO statement transfers control on the n-th example to the CONTINUE statement numbered $n * 100$. The user then inserts an appropriate section of code to set the elements of the array $A(I, J)$ equal to the elements ( $a_{i j}$ ) of the matrix whose eigensolution it is desired to calculate. This may be done either by generating the elements of $A$ or by reading them from data cards. Finally, after inputting $A$, control must pass to a RETURN statement in order to leave the subroutine.

This concludes the description of each section of the program.
4. DATA REQUIRED BY JACO

The data required by the program is very simple and takes the following form.
i) The first data card (read from the Master segment) must contain three integers punched in the format (2I2,I3). The first of these is the number of examples to be run, the second is the size of the arrays as dimensioned in the Master segment and the third is the width of output line
required.
ii) The second data card contains information about the first example and this is given in the format (I2,I1,A6,2I1). The first number is the dimension of the matrix $A$ for this particular example; this must be less than or equal to the dimension of the array $A$ in the Master segment. The second number is 1 or 0 depending on whether or not it is desired to calculate the eigenvectors. The third is a text string defining the output format required. Typical values might be F16. 8 or E2O.10. The last two numbers are flags and if nothing is punched these are taken as zero. If however a 1 is punched in the first of these two positions then subroutine Check is called; a 1 in the second position calls subroutine Normalisation.
iii) If the elements of $A$ are to be read from cards these should now follow. The format is obviously dependent upon what the user has specified in subroutine Input.
iv) After the data cards of iii), or if there are none, a second card as in ii) should follow for the second example. A similar pattern now follows for the subsequent examples.

## 5. TEST RESUITS

A listing of the program together with a sample of the output from one of the test runs is
to be found in appendix 1 and we give here some comments on the test runs. Examples 1 to 7 are all taken from Gregory and Karney (1969) and example 8 is due to Rutishauser (1966) and quoted in Wilkinson and Reinsch (1971). These two excellent books have provided the author with much inspiration. For convenience we shall refer to Gregory and Karney as GK and list the example number in their book.

Example 1, GK 4.1 , is a $4 * 4$ matrix typical of the type that occurs within simultaneous iteration. The eigenvalues and eigenvectors were obtained to 10 significant figures after 10 rotations in 0.042 seconds.

Example 2, GK 4.2 , is a $4 * 4$ matrix with a repeated eigenvalue. Again the eigensolutions were obtained to 10 significant figures, this time after 17 rotations in 0.057 seconds.

Example 3, GK 4.15 taking $n=10$, is a matrix of order 10. The first eight eigenvalues were computed to 10 significant figures and the last two to 9 significant figures with a similar accuracy in the eigenvectors. 120 rotations were needed taking 0.644 seconds.

Example 4, GK 4.13 taking $\mathrm{n}=10$, is the Hilbert matrix of order 10. The computed eigensolutions are all correct to 10 decimal places. The execution time was 1.128 seconds in which 231 rotations were
performed.
Example 5, GK 4.20 taking $n=10$ and $a=3$, needed 234 rotations taking 1.125 seconds to produce eigensolutions to 9 decimal places.

Example 6, GK 4.20 taking $n=10$ and $a=0$, needed 89 rotations taking 0.512 seconds to produce eigensolutions to 9 decimal places.

Example 7, GK 4.10, is the Rosser matrix. 125 rotations in 0.546 seconds produced the eigensolutions to 7 decimal places.
Example 8, Rutishauser (1966), is a matrix of order 44. Our program used 6280 rotations in 1 minute 39.8 seconds. The eigensolutions are all correct to 9 decimal places and compare favourably with Rutishauser's results.

## 6. A JACOBI PROGRAM FOR HERMITIAN MATRICES - HMJO

The program takes as data a Hermitian matrix A of order $n$ and calculates its eigenvalues, $\lambda_{i}$, and optionally the eigenvectors, $\mathrm{v}_{\mathrm{i}}$. Also printed are the number of rotations needed to diagonalise the matrix to a preset tolerance. Should the total number of sweeps exceed fifty the program is terminated and a warning message printed. Additionally the program will, if requested, form the matrix $\mathrm{V}^{\mathrm{H}} \mathrm{AV}$ and normalise the vectors such that

$$
\begin{equation*}
\left\|v_{i}\right\|_{\infty}=1 \quad i=1,2, \ldots, n \tag{6.1}
\end{equation*}
$$

The routines are very similar to those for the real symmetric case and we describe only the differences between the two.

## Master segment

Throughout our programs we have used only real arithmetic and since the original matrix A and its matrix of eigenvectors $V$ may be complex two additional arrays are needed now for storing $A$ and $V$. In our programming we have, without exception, used "R" and "I" as the last letter of an array name to indicate that that array contains either real or imaginary components. Thus, instead of a complex array $A$, we use two real arrays $A R$ and $A I$.
$A R(n * n)$ - stores the real components $\operatorname{Re}\left(a_{i j}\right)$ of the original matrix $A$.

AI ( $n * n$ ) - stores the imaginary components $\operatorname{Im}\left(a_{i j}\right)$ of the original matrix $A$.

VR ( $n * n$ ) - stores the real part of the matrix $V$, whose columns approximate the eigenvectors of $A$.

VI ( $n * n$ ) - stores the imaginary part of the matrix $V$. Subroutine Hmjo

The coding follows the computational details given in section 12 of chapter 2 . The same device employed in the real symmetric case is used to ensure maximum accuracy in the eigenvalues.

## Other subroutines

The other subroutines are identical to those described in section 3 except for the slight modifications needed for complex working in Normalisation, Check and Input.

## 7. DATA REQUIRED BY HMJO

The data is input in exactly the same form as that described in section 4. It is the user's responsibility to ensure that the real and imaginary parts of A are correctly input.

## 8. TEST RESULTS

A listing of the program together with a sample of the output from one of the test runs is to be found in appendix 2.

Example 1, GK 6.6, is a $4 * 4$ matrix typical of the type that occurs within simultaneous iteration. The eigensolutions were obtained to 10 significant figures after 13 rotations in 0.090 seconds. Example 2, GK 6.7 , is a $4 * 4$ matrix with a repeated eigenvalue. Again the eigensolutions were obtained to 10 significant figures after 17 rotations in 0.115 seconds. Example 3, GK 6.8 , is a matrix of order 5 and 46 rotations in 0.327 seconds produced the eigensolutions to 9 decimal places. Examples 4 to 9 , GK 7.10 taking $n=6$ to 11 in example

B, have only imaginary components. All the solutions were produced to 9 decimal places. The number of rotations needed and the time taken were 101 ( 0.861 ), $131(1.245), 178(1.843)$, $220(2.534), 305(3.741)$ and $319(4.212)$.

## 9. A JACOBI PROGRAM FOR NORMAL MATRICES - NMJO

The program takes as data a normal matrix A of order $n$ and calculates its eigenvalues, $\lambda_{i}$, and optionally the eigenvectors, $\mathrm{v}_{\mathrm{i}}$. Also printed are the number of rotations needed to diagonalise the matrix to a preset tolerance. Should the total number of sweeps exceed fifty the program is terminated and a warning message is printed. Additionally the program will, if requested, form the matrix $\mathrm{V}^{\mathrm{H}} \mathrm{AV}$ and normalise the vectors such that

$$
\begin{equation*}
\left\|v_{i}\right\|_{\infty}=1 \quad i=1,2, \ldots, n . \tag{9.1}
\end{equation*}
$$

Again we describe only the differences between this program and the previous one.

## Master segment

As well as the original matrix A and the eigenvectors $V$ being complex the eigenvalues may be too. This means that the arrays $D, B$ and $Z$ must each be replaced by two arrays. In addition, since the whole matrix is acted upon in the program, it becomes necessary to keep a copy of
the originfal matrix. Thus we have the following additional arrays.

AAR ( $n * n$ ), AAI ( $n * n$ ) - store a copy of the original values of $A R$ and $A I$.

DR (n), DI (n) - store respectively the approximations to the real and imaginary parts of the eigenvalues.

YR (n), YI (n) - used as workspace.
ZR ( $n$ ), ZI (n) - used as workspace.
The change of array name from $B$ to $Y$ is to avoid any possible confusion with the theory as given in section 13 of chapter 2.

Other subroutines
The coding for subroutine Nmjo follows exactly the computational details given in section 13 of chapter 2. The other subroutines are unaltered from the Hermitian program.

## 10. DATA REQUIRED BY NMJO

The data is input exactly as in section 7.

## 11. TEST RESULTS

A listing of the program together with a sample of the output from one of the test runs is to be found in appendix 3 . Examples 1 and 2, are both $4 * 4$ matrices constructed for test purposes. 23 rotations in 0.2 seconds were needed in both cases to produce solutions
to 9 decimal places.
12. A JACOBI PROGRAM FOR GENERAL MATRICES - GLJO

The program takes as data an arbitrary complex matrix $A$ of order $n$ and calculates its eigenvalues, $\lambda_{i}$, and the left and right eigenvectors, $w_{i}$ and $\mathrm{v}_{\mathrm{i}}$ respectively. Also printed are the number of rotations needed to diagonalise the matrix to a preset tolerance. Should the total number of sweeps exceed fifty the program is terminated and a warning message is printed. The routines are now described.

## Master segment

As with the other Jacobi programs it is at the beginning of this segment that the arrays are dimensioned and it is here that any change to their size must be made. The arrays used are as follows.

AR, AI ( $\mathrm{n} * \mathrm{n}$ ) - store respectively the real and imaginary components of the original matrix $A$.

AAR, AAI ( $n * n$ ) - store a copy of the original matrix.

WR, WI ( $\mathrm{n} * \mathrm{n}$ ) - store the elements of the matrix whose columns approximate the left eigenvectors of $A$.

VR, VI ( $n * n$ ) - store the elements of the matrix whose columns approximate the right eigenvectors of A .

DR, DI (n) - store the approximations to the eigenvalues $\lambda_{i}$.

EN, EM (n) - used as workspace.
The value given to $n$ must be the same for each of twelve
the arrays.

## Subroutine Glio

The coding follows that given by Eberlein (1970). The only difference is that described in section 20 of chapter 2. Thus no ordering of the eigenvalues takes place during the execution of this routine until immediately before returning to the Master segment to output the results. The ordering is such that on output,

$$
\begin{equation*}
\left|\lambda_{1}\right| \geqslant\left|\lambda_{2}\right| \geqslant \cdots \geqslant\left|\lambda_{n}\right| . \tag{12.1}
\end{equation*}
$$

## Subroutine Check

This routine, if called by the user, uses the calculated values of the left and right eigenvectors to form the product $W^{T} A V$, where $W$ and $V$ are the matrices whose columns are given by $w_{i}$ and $v_{i}$ respectively. All the summations are performed in double precision and the resulting product is stored in $A$. Other subroutines

These are as previously described.

## 13. DATA REQUIRED BY GLJO

The form of the data is very similar to that
described in section 4. The difference occurs in (ii) where the data card is in the format (I2, $A 6, I 1$ ). The first number is the dimension of the matrix

A for the particular example; the next is a text string defining the output format required and the third is a flag to call subroutine check.

The real and imaginary elements of $A$ must be input separately and this is the user's responsibility.
14. TEST RESULTS

A listing of the program together with a sample of the output from one of the test runs is to be found in appendix 4.

Example 1, GK 5.1, is a $3 * 3$ real non-symmetric matrix with real eigenvalues. 33 rotations in 0.366 seconds produced the eigenvalues and the lefthand and right-hand eigenvectors to 9 decimal places.

Example 2, GK 5.3, is also a real non-symmetric matrix of order 3. The eigensolutions were obtained to 8 decimal places after 21 rotations in 0.237 seconds.

Example 3, GK 5.5, is a real non-symmetric matrix of order 4 with real eigenvalues. The solutions, correct to 8 decimal places, were produced in 0.557 seconds after 42 rotations.

Example 4, GK 5.8, is a real non-symmetric matrix
of order 4 with two real eigenvalues and a complex conjugate pair. 18 rotations in 0.246 seconds produced the eigensolutions correct to 9 decimal places.

Example 5, GK 5.2, is a $3 * 3$ real defective matrix. After 60 rotations taking 0.511 seconds the isolated eigensolution was obtained to 9 decimal places with the repeated eigenvalues and their associated vector being obtained to 5 decimal places.

Example 6, GK 6.5, is a complex matrix of order 4 and the results were obtained to 8 decimal places after 54 rotations taking 0.753 seconds. Example 7, GK 6.4, is a complex matrix of order 3 and the results were obtained to 8 decimal places after 21 rotations taking 0.234 seconds. Example 8, Eberlein (1970) example I, is a real matrix of order 7 with one real eigenvalue and the rest complex conjugate pairs. 126 rotations in 2.714 seconds produced the results to 10 decimal places and this compares favourably with Eberlein's results.

Example 9, Eberlein (1970) example II, is a real matrix of order 5 which is defective. 240 rotations taking 3.052 seconds produced the isolated real eigenvalue and its corresponding vector to 10 decimal places. The complex conjugate eigenvalues and their corresponding vectors were obtained to 5 decimal places.

## 15. A RITZ ITERATION PROGRAM FOR SYMMETRIC MATRICES <br> - QKRZ

For a real symmetric matrix $A$ of order $n$ the program calculates the em absolutely largest eigenvalues, $\lambda_{i}$, and their corresponding eigenvectors, $x_{i}$. There is no need to store the matrix A; all that is required is to be able to form the vector w where

$$
\begin{equation*}
\mathrm{w}=\mathrm{Av} \tag{15.1}
\end{equation*}
$$

without altering $v$. The iteration is carried out with $p$ vectors where $p \geqslant e m$ and usually $p>e m$. The optimum value of $p$ will depend on the distribution of the eigenvalues but if no knowledge of this is available a reasonably good rule of thumb is to choose $p$ equal to em plus 2 or 3 for smallish values of em. The eigensolutions are obtained to the tolerance requested and optionally the eigenvectors may be normalised such that

$$
\begin{equation*}
\left\|x_{i}\right\|_{\infty}=1, \quad i=1,2, \ldots, p \tag{15.2}
\end{equation*}
$$

We now describe the program.

## Master segment

All the dimensioning of the arrays is performed at the beginning of this segment and this is the only point at which any change may need to be made. The following arrays are used and as far as possible their names have been chosen with reference to the earlier theoretical
discussion.
X ( $n * \mathrm{p}$ ) - stores the matrix $X$ whose columns approximate the eigenvectors.
$\mathrm{V}(\mathrm{n}), \mathrm{W}(\mathrm{n})$ - used as workspace in forming the product.

RV ( $p * p$ ), B ( $p * p$ ) - used as workspace.
D (p) - stores the approximations to the eigenvalues $\lambda_{i}$.

F (p) - stores the error vector as described in chapter 4 , section 19.

BB ( $p$ ), Z ( $p$ ), DOLD ( $p$ ), LARGE ( $p$ ) - used as workspace.

The values given to n and p respectively must be the same for all the arrays.

There then follow three READ statements which input the data required by the program. These statements refer to the FORMAT statements labelled 10, 20 and 30.

There is a call to an I.C.I. subroutine TIME(T). This returns in $T$ the time of day as an eight bit character string. All the other subroutine calls are to segments appearing later in the program.

Subroutine Qkrz
The coding follows exactly the computational details given in sections 17 to 19 of chapter 4 and we desiribe only the additional features not mentioned there. After the tests for convergence
there is a call to subroutine INFO. This outputs, on channel 4, intermediate information concerning the progress of the program. We describe INFO fully below. A.test is also made to see whether it is likely that the required number of solutions will be obtained in the next few steps. If this is the case the value of $m$ (the number of premultiplications to be performed) is reduced to 2. Finally a check is made to ensure termination in the event of the number of iterations having exceeded some preset value.

Subroutine Jaco
This is exactly as described in section 3.

## Subroutine Ortho

This routine uses the modified Gram-Schmidt process with reinforcement to orthogonalise a set of vectors $X(n * p)$ with $n \geqslant p$. For the sake of generality the routine assumes that the first $F$ columns of X are already orthonormalised but for our purposes we always take $F$ equal to zero. The coding follows equations (3.1) of chapter 3 with the reinforcement as described in section 4 of the same chapter. If reinforcement is found to be necessary the message "Warning 1 in ortho" is output on channel 4; if a column of $X$ is found to be linearly dependent and is thus set identically equal to zero as in equation (4.7) of chapter 3 the message "Warning 2 in ortho" is
output.
Real Function Inner Product
This routine is called by Ortho and calculates the inner-product of columns $k$ and $l$ of the vectors held in $X$. The summations are performed in double precision arithmetic.

## Subroutine Randomisation

Randomisation places ps : do random numbers in the range ( $-1,1$ ) into the columns of $X$; these then form the starting vectors for the iteration. If approximations to the eigenvectors are already known a facility exists for using these. This is detailed in the next section. The random numbers are obtained from the I.C.L. routine FPMCRV which generates pseudo random numbers in the range ( 0,1 ). Most machines have a similar facility to this and there should be no difficulty in making the necessary alteration.

Subroutine Info
We have briefly mentioned this routine which outputs, after each test for convergence, sufficient information for the user to see the progress, or otherwise, of his program. The subroutine is split into two halves; both output the same information but the first does this in display form suitable for a line printer whilst the second is more compact and suitable for a teletype. Whichever form the output takes
the information displayed is as follows:
Number of steps performed,
Number of eigenvectors accepted,
Number of eigenvalues accepted,
Number of solutions to be computed,
The error vector,
The present approximations to the eigenvalues. Clearly the user could alter this routine if he felt more or less information was required but we have found the above to be most useful.

Subroutine Normalisation
This routine, if called by the user, normalises the eigenvectors $\left\{x_{i}\right\}$ such that

$$
\begin{equation*}
\left\|x_{i}\right\|_{\infty}=1, \quad i=1,2, \ldots, p \tag{15.3}
\end{equation*}
$$

Subroutines Elapse and Mxop
These are exactly as described in section 3 . Subroutine Product

Product performs a similar role to subroutine Input in the Jacobi programs. A computed GO TO statement transfers control on the n-th example to the CONTINUE statement numbered $n * 100$. The user must then insert a section of code which is such that it computes

$$
\begin{equation*}
\mathrm{w}=\mathrm{Av}, \tag{15.4}
\end{equation*}
$$

where $w$ and $v$ are both vectors of $n$ components, without altering v. Finally, after computing w, control must pass to a RETURN statement in order to leave the subroutine.

This concludes the description of each section of the program.

## 16. DATA REQUIRED BY QKRZ

The data required by the program takes the following form.
i) The first data card (read from the Master segment at the format statement numbered 10) must contain four integers punched in the format (I2,I5,I2,I3). The first of these is the number of examples to be run, the second and third are the values of $\mathbb{N}$ and $P$ respectively used to dimension the arrays in the Master segment and the fourth is the width of output line required.
ii) The second data card contains
information about the first example and this is given in the format ( $I 5, I 2, I 6, I 2, E 9.2, A 6, I 1$ ). The first two numbers are the dimensions of the array $X$ for this particular example; these must be less than or equal to the dimensions given to X in the Master segment as input in (i). The third number is the maximum number of iterative steps that it is wished to perform. If there has been no convergence after this number the program is automatically terminated. The fourth parameter is the number of solutions it is desired to compute and the fifth the accuracy to which they are required. The sixth parameter is
a text string defining the output format required, a typical value might be E18.8. Finally we have a flag which, if set to one, normalises the vectors as in (15.1).
iii) If in advance approximations to the eigenvectors are known a considerable saving in computer time can be effected by starting the iteration with these approximations instead of using random numbers. For this reason the following facility is available. If on the second data card described in (ii) the third parameter, the maximum number of steps to be performed, is given a negative value then it is assumed that initial approximations to the eigenvectors are to be input and randomisation is suppressed. The input is controlled by the format statement labelled 30 and the IF statement immediately preceding it. The user is advised to alter the format statement to suit his particular needs. Although the maximum number of steps has been given a negative value the upper limit is set as the absolute value of that read in.
iv) After the data card described in (ii) and any possible cards for (iii) a second data card as described in (ii) should now follow for the second example. A similar pattern is followed for each sipsequent example.
A. listing of the program together with a sample of the output from one of the test runs is to be found in appendix 5. In all the examples which follow we requested the solutions to an accuracy of $10^{-8}$.

Example 1, GK 4.13, is the Hilbert matrix of order 10. The iteration was performed with four trial vectors and requested two eigensolutions. In 6 steps taking 1.921 seconds the program had accepted 3 eigenvalues and 3 eigenvectors. Example 2, GK 4.15 taking $n=10$, was described in section 5. We used four trial vectors and requested two eigensolutions. 8 steps taking 1.275 seconds in fact produced 4 eigensolutions.

Example 3, is a diagonal matrix included to check consistency of the program.

Example 4, GK 7.2, is a tridiagonal matrix of order 21. Five trial vectors produced 3 eigensolutions after 75 steps taking 8.275 seconds. It is worth noting that as the eigenvalues are poorly separated the value of $m$ is increasing throughout the program; that is, an increasing number of intermediate premultiplications are performed at each stage.

Example 5, GK 7.3, is again a tridiagonal matrix of order 21. Five trial vectors produced 4 eigenvalues and 2 eigenvectors after 67 steps in 12.289
seconds. Again the value of $m$ is increasing throughout.

Example 6, GK 7.4 taking $a=0, b=1$ and $n=20$, is a tri-diagonal matrix of order 20 with very poorly separated eigenvalues. After 132 steps taking 17.911 seconds and iterating with six trial vectors 4 eigenvalues and 3 eigenvectors were obtained. As the eigenvalues are so close the value of $m$ is constantly increasing. Example 7, GK 7.10 taking $n=19$ with $x_{k}=y_{k}=$ $=[k(n-k+1)]^{\frac{1}{2}}$, is a tridiagonal matrix of order 20 . Using six trial vectors 4 eigenvalues and 2 eigenvectors were obtained after 64 steps in 15.022 seconds. In this example the eigenvalues are well separated and m increases only slowly. Example 8, Rutishauser (1966), is the matrix of order 44 described in section 5. Four trial vectors produced 3 eigenvalues and 2 eigenvectors after 189 steps taking 21.983 seconds. With the very close eigenvalues m increases rapidly.
18. A RITZ ITERATION PROGRAM FOR HERMITIAN MATRICES - HMRZ

For a Hermitian matrix of order $n$ the program calculates the em absolutely largest eigenvalues, $\lambda_{i}$, and their corresponding eigenvectors, $x_{i}$. It is not necessary to store the matrix A, all that is required is to be able to form the vector $w$
where

$$
\begin{equation*}
\mathrm{w}=\mathrm{Av} . \tag{18.1}
\end{equation*}
$$

without altering v. The iteration is carried out with $p$ vectors where $p \geqslant e m$ and usually $p>e m$. The eigensolutions are obtained to the requested tolerance and optionally the eigenvectors may be normalised such that

$$
\begin{equation*}
\left\|x_{i}\right\|_{\infty}=1, \quad i=1,2, \ldots, p . \tag{18.2}
\end{equation*}
$$

The program is similar to the symmetric case and we concentrate our description on the differences.

## Master segment

As before the arrays are dimensioned at the beginning of this segment but as the eigenvectors may be complex most arrays now have to be doubled to hold the real and imaginary parts.

XR, XI $(n * p)$ - store the real and imaginary parts of the matrix $X$ whose columns approximate the eigenvectors.

VR ( $n$ ), VI. ( $n$ ), WR ( $n$ ), WI ( $n$ ) - used as workspace in forming the product.
$\operatorname{RVR}(p * p), \operatorname{RVI}(p * p), B R(p * p), B I(p * p)-$ used as workspace.

D (p) - stores the approximations to the eigenvalues $\lambda_{i}$.

F (p) - stores the error vector.
BB (p), Z (p), DOLD (p), LARGE (p) - used as workspace.

The values given to $n$ and $p$ respectively must be the same for all the arrays.

Subroutine Hmrz
This is identical to Qkrz except for the complex arithnetic which is performed by working separately with the real and imaginary parts of the variables. Subroutine Hmjo

This is exactly as described in section 6. Subroutine Cortho

This is a complex arithmetic version of Ortho. It produces exactly the same warning messages. Subroutine Hinp

This subroutine replaces the function Inner Product in the symmetric case. It calculates, using double precision, the Hermitian innerproduct of the columns $k$ and $l$ of the vectors held in $X$. Subroutine Cabs

We now describe three routines not needed in the real symmetric case. The first of these is CABS which calculates the absolute value of a complex number, returning this as a real variable with the original number unaltered. Subroutine Cdiv

This divides one complex number by another returning the result as a third parameter. Both of the original numbers are unaltered.

## Subroutine Csqrt

Given a complex number CSQRT calculates its with argument
square root $h^{l y i n g}$ in $\left[-\frac{1}{2} \pi, \frac{1}{2} \pi\right]$ and returns this as a second parameter leaving the original number unaltered. Subroutine Randomisation

This is as previously described and in the Hermitian case random numbers are only put in the real part of the array $X$. This ensures that if the vectors are all real no unnecessary imaginary components will be introduced.

Subroutines Info, Normalisation, Elapse and Mxop
These are as previously described save for the adaption of Normalisation to complex arithmetic.

## Subroutine Product

Product is as described before but the user must remember that the vectors $w$ and $v$ now are represented each by two arrays WR, WI and VR, VI respectively and that the inatrix product

$$
\begin{equation*}
\mathrm{W}=\mathrm{AV} \tag{18.3}
\end{equation*}
$$

must be programmed as

$$
\begin{align*}
\mathrm{WR} & =\operatorname{Re}(\mathrm{A}) \cdot \mathrm{VR}-\operatorname{Im}(\mathrm{A}) \cdot \mathrm{VI} \\
\mathrm{WI} & =\operatorname{Re}(\mathrm{A}) \cdot \mathrm{VI}+\operatorname{Im}(\mathrm{A}) \cdot \mathrm{VR} \tag{18.4}
\end{align*}
$$

19. DATA REQUIRED BY HMRZ

The form of the data required by HMRZ does not differ from that described in section 16.

## 20. TEST RESULTS

A listing of the program together with a sample of the output from one of the test runs is to be found in appendix 6 . In all the examples which follow we requested the solutions to an accuracy of $10^{-8}$.

Example 1, GK 4.13, is the Hilbert matrix of order 10. The Hermitian program produced identical results to the symmetric program. Examples 2 and 3, GK 6.6 and 6.7, are both small matrices but three trial vectors produced 3 eigensolutions in 6 steps in 1.3 seconds. Example 4, GK 7.10 taking $\mathrm{n}=11$ in example B, is a tridiagonal matrix of order 12. Four trial vectors produced 2 eigensolutions after 50 steps taking 10.341 seconds.

Example 5, GK 7.10 taking $\mathrm{n}=19$ in example B, is a tridiagonal matrix of order 20. As in example 4 we used four trial vectors to produce 2 eigensolutions after 101 steps taking 23.660 seconds. In both these examples m increases slowly throughout.

## 21. A RITZ ITERATION PROGRAM FOR GENERAL MATRICES

- RITZ

For a general matrix $A$ of order $n$ the program calculates the em absolutely largest eigenvalues, $\lambda_{i}$, and their corresponding left and right
eigenvectors, $y_{i}$ and $X_{i}$ respectively. It is not necessary to store the matrix A; all that is required is to be able to form the vector w where

$$
\mathrm{w}=\mathrm{Av}
$$

or

$$
\begin{equation*}
\mathrm{w}=\mathrm{A}^{\mathrm{H}_{\mathrm{v}}} \tag{21.1}
\end{equation*}
$$

without altering v. The iteration is carried out with $p$ vectors where $p \geqslant e m$ and usually $p>e m$. The eigensolutions are obtained to the requested tolerance and optionally both sets of eigenvectors may be normalised such that

$$
\left\|y_{i}\right\|_{\infty}=\left\|x_{i}\right\|_{\infty}=1, \quad i=1,2, \ldots, p \cdot \quad \text { (21.2) }
$$

The program is related to the Hermitian case but appears more complex by the need to introduce left and right vectors. Master segment

We list the arrays dimensioned in this segment.

YR $(n * p), Y I(n * p)$ - store the real and imaginary parts of the matrix $Y$, the columns of which approximate the left eigenvectors.
$X R(n * p), X I(n * p)$ - store the real and imaginary parts of the matrix $X$, the columns of which approximate the right eigenvectors.
$\operatorname{VR}(n), V I(n), W R(n), W I(n)$ - used as workspace in forming the product.

LVR, LVI, RVR, RVI, BR, BI (p*p) - used as workspace.

DR (p), DI (p) - store the approximations to the eigenvalues $\lambda_{i}$.

LF (p), RF (p) - store the left and right error vectors.

EN (p), DOLD (p,2), LARGE (p,2) - used as workspace.

The values given to $n$ and $p$ respectively must be the same for all the arrays.

Subroutine Glrz
The coding follows exactly the computational details given in section 22 of chapter 4. The need to test the left and right vectors is the only real difference between this program and the Hermitian case.

Subroutine Gljo
This is exactly as described in section 12. Subroutine Biortho

This routine uses the modified biorthonormalisation process with reinforcement to biorthonormalise two sets of vectors $Y$ and $X$. The coding follows sections 7 and 8 of chapter 3 . If reinforcement is found to be necessary the message "Warning 1 in biortho" is output on channel 4; if it is found that it is not possible to biorthonormalise at a particular stage the message output is "Warning 2 in biortho".

Subroutine Cinp
This subroutine calculates, in double
precision, the inner-product of two complex vectors $\mathrm{y}_{\mathrm{k}}$ and $\mathrm{x}_{\mathrm{I}}$.

Other subroutines except Product
These are as described in Hmrz.

## Subroutine Product

This is of a similar pattern to that in Hmrz but as well as being able to form the matrix product

$$
\begin{equation*}
w=A v \tag{21.3}
\end{equation*}
$$

it is necessary to be able to form

$$
\begin{equation*}
\mathrm{w}=\mathrm{A}^{\mathrm{H}_{\mathrm{v}}} \tag{21.4}
\end{equation*}
$$

These must be programmed as

$$
\begin{align*}
\mathrm{WR} & =\operatorname{Re}(\mathrm{A}) \cdot \mathrm{VR}-\operatorname{Im}(\mathrm{A}) \cdot \mathrm{VI} \\
\mathrm{WI} & =\operatorname{Re}(\mathrm{A}) \cdot \mathrm{VI}+\operatorname{Im}(\mathrm{A}) \cdot \mathrm{VR} \tag{21.5}
\end{align*}
$$

and

$$
\begin{align*}
& W R=\operatorname{Re}\left(A^{H}\right) \cdot V R+\operatorname{Im}\left(A^{H}\right) \cdot V I \\
& W I=\operatorname{Re}\left(A^{H}\right) \cdot V I-\operatorname{Im}\left(A^{H}\right) \cdot V R . \tag{21.6}
\end{align*}
$$

An additional parameter, Hermit, is passed to the subroutine to determine which product is required. If Hermit is negative (21.1) should be formed but if it is positive (21.2) is needed.
22. DATA REQUIRED BY RITZ

The form of the data required by Ritz is basically the same as for Qkrz as described in section 16. However, the second data card is in the format (I5,I2,I6,I2,E9.2,A6,2I1). The first six parameters are exactly as described previously
and the eighth is the normalisation flag, previously the seventh parameter. The only addition, the seventh parameter, is an integer used to control the computed GO TO statement in subroutine Product. It has been found advantageous for our purposes to introduce this additional parameter but a user may well wish to revert to the same pattern employed in the symmetric and Hermitian programs.

## 23. TEST RESULTS

A listing of the program together with a sample of the output from one of the test runs is to be found in appendix 7. In all the examples which follow we requested the solutions to an accuracy of $10^{-8}$.

Example 1, GK 5.5, is a small matrix but nevertheless is a useful test. Three trial vectors produced 3 eigensolutions after 36 steps in 7.828 seconds. Example 2, GK 5.8, has a complex conjugate pair of eigenvalues. Three trial vectors produced 3 eigensolutions after 44 steps in 7.242 seconds. Example 3, GK 6.5, has four well separated complex eigenvalues. Three trial vectors produced 3 eigenvalues and 2 eigenvectors after 68 steps in 10.695 seconds.

Example 4, GK 6.10, is a Hessenberg matrix of order 10. We used four trial vectors to produce

4 eigenvalues and 3 eigenvectors in 1 minute 40.3 seconds after 128 steps.

Example 5, Clint and Jennings (1971) Table 4, is a Hessenberg matrix of order 7. We used four trial vectors and in 41 steps computed 3 eigenvalues and 2 eigenvectors. The execution time was 23.376 seconds. Our results compare well with those given by Clint and Jennings.

Example 6, GK 5.26, has as its dominant values a repeated eigenvalue with linear elementary divisors and a pair of complex conjugate eigenvalues. Iteration with four trial vectors determined the 4 eigenvalues and 2 eigenvectors after 29 steps taking 14.790 seconds.
Example 7, GK 5.23 taking $\varepsilon=10^{-10}$, is a sparse matrix of order 20. Using six trial vectors we obtained 5 eigenvalues and 2 eigenvectors after 123 steps taking 1 minute 45.5 seconds. Example 8, GK 7.10 taking $\mathrm{n}=19$ in example A , is a sparse matrix of the type particularly suited to simultaneous iteration. We used six trial vectors and obtained 4 eigenvalues and 2 eigenvectors in 1 minute 3.3 seconds after 70 steps.

## CONCLUSION

We have written a program to find the dominant eigenvalues and the corresponding lefthand and right-hand eigenvectors of an arbitrary complex matrix using simultaneous iteration.

In general simultaneous iteration produces results accurately and with great reliability, although running time can be high. The method really comes into its own for large sparse matrices having no particular pattern.

In his program for symmetric matrices Rutishauser (1970) uses Chebyshev iteration in the premultiplication steps. The inclusion of some device similar to this would probably enhance our program for general matrices, particularly in the case of poorly separated eigenvalues.

It certainly appears that there is a need for a simultaneous iteration program for arbitrary matrices and the author hopes that his program may prove its worth (or otherwise) through practical application.

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## APPENDIX 1

A JACOBI PROGRAM FOR SYMMETRIC MATRICES

DA
$\mathrm{K}=1$
CAI
$\mathrm{MC}=$ LIINIT3*1H*)
ELAPSE (E,DATE, $2, K$ ) READ (5.10) NUMBER,DIHN,LENGTH

CALĹLHPUT (A,DIMA.H.NO, EIVEG,RES,NORM, FIELD)
CALS TIIF (T) 109



? ExAhptEn

$140^{\prime}$ '/'́'A DATE:',



200

L. JACO (A, D,V,B,ZZODIIN,N,ROT,EIVEC,MC)

210 WR J \{K ( 2302609,210


250 1F $2 \mathrm{~K}, 280,999.260$








400



stop OK
stop NOHH
END

```
10
30
    SUBPNHTINE JACO (A,D.V,B,Z,DIAN,N,ROT,EIVEC,MC)
```



```
    ROTJIE SRECISIOH SUA
        ta. (j) GO TO 30
```



```
    Do
yo
DO
18
    \(v(D, R)=\bar{T}^{1} 0^{\prime \prime}\)
    \(n 0(D)=A(p, p)\)
\(D(D)\)
```



```
    \(7(0)\)
ROT
\(=0\)
```



```
    SU14 \(=0\)
    So 100 pol, 101
```



```
100
    sch: cut
    if
    TRESH=0
```



```
    \(G=900.0=A B S(A(P, Q))\)
```




```
    \(H=D(A)-B(P), E Q\). AlS \((H)) G 0\) ro 110
```



```
    \(T=1 . A^{\prime}(\dot{A S S}(T H E T A)+S Q R T(1.0 * T H E T A * 2)\) )
```



```
10
```



```
    SEもま
    \(\mathrm{S}=\mathrm{T}+\mathrm{C}\)
\(\mathrm{T}=\mathrm{S} /(1,0+C)\)
    \(H=T * A(P, 0)\)
    \(7(0)=7(0)=+\)
    \(2(0)=2(0)+\)
\(0(0)=0(\rho)\)
\(0(0)=0(1)+H\)
    \(A(P)=0 \quad 0 \quad 1)\), 0 TO 210
```




```
    \(A J G=A(J, n)\)
\(A(J, p)=\{1 P-s\)
    290
```





```
    \(A(P, I)=, P J=S *\{A J \cap+A P J * T A U\}\)
230
    If (O RAO GO TO ? 50
    \(A P J=A<p, J\}\)
\(A Q J=A \in Q\)
    \(A(D=A(S j D J=(A B J \pm A D J+T A U)\)
250
    IF (FIVEC.EA. U) GO TO 300
```



```
    \(V J P=V(J, P)\)
\(V J O=V(J, R)\)
```



```
200
300
    \(R O T E R O T+1\)
fota \(3+0\)
310
320
330 مि19
```



```
    \(\left.340 \begin{array}{l}n(p)=8(p) \\ 2\end{array}\right)\)
400 COUTINIF
    COTE-ROT
500
```



```
    TErPAABN(D(P))-ABS(D(Q))
    IF (TElip) \(510,530,530\)
    590
520
330
    \(\begin{aligned} & S H=D(D) \\ & B \\ & B\end{aligned}=0=D(1)\)
```



```
    \(n 0570\)
ch= 191.4
```



```
\(\stackrel{a}{c}\)
```



```
COPTYHUE
COMT THU
```



```
A(I
QETUR
END
    FND
END OF SEGMENT, LENGTH 8?1, NAME JACO
```

SUBROISTINE JORMALISATION (V,DIMN,N)
INTEGER DIN: NIMN)
no 3 ? $\quad$ =id
$A J X=1 / 2, d)$
If $(A B S i V(I, J))$ GT. ABS (AUX)) $A U X=V(I, J)$
0 continue
no $2 n \quad j=1, N$

20
30
30 CONTINUE
RETURN
END OF SEGMENT, LENGTH O3, NAHE NORHALISATION
$=$




```
    DATA CALLY?'JAN', 'FER', 'MAR', 'APR', 'MAY', 'JUNI, 'JLY', 'AUGI, ISEP',
```



```
    100 CALL IITIME (N)
    fen
```



```
    FEEER
110
    FEE-FE
```



```
    200 RALL DEFRUF \((2,8, B U F F E R)\)
```






```
    \(F=F E\)
\(F E=E E / 2\).
\(G O \quad\) O 230
    240 RETURN \(370,370,310\)
    510 iF (F,GE, 60.0) GO TO 330
```





```
    340 ERITF
    1)
```




```
    1 ONOS:
ODO
300
```



```
    RETHA
END
END OF SEGMENT, LENGTH 182, NAME ELAPSE
```

SUBROUTINE IXUP (A, DIHN, NIMP, N, P, FIELD, LFNGTH,STREAM,IFLAG)
JNTERER DII:I, DIIP, P, NIDTH, STREAA



ERUIA\{S:'FRMTS(S)=FIELD
FRITA (S: FRMT? (5)
WRTFF
FORUAT
FOR'IAT (AU) WIDTH
READ $(2,3 U)$ WID
READ $(2,3 U)$ WID
FORHAT $\left.{ }^{\prime} X, I ?\right)$


N? = D/ 11
A AST=P-N1*N2
IF (IFLAG) 50.979,60
$N .5=1$
$N 4=1$
40 TO 70
N3=(I.ENGTH-N4*NIDTH)/Z+1


FOPMAT ( $C A 4)$
foro 300
$\mathrm{N} 2=0$
$1 F(1 F L A G)$
$N=110.999 .120$
की TO 17n

URITF $(\underset{\sim}{2} ; 140)$ NS,P
FORIAT $(7.14)$

no to ziń
IF (N? $299.210,300$
NRITF (STREAM, FKMT1) ( (A(I, J) , $J=1, F), ~ I=1, N$ )

if $(N-1 ; 900,400,340$




350 FCRIAAT:HOM, COLIIMN', I3, IS: ')
URITF (STHE思N,FRMTZ) (A(I,P), I=9,N)


370
400

410 NOITF (STREAM,FKMT1) (A(1,J), JEK,KK)
40 IF (I.ASTGT) $4+n, 42\}, 43$
20 URITF (:TREAM,FRMT2J $A(1, P)$
430

NRITF (STHEAM,FRMTZ) (A(1, J), $J=K K, P)$
440 PETURH
STOP MXOP
END
477. NAIHE MXOP

```
                                    SHMFOUTINEINRIUT SALELMN,N,NO,EIVEC,RES,NORM,FIELDS
                                    REAL A(DIHN,DIMN)S'FIELDELD, RES, NORM
```



```
                            C:ONTT\lj:!10) ((A(1,J), J=1,4), {=1,6)
```



```
                            RETMaH/
                            GO TO 1:0
                                    cOHTINUF
                                    #0 3^0 Iz1:|
                            |0 A(f,j)=0 0
                            0.0
```




```
410 A(c,i,N)=i:J/FLOAT(t+J-1)
suo
```



```
\(x=-n\)
no \(2=20^{2}=1,1\)
520 A \(1: 1\}=-1.0\)
```



```
A \((1+1+1)=x\)
``` \(\qquad\)

```

540 A $\left(1+{ }^{2}+\mathcal{C}=1:\right.$

```

```

700 COMTOT5!
710 READ $5: 710)((A(1, J), ~ J * 1,8), 1=1,8)$
suo RETMAH (8GO.0)
800 coutipul

```

```

810 A $(1,1)=0.0,1,1)=5$.

```



```

$840 \begin{array}{ll}\mathrm{J}=1+\mathrm{l} \\ \mathrm{I}, \mathrm{I}\end{array} \mathrm{A}, \mathrm{A}(\mathrm{J}, 1)=1.0$

```

```

$850 \mathrm{~A}(1,1), A(\mathrm{~J}, \mathrm{I})=1.0$
$900 \underset{\text { RONTIHUE }}{\text { ENO }}$

THIS PROGRAM HAS RUN ON 13 AUG 74
AHD EXFCUTION STARTED AT CG/11/41
EXAMPLE NUMBER 2



17 jacobi rotations have been used


THE MATRIX OF CORRESPONDIJG EIGETVECTORS IS GIVENPELON:


the residual hatrix v'av is givein belon:

execution time was 0.057 seconns

APPENDIX 2

A JACOBI PROGRAM FOR HERMITIAN MATRICES

#  <br> REALAR(12,12):AC(12,12); VR(12,12),VI(12,12), D(12), B(12), z(12) 


call elapsa (e, date,, ,k)
10

If (LENTH. (T) 120) ka-1






liso


161

NIFE(DILENGTH:G,0)


200



<30 WRITE $\{3,1,2,40\}$

30 IF (K) 230,009,260
60 WRIF



STU FORTAT $\left(9 H^{\prime}, / / / /:\right.$ THE EIGEMVA/UES OF AARE;')


 REAL D（DIMY）D DIMH），Z（DIMNS，ME
IF（EIVRC．EQ．O）OO TO 30
00103 jad
10
30
40
ROTVN
辟
品 1000 pat $10-1$
100
SMESith LE．EPS） 90 TO 610






400
STETHO／SQRT（1．0＋T＊T）
GOTOS220
CTコ1
220 OHFGA $=E * C T+F * S T$


230
240

SETHC
TAUS
S
Me
2
（

$0(f)=n(p)-H$
$0(0)=D(n)+H$
$A R(p, 0\rangle=0, ~$
A1 $\left\{\begin{array}{c}0,0 \\ 10 \\ \text { a } \\ 0\end{array}\right.$


```
300
AI(J, D)=AIJP=S*(AIJQ*CT-ARJQ*ST*AIJP*TAU
AD F2OJEP+j
```



```
AROJ=AR{路:,
AROJ=A{(RRJ)
340
*)
400
4 9 0
4<0 COHTI?}JEO
```



```
    0 之(р)=0(员)
510
    C01T=-RのT
610
    ROT=-ROT
620
    EITN=ABS(D{R})-ABS(D(Q))
830
    \
ARGR:J}=ARQJ*S*{ARFJ*CT+AIPJ*ST=ARQJ*TAAU
GO T0 420
AI(P,B)=0.0
=1
SM=D(%)
```



```
670
```


END OF SEGMEHT, LENGTH 12II. NAHE HMJO

```
8
    SNPROITINE,IORMALISATION (VR,VI,DIMN,N)
    GEALVVR(DD:U,DIIN),YI(DIMN,DIMN)
    Auxarcat,y
    AUXロVR(1,N)**2*V1(1,J)**2
    TEMP=vR(i,d)**?+VF(fux)**2
10
    AUX=SRT (A!x)
    AUX=SNRT{A!(x)
    VR(1,J)=VR(1,J)/aux
    30 V!(1 J.J.EV(I',J)/AUX
    GET!RN
end of segment, length 126, nalie norhalisation
```




END OF SEGMENT, LENGTH 182, NAHE ELAPSE

THIS PROGRAH WAS RUN ON 22 AUG 74
AND EXECUTION STARTED AT IYIRG/OT
example number $?$

```
ThE ORIGINAL 4X & matrix a IS QIVEN bELOU,
REAL PARI
```



```
IMABIMARY PART
```



```
                                    If Jacobi-bike rotations have meen usid
```



```
THE MATRIX OP CORRESPOMDIPIG EIGENUECTORS IS GIVEN GEGOWI
EEAL PARI
```



```
JMAOIMARY PART
```



```
TME RESIDUAG mATRIX Y*AV IS GIVEN bELOH:
aEAL PARI
```




```
                                    EXRCUTION TIME WAS 0.116 secondi
```


## APPENDIX 3

A JACOBI PROGRAM FOR NORMAL MATRICES

10


20

160

## $\angle 00$

500
510

560

350

400
410
420

340
Y44

FORIIA
ASTER


LIMETG*iH*J
ALL ELAPSE (E, DATE,2,K)

(LENCH: ${ }^{(3)} 120$ ) $\mathrm{K}=-1$
SOOMOE N NUINER

0020 =1:
R $\left\{\begin{array}{l}\left\{\begin{array}{l}1 \\ \{ \end{array}, j\right\} \\ 1\end{array}\right)$



 3 54x, EXALIPLE NMAER1:I3)
120 WRITE $\left(Z_{1}^{0}, 130\right)$ (LINE (1), $\left.t=1,40\right)$, (DATE (I), $\left.I=1,3\right)$, $T$, NO


140 WRITf $(6,150)$ y, N

WR: ${ }^{\circ}$ ) ( 6,160 )



CALL :MIJO (ARCAI:UR:DI,VR,VI,YR,Y!,ZRIZIIDIMN,N,RDT,EIVEC,MC)



1N CTMP(ETEO **i)
$\angle 30$ WDIT








WRR'A A
WALLEMKO (YR, DIM! , DIMH,N,N,FIELD,HENGTH,6,0)

IF SOES ETO ij) GO TD 400
WRITEM\{息P? ? ? AR, OIFIN, DIHN, M, IN,FIELD, LENGTH, 6,0 )
WRITE (6, 1uj)





COT
STOP
STO
ENO
END DF SEGMENT, LENGTH
437, NAPIE NOHIN

```
    SUBPOITINE HMJO (AR,AI,DR,DI,VR,VI,VR,YI,ZR,ZI,DIMNIN,ROT,EIVEC,
    I NTEGER DIMH,N:EIVEG,ROT,P,Q
```



```
    aEAL 2r(DI:M),21(DImW). MC
    OOISGERREGISIOM,SUG To 30
    10
    4
    40
    YI(P)=DI(P)
    ROYS=N*N*HC
    EPSON*N*HG
    SUH=0,0
    00 100 p=1:y-1
10
    SU:=SU!
    IF (SII .LE. EPS) GO TO 690
    IRESH=0.0. 4) TRESH=0.2*SM/N**2
    DO 500 pza, i=1
```



```
    BRPQ=(AR(P,Q)+AR(Q,P))/2,0
    CIPO=(A?(D;P)-AR(P;Q))/Z:U
    E=GPPQ**2*\etaIPQ**2
    F=CRPQ**2*CIDQ**2
    F=CRPQ**2*CIPQ**2
20
    00 in J=1:1
```




```
    O1{员}三AR{PSP
    TEMP=SROT(AR{{&R}**2*AI(P,Q)**2)*SQRT(AR(Q,P)**2*AI(Q,D)**2)
    |FL{E+G-F-H) 200.210.210
    |F|I.GT. 4.A!|D.ABS(DI(P))*G,EQ,ABS(DI(P))
```



```
        F(G.LE. TRESH) G0'TO.420
            E=CRPR
            FE=BRPQ
            H=0|(P)-DI(P)
            GO TO 220
<10
```



```
            IF (G. הES(UR(R))+G
            E=nPPQ
            FESIPQ
            EE=CRPQ
            FF=CIPQ OR (P)
<2U IF { { ADS(E)-ABS(F)) 230.240.240
    TEE/FFO/SQRT(1.0+T*T)
            CT=T'ST
<40
            T=F{F
C3O
    OMEGADARH=EE*ST
    OMEGADASH=EE+ET*FF*ST
    THETA=0.5*H/0.1EGA
    TE: N/(京GS(THETA)+SQRT(1.0&THETA**2))
    IF (THETA .LT. 0.0) Ta=T
CO
GOTONG?'?
= = .O/S\RT(1.0+T*T)
    S=T"#C/(1,0+C)
    Aリ二S/(9,0+C)
    H=T*NHECAA
        2d(n)=2t(p)=H
    Ea(C*C-S*S)*(ORPQ*CT*BIPQ*ST)*(OR(P)=DR(Q))*S*C
    Em(C*C-S*SS*(BRPQ*
```



```
    A1PA=F*CT*F*ST
    A1PQ=F*CT*F*S
    AI(D,Q)=BIDR
    AR(D,Q)=BAR?
```



```
    R(%)=2R(P)-H
    OR(O)=DP(P)*H
    OR(\eta)=DR(Q)+H
    OR(7)=DR(
```





```
                                    SUBROITIME ELAPSE (E, DAT, NO,K) \(\quad\) INTEGER CALL, DAT (S): MONTH(12), BUFFER(2)
                            DATA CALIGZ! JAN', 'FEB', 'MAR', 'APR', 'HAY', 'JUN', 'JGY', 'AUGI, 'SEP'.
```



```
\(100 \underset{E}{C} A L L H\) HITE (N)
\(E=A L L=3-C A L G\)
IF
    \(I F\)
\(E E E\)
    EEEE
110
```



```
CALL DATE, \(\left\{\begin{array}{l}\text { E } \\ \text { WRI } \\ \text { E }\end{array}\right.\)
\(\angle 10\) FOR'IAT (ÁO)
```




```
    \(E E E F\)
\(E E=E F / 2.0\)
\(<40\)

```

SSU GO TO 3RO. 120.0 ) GO TO 350
WRITEE $\left(\begin{array}{l}0 \\ W, 340) \\ \text { K }\end{array}\right.$

```

```

$350 \quad 1=E / 80.0^{30}$

```


```

    \(10 N O S '\)
    GO TO 300

```

```

SOU FQR'IAT GYH /////, EXECUYION TIME WAS',F9.3,' SECONDS'
END
END OF SEGMENT, LENGTH 982. NAIIE ELAPSE

```
SUBPOITTINE IXXOP（A，OIMN，OIMP，N，P，FIELD，LENGTH，STREAM，IFLAG）
INTEGER NIG：GOIIP，PGUDTH，STREAM

10

FORTAT（AG）FIEL
FOR？AT（9X，12）
IF（P＋11IDTHELETGTH） \(100,900,40\)
\(N \mathrm{CENGTH} \boldsymbol{H}\) IDT

IF（IFLAG）SO，9：9，60
\(N 3=1\)
\(N 4=7\)


WRITE \((5,00) \mathrm{NB}, \mathrm{Ni}, 114, \mathrm{LAST}\)
READ（2．90）FRHTY（2）．FRMT1（4），FRMTZ（Z），FRMTZ（4）
FORTIAT \(\left.3044_{4}\right)\)
\(G O\) TO 300
700
N2 \(=0\)
0
170 N3a7 \({ }^{17 F L A G)} 110,999.120\)
GOTO \(17 n\)
150 N \(3:\left\{\begin{array}{l}L E N G T H-P+N I D T H) / 2+1\end{array}\right.\)
140 FOR：！AT（íIL）N3IP
READ（2，1＇jO）FRIIT1（2）．FRMTY（4）
FGR＇IAT（2AG）
くUU IF（N2） \(999.210,300\)

RETIRI

\(K K=V+i q-1\)
WRITE（STREAM，32D）K，K

S4U IFR（LASTAT） \(370,540,360\)

WRITE（STREXM，FRHT2）（A（I，P），\(=1, N\) ）
360 KK＝リスHI 1

37U RETIRH
\(K K=4, K=1, N 2 H 1, N 1\)


450 GK TO 420
\(\begin{array}{ll} & \text { WRITE ST } \\ \text { 44U RETHRHMOR }\end{array}\)
END
END OF SEGMENT，LENGTH 427，NA！IE HXOP


A JACOBI-LIKE METHOD FOR OBTAINING THE EIGENSOLUTIONS OP A HxN NORMAL MATRIX
ThIS PROgRAM YAS RUN ON 22 AUG 76
ANO EXECUTION STARTEO AT \(17 / 32100\)
EXAMPLE NUMERR 2
```

TME origimal \&X \& matrix a is glven belol
mEAL PARI
imagimanr pant

```


```

    23 JACOBlmLIKf ROTATIONS HAVE EEEN UBED
    the eigenvagues of a are giveH 挭OH:
NEAL PARI 8.7424234466E=01 4.9U51846392E-01 2.9933140445E=09 1,5702059847E=0<
IMAGINARY.PART 3.9311659U81E.01 4.0506134132Em01 7.6137083077E=01 6.6866028722E-01
THE matrix of currespondi'NG EIGENVectors is given belou,
REAL PARI
imagimary part

```


```

the regidual matrix y*av is given belom;
meal pari
jmagimary part

```



\section*{APPENDIX 4}

A JACOBI PROGRAM FOR GENERAL MATRICES
```

1 0

```

20
100 wFo K ) 129,909 100







YOWITE (6.160)

HRITE (Óg61) ,





\section*{\(<00\)}

10 WRITE) \(230,999.210\)
CLU FOR'IAT SIH, /l/f,32X,'** WARNING A MAXIMUA OF 50 SWEEPS HAVE BEE

\(\angle 30\) KFITE (Ef 240 )

\(\angle 30\) IF (K) \(280,799,200\)
\(\angle C O\) FOR'IAT (ih, \(/ 1 / 1,36 K, 14 \prime^{\prime}\) JACOBI-LIXE ROTATIONS AND SHEARS HAVE \(8 E\) TEN INSERAB
く8U WRITE (6,290) ROT

SOU \({ }^{1 N}\) USED?



320

330
TORS IS GIVEM BELOW:') MATRTX OF CORRESPONDING RIGHT-HAND EIGENVEG
WRITE (6,
CALL HXAP YYI, DIMN, DIMN,N,N,FIELD,LENGTH, 6 , O)

ORSTES GIYE! DELOW: ') HATRIX OF CORRESPONDIN
CALL MROP (HR, DIMH, DIMN,N,N,FIELD,LENGTH, 6,0 O

IF (RES.ER. O) GO TO 400

CALGEMXPP (,AR, DIIN, DIM:I,N,N,FIELD,LENOTH,6,O)
WALLE SKSP GTA, DIMN,DIMI,NIN,FIELDILENGTH,6,O)
CALL ELAPSE (EA, DATE, J, K)
IF (x) \(30.099: 410\)

420 FOR'IAT \((9 H, / 1 / 1,31 \% .60\) A1)


SOU COYTIHUE
YYY STOP NOIIM
SND
ENOTM
```

    WR(!:,i!),VR(i!,i|}=1,
    00 4f') T=9,50
    ```

```

    TAM=0.0
    TEPM=0.0
    %on
    ```

```

    100
    AIEMKAI{I:KY
    ```
```

    COMTIHUEGLGE, EPS) 00 T0 450
    MARKE{
    MARKE,
    M, (% EQ, M) GO TO 300
    BR=ARUE
    ```


```

    CI=AI(K,K)EAI(H,M)
    ```

```

    lF
    DEOR . . 
    ROT%-33R
    C=BI
    S=BER
    OEDI
    RONTR=SNRT(TEE)
    ROnTI=SQR
    ```

```

    CA=1.0
    ```

```

    SX,SA=0.0
    E=E?
    l
    540 ND=O*D+TF*DF
    3>0
    GO (O STO, &E. EPS) GO TO 360
    CA=C/ROATH
    30v COTVX=0/NOnT*

```


```

    Cx=SX+Ci) Y X
    FTA={ER*GX+!I*E!)/R\capOTT
    ISE=(NR*BI-ER*ESI/RNOTH
    TEE=ID*NE+ZNOT1*TSEJjROOTZ
    NDaROOTZ*HDOTZ*TEE*TEE
    ```
```

1.1
380

```

```

TE $=H J * C X * S X$
$C O S A=C i E A-S A * S A ~$
SINAAFDG*CA*SA

```



```

360

```

``` RO (ROOT (GE. EPS) GO TO 389
```



```
SBE5/ROOT
```



```
TAMH=ROFT \((G+2.0 *(N C+N D))\)
390
\(C A=C H * J H H\)
\(T E D=S X * S A * C B-S B+C A)\)
```



```
C2R=CX*G*YFHK(CA*CB*SA*S日)
```



```
STR=TEP-TEH
```



```
\(S 1 I=T E P+T E I I\)
\(S T I=T E P-T E Y\)
TEHESGRT(S1R*S1R*S1I*S1I)
```



```
\(M A R K=0\)
\(O D R O\)
400
```







```
WR (I,KS \(=C 1 R * H R I K-C 1 I * H I I K+S 1 R * J R I H-S 1 I * 111 M\)
```





```
AI \(A=A\}\)
AI (I, K) =C CRARIK-C2I*AIIK-S2R*ARIM+S2I*AIIM
```



```
VRIK=VR(I,K;
VRIMEVRG:
```



```
VR(I,K)=C2R*VRIK-C2I*VIIK-STR*VRIN+S21*VIIM
```



```
420
420
ROT \(=\) ROT +
430
440
RO!T:THUE
440
ROT=~ROT
430
460
DR(I) \(=\lambda R(\mathbb{N}: I)\)
```



```
DREDRR
\(01=7 D 1\)
ouv
-
\(80640 \quad K=1,11-1\)
\(T E H=E N(K)-E i N(L)\)
670
```



```
\(E N(L)=T E M\)
TEM=TPR (k)
DOR (x) =iDR ( 6 )
```



```
DO1(k)ngTS(
0598
```

```
            C399.**)
END OF SEGMENT, LENGTH q707, NAHE GLJO
C336
    SUNROITINE CHECK (AR,AI,HR,HI,VR,VI,EN,EM,DIMN,N)
```




```
    DOUSLE PRECISIO:N SUUIR,SUMI
    lol
    SO
    20 SUM! =S!!!I+AR(I,X)*VI(K,J)+AI({I,K)*VR(K,J)
    su EN(J)=S'IIR
    EN(J)=S:NH,
    40 AR{!,J}=ENH{J}
    AOD30
    SUMR,SUMI=0.0
    SUMP=S!I!R+MR (K,I)*AR (K,J)-WI (K,I)*AI (K,J)
    OU SU:!I=S!!iI*'JR(K,I)*AI(K,J)=WI(K,I)*AI(K!J)
    TO EN(IG)=SUMR
    EM(I)=S'MM
    AR(I,N)=E1M
    .REND
END OF SEGMENT, LENGTH 350, NAIIE CHECK
```



```
l
```



```
    SURPOUTINE,IXOP (A,DIMN,OIMP,H,P,FIELDILENGTH,STREAM,IFLAG\
```



```
    OATA &P\TJ/{H{ , ,1HH,BfX,1P ,{HN,1HE,8H
    0 CAL{IFLGG) i0,200,10
```



```
    10
    FRMT, (5):FRMTOTGSBIJFFER
    WRITE (2,20) FIELD
    Z0
    FORNAT(10) WIOTH
    IF(OAI!DTMIEENGTH) 100,100,40
    N1=LFHGTH/WIDTH
    NZ=\Gamma/|g
    LAST=P-114*N2
    1F(IFLAG) 50,999,60
    N3=1
    GO T0 70
```



```
    N4E{LENGTNGLASTHWJDTLSHZ*T
    FORMATZ(41,0),FRHT1(2), FRHTY(4), FRMTZ(2), FRMFZ(4)
    FORPIAT i4A4
    GO TO 300
    N
    G0 T0G130
    URITE (5;{4})N3,P
    READ (2;15D) FRIIT1(2), FRMTM(4)
    FURIIAT (2A4)
    G% TOR2?:900,210,300
    WRITE (STREAM,FRMTI) ((A(I,J), JmI,P), I=I,N)
    RETIRM
    N2#T=N2-N1
    00 330% K=19%400,310
    KK=k+H1ニ二
    WRITE (STREAM,320) K, KK
```



```
    WRITE (STREAU,{RHTG), (SA(I,J), J=K,KK), I I={,N)
```



```
    WRITE (STREA(A,FRMTZ) (A(JIP), II=GN)
    G0 T0 370
    KK=\\:17+9
    WRITE (GTREAM,320) KK,P
370
    DO 410 K=1,H2H1,N1
    KK=K+H\(-1 (REAM:FRMTq) (A(q,N), d=K,KK)
```



```
    60 T0 4K?
```



```
4 4 0
    RET!lRM SHEAMOFRMT2) (A(1OJ., J=KKIP)
    STOP RIXOP
    END
END OF SEGMENT, LENGTH 427, NAME MXOP
```


## 


EXAMPLE NUMEER 6
the original gx hataix a is given belowi
real pari
jmagimary pant

## 

## 

54 Jacosi-bike rotations and shears have gesn Uged

```
ME EIGEnvalues of a abE given beloh
AEAL PARI \(4.0000000005 E 00\) 3.0000000007E 00 2,0000000003E 00 1.0000000006E 00
MAGIMARY PART 8.0000000024E \(\because \dot{O}\) T.0000000017E OU 6.0000000097E 00 S,000000001《E 00
```

TME MATRIX OF CORRESPONDIHG RIGHT-HAND EIGENVECTORS IS GIVEN 日EGOH: REAL pari
imagimant pant

TM\}

- The matrix of currespondito left-hand eigenvectors is given below,



## the residuag matrix wiav is given oeloni

real pari
imagimary pant


EXECUTION TIME WAS 0,753 SECONDS

## ******************************************************

-•
$\vdots$

## APPENDIX 5

A RITZ ITERATION PROGRAM FOR SYMMETRIC MATRICES

```
NOM
    SUGROITTINE,JACO(A.D,V,R,Z,DIMN,NIROT,EIVEC,MCIEPSZ)
```



```
    DOLDLE PREgisio!' SUN
    DO in y=1,N
    10
    DO ? P Pi,N
    20
    DO;Op=i
    A(P)=0(p)
    O
    EPS=5.0*H*(N-1)*MC
    EPS=5*ON**(N-1)*MC
    DO 200 p=1,N-1
```



```
100 SU:Y=S[II+DBLE(TEIP)
    SM=S
    TRES(H=0:0.%.4) TRESH=0.2*SM/H**2
    N0 330. P=%,4)
    G=FOn.0#ARS(A(P,Q)), AS(D(P))+G.EQ, ABS(D(P)),AND,
```



```
    HFD(A)-D
```



```
    IETCNMGABS(THETA)+SQRT(%.0*THETA**Z))
170
    C=? N/SgkT(1.0+T*T)
```



```
    H=T*A'(P,O
    2(D)=?(p)=4
    O(Q)=D(O)+H
    A(P,Q)=0 O
    1f (DO.jop,p),GOTO 210
    AJP=A(J,P)
    AJO=A(J,OP-S*(AJQ*AJP*TAU)
```



```
    IF \P+1 Jap+j,A-{
    APJ=A(P,J)
    A(PDJ)=:PJ-S* (AJQ+APJ*TAUS
```



```
    DO{40.EOG+1)NG
    APJ=A{P:J}
    A
<40 A(Q,J)EAQJ+S*(APJJAQJ#TAU)
    DO 2GO J={名
    VJP=V{J,P
    V(J,p) &'IP-S*(VJQ+VJP*TAU)
\angleOU V(J,O)EENQ
S10 A(P,QQ品.0
3Cu GONTI|HF
```



```
    8(口)口B(?)*
S40 2(P)nm%0
UO COMTINUE
y00 00 540 N=1:A-1
```



```
    TEPG#ABR(D(P))-ABS(N(Q)S QOGTO 530
\u SM (TE!1P) 510,530,530
    SMap(p)
    O(Q)=-5|
```



```
    S"A!!?I:P)
320
340 CONTINUE
    RETUR
END OF SEGMENT, LENGTH TOS, NAIYE JACO
```

```
    SUBROUTTNE ORTHS (X,B,DIMN,DINP,N,P,F,MC)
```



```
    M,
    ORIG=1
    u suman.0
    IF (k jea. 1) GO TO 40
```



```
    if (ONiG.ER. 1) A(p-k+1,i)=s
```




```
Su
4U SaIMHER PRODUCT (K,DIMN,OIMO.N,K,K)
    SUH={UH+S
    TEF!\!
    WRITE (4,100)
luO FORYAT(U'; NARNING, IN ORTHOD)
    IF (S*1!C ; 乍;O.O) GOTOO 10
    |OR!IAT <: MARNING 2 IN ORTHOD
    s=0.0
    S=(p: k+1,k)=0.0, GO T0 60
    S=S\RT(E)
    S=`\mp@code{N*}
6u pocin }=1&'l
80 colif!ulie
    RETURN
END OF SEGMENT, LENGTH 264, NA:IE ORTHO
```







```
                                    DATA GOTGIVIJA:J', FEBI, IMAR', IAPR', IMAY', IJUNI, IJLYI, IAUGI, ISEPI,
```



```
                            100 CALL TITIME (N)
            CALL=3-CALL
```



```
            10 REFMR
            EEENEOE-3
```






```
                            \(E \cdot E E=1.0 E-03\)
```



```
                        EFEF.
                            GEFER 230
S40 RETMRH \(300,370,310\)
```






```
    \(1)\)
    \(G 0 T 0300\)
```



```
    300 WRiTf
    \(10 \mathrm{NDS:3} 3 \mathrm{O}\)
```



```
end of segment, lengit 182 , nalle elapse
```

```
10
```





```
10
20
30
so
60
10
```



```
20 NOTO 130
SU NRIT \(\mathrm{FENGTH-PAHIDTH)/2*}\)
130
10 WRITF (STREÁ10,300
```







```
WRITE (STREAM,FRMTZ) (A(i, P), \&:1?
\(s o u\)
370
410 WRITE (STREAM,FRMTI) (A(9.J), JGK,KK
```



```
430 KK= Ti?nt
G4U RETYTRN (STREAM,FRMT2) (A (Y, dle JaKK,P)
440
RETOP
STOP
ENO
```

    SURROUTINE PRODIJCT (V,W,OIMN,N)
    ```

```

    REAL V(DIG!)& IJ(OIMI)
    DORBIE TRECISION SUII
    G0 70 (%00,200,300,400,500,600,700,800,900), NO
    COHTY:NUE
    D0 120 I=7,:1
    no 9i00 Ja1, I
    SOM=SJM+(1.0/FLOAT(I+J=1)) &V(J)
    Cg"Ty=5!FELC(SUM)
    CONTIIUE
    RETHRA
    CUU CONTINU
W(I)=V(T)+FGOAT(I)*V(N)
COHTIMUP
SUA=0.0
SUMES!M!FGOANT(I)*V(I)
C20
W(N)=SNGL(SUH)
RETITR!,
s0
W(7)=4.0*V {
W
W(I) aV(i
RETITRN
40
K=(I|-1)/2
W(1)=F-f(1)+V(2)
W(Y+i)=V(K)+V(K+Z)
L_K
DO 490 I=2,K
LEL=1
W(I):+N(I-1)+L*V(I)+V(I+1)
w(j)=w(j-1)+L*V(I)+V(I+1)
4 7 0
300
RET!IRN
K=(:1-7)(G
N(K+1)='(K)+V(K+2)
W(N) aV(it-7)-K*V(N)
\&%K
O 510 I=Z,K
l=l-1

```

```

2%
OU
contruy,
W以?

```


```

    10 conTifu
    CUO COMTINIJF
X=S\capRT(FLOAT(N-1))

```

```

    Y=Y
    Y=X (#ORT(FGOAT(I*(N-I)))
    W{I)=Y&Y(I-I)+X*V(I+q)
    10
Y=Y
W(N4)=?*! (N-1)
800
\T IIUE

```

```

    W(3)=\({)+3+{*V({)+R'U*V(3)+3.g+V(4)+V(S)+V(6)
    ```

```

    n0~R&\
    W(I) =SNHL(S'JM)
    810
yUu com*RNU
RET!IRM
END
END DF SEGMENT, LENGTM
805, NARE PRODUCT

```


IIFORMATIMNAL OUTPUT ON LOOICAL STREA, FOR EXAMPLL NUMEER. 1 .

```

THE ERROM VECTOR 1SI -1 000000N000E DO -1.0U00000000E OU -1,000000GOUQUE OO -1,00000U0000E OU

```


THE ERROR VECTOR 1SI \(\mathbf{- 2 , 8 6 3 9 3 4 9 0 8 8 E - 0 3 ~ 2 . 3 1 4 5 7 7 2 2 3 1 E - 0 3 ~ 9 . 7 8 2 4 2 3 7 6 7 3 E = 0 3 ~ - 1 . 1 6 6 1 2 2 5 3 7 6 E = 0 2 ~}\)





\section*{APPENDIX 6}

A RITZ ITERATION PROGRAM FOR HERMITIAN MATRICES


```

                                    REEL XR(SU,G),XI(5N,B), VR(50),VI(S8),WR(50),WI(50)
    ```

```

    GEL.L EL,IPSE (E,DATE,2,K)
    REAS (5,10) NUMgER,DIMN,OIMP,LENOTH
    10
<0

```

```

30 FOR(K'1 :LP: O READ'(5, 30) (XR(I, J), XI(1,d), J=1,P), Iaq,N)
CAL}(:UE(T)

```

```

    *)
    3ER'+13
    ```




```

604
GDEIACGEPTED TO, ANXAGCURAGYGEFYALUES AND',I3,' EIOENVECTORS HAVE

```



```

CAIL MXOP (O,I,DINP, 1,P,FIELD,LENGTH,G,K)
S10 \&ORMT\{价?|/H/, THE MATRIX OF CURRESPONDINO EIGENVEGTORS IS GIV
WRITEGOM: \{%0)

```

```

3<1
FORIAAT (9H,', IIIAGINARY PARTI)

```



```

400

```

```

200
200 CONTIN
y9y STOP NOHM


```
        SURRGUTINEMHRZ (XR,XIGVRNVAWR,WIGRVR,RVIABR,BI,D,F,BS,Z,DOLD,
        INTCGER OI:I,DIIP,P,EA,H,G;HG,G,GAMG,EPSS
        EAL XR 位:,DIHP),YI(DIMN,DIMP), VR(DIMN),VI(DIMN)
```



```
        REAL Z(OIMP): DOLO(PIMP), GARGE(DIMP), MC
        O 10 !
    DOLO(1)=0:0
    C38 IS 7E/2,S76'SSSGRGEST EXPONENT ON M/C)
        KS{S,HIC1،M1m0
        z2この,
        Z2=O\10.0*EPS
        O>0 Jj1.j n) GO ro40
```



```
        80 3n f=1:员
    SO XI{I,N)=O&G (XR,XI,DIMN,DIMP,N,P,O,HC)
    c form KM= =vNAS(KII)
    100 00 $301 X =G+1,P
    110
```



```
        Su!aj{1J:11=0.0
    120
```



```
    120
        AR{J-\mp@subsup{r}{1}{\prime},1-G
```



```
            A
    140
    15000 150 1:1,
    -150 D(1)=001日(1)
    C FORH X=YV WIEREYYAX
        <u0 00 z?0 j=6+1,
    <10
        CALI PRODUG'T (VR,VI,WR,WI,DIMN,N)
```



```
    2%0
```



```
    <30
        Z BB(J)=S!jinR:
        l
    C CS
```




```
    300
```



```
    C FORMXSMKS**
```



```
end of segmenta length 9093. nalle hmrz
```

    SUNPOUTINE,HMSOGEAR,AL'R,VR,VI,B,ZIDIMN,N,ROT,EIVEC,MC,EPSZ)
    ```
```

    SUNPOUTINE,HMSOGEAR,AL'R,VR,VI,B,ZIDIMN,N,ROT,EIVEC,MC,EPSZ)
    ```


```

    REAL D(CIH!!): B(DIMM), Z(DIMN), MC
    ```
    REAL D(CIH!!): B(DIMM), Z(DIMN), MC
    DOUBLE TRECISSON SUAG
    DOUBLE TRECISSON SUAG
    00}90{=1,
    00}90{=1,
10
10
<u
<u
    30 DO
    30 DO
4 0
4 0
    2(p)=0.0
    2(p)=0.0
    RPS=5,0*N*(j-1)*MC
    RPS=5,0*N*(j-1)*MC
    DO 60% I
    DO 60% I
    SU'4}=0.
    SU'4}=0.
    009n0 P=1:N-Y
    009n0 P=1:N-Y
    TEMP=SRRT(AR(D,Q)** Z*AI(P,Q)**2)
    TEMP=SRRT(AR(D,Q)** Z*AI(P,Q)**2)
        SU"=SUHH+DBLE(TE!IP)
        SU"=SUHH+DBLE(TE!IP)
        IF (S!1.LE. EPS) GO TO 610
```

        IF (S!1.LE. EPS) GO TO 610
    ```






```

        G=700.0*TE'lP
    ```
        G=700.0*TE'lP
        IF (TEIIF.LE. TRESA) GOTO 42O
        IF (TEIIF.LE. TRESA) GOTO 42O
            EmAR(P:?)
            EmAR(P:?)
        IF
        IF
    U
    U
    VR(1,J=21,N
    VR(1,J=21,N
    V
```

    V
    ```


```

    (P)=AR(P;P)
    ```
    (P)=AR(P;P)
    |
    |
        STEq.11/SART(9.0+T&T)
        STEq.11/SART(9.0+T&T)
        GOTO220
        GOTO220
6%O
6%O
            CT={品(SQRT(1.0+T*T)
            CT={品(SQRT(1.0+T*T)
<<0
<<0
    H=DA=E*CT+F*ST
    H=DA=E*CT+F*ST
    H2?(n)-D(P)
    H2?(n)-D(P)
    TF (ABS(H)+G -EQA ABS(H)) GO TO 230
    TF (ABS(H)+G -EQA ABS(H)) GO TO 230
    T&7(TG{ANS(THET{)+SQRT(9.0+THETA**2))
    T&7(TG{ANS(THET{)+SQRT(9.0+THETA**2))
    GOOTOGF:O
    GOOTOGF:O
44U CE1.N/SतRT(9.0+7*T)
44U CE1.N/SतRT(9.0+7*T)
    S=T; C
    S=T; C
    TAM=S/({q, 0+C)
    TAM=S/({q, 0+C)
    (P)=2(只)
    (P)=2(只)
    2(D)=2(a)+4
```

    2(D)=2(a)+4
    ```


```

        AI (S,Q)DO:O Q) GO TO 310
    ```
```

        AI (S,Q)DO:O Q) GO TO 310
    ```




REAL XR RI: I:DINPSUF (OIMNTDIMP), MC

10


CALL GABS (SRISI,S)


30
0 contint

sutsinilis
WRTIE © iT: T/100
100




\(T E^{\prime 1(1)}=S R \pm \neq R(J, K)-\$ 1 * X I(J, K)\)
XR(J, K) =TEIIP
- XR(J) K)
COHTHM
RENORN
END
END OF SEGMEIIT, LENGTH 307, NAHE CORTHO

SUAROMTINE HINP (XR,XI, DIMN, DIMP, N, K, K, SR,SI)
INTEGER DIMI,DIPP), XI (DIMN, DIMP)
DDINIE PPEEISIO:I SUMR,SUMI
SUM? SUMi=0. 0



RETIRN
END Of SEGMENT, LENGTH 169, NARE HINP


SUMPOUTINE CDIV (XR,XI,WR,WI;ZR,ZI)
YRJilR
IF (ABS (YR)-ABS(Y1)) 20.20.90
\(H E Y I / Y R+Y R\)
\(Y R=I \phi Y\{+Y\)
\(Z R=(X P+11+X I) / Y R\)
\(Z I=(X I-H * X R) / Y R\)
RETVRI-H*XR)/YR
20 HEvn 1 Yi
ME
\(Y I=114 Q+Y I\)
\(Z R 2(H+X I+X I) / Y I\)
ZRZ \((H+X R+X I) / Y I\)
\(Z I=(H * X I-X R) / Y I\)
ZIGTH*
RETIRU
END

```

END Of SEGMENT, lengTh 8s, NA:IE CSQRT

```

\begin{tabular}{|c|c|}
\hline  & \begin{tabular}{l}
 \\
 \\
COH:CII MO FIELD, EENGTH, K \\
wo IF SORF (1) \\
 \\
 \\
 \\
 \\
 \\
LUO 60 TO TPRYO \\
 \\
 \\
 \\
\(215)^{\circ}\) \\
SOU WRITE (4; 3! \\
 \\
 \\
 \\
RETIRAI \\
END
\end{tabular} \\
\hline & Ih 173, NAlle info \\
\hline
\end{tabular}


END OF SEGMENT, LENGTH 176 . NAIIE NORIIALISATION

```

END OF SEGMENT, GENGTH 427, NAILE MXOP

```
```

    SUAROISTINE PROD'JCT (VR,VI,WR,WI,DIMN,NJ
    METGGR AI! ! ! PRZVI (DIMN), WR(DIHN), WI(DIMN)
    ```


```

    fo To ( \(00,200,300,400,500,600,700,800,900)\), NO
    for To
    Bo i? 0 i=1!"
    sump sumi=o.
    ```



```

    RETMRH
    revtriue
    1F (PREV, ER. NA) GO 50220
    REAP(PRE,
    fortat (दan.o)
    a
    ```


```

    SUMP=SURR \(+A R(I, J) * V R(J)-A I(I, J) * V I(J)\)
    230

```


```

    RETMR
    continue
    60 T0 \(20^{2} 0\)
    X1=509T(FLNAT(N-1))
    WR(1) \(=-\times 1 * V(2)\)
    ```

```

    \(x_{1}=-x 1\)
    x 1 ESRRT(F6ORT(K*(HmK)))
    ```

```

    Y| \({ }_{a}=x^{1}\)
    ```

```

    WI (ㅍ) =Yq*VR \(\left(\begin{array}{c}(-9)\end{array}\right.\)
    buU
GO T:IUE
GU0 COHTTHADE

```

```

    GUU COHTL:HE
    GUU CONTINUE
YUU CONTINUE
CONTMNUE
ENO
END OF SEGMENT, LENGTH 496, NAIIE PRODUCT

```

\section*{THI METHDD OF "quICK RITZ" ITERATION POR AN HERHITIAN MATRIX}
 EXAMPLE NUMAER 4

\section*{2 eloghvalues and 2 eloenvectons have meen accepted to an accuracy of q.overob}

the matrix of corresponding eigemyectors is given below
aEAL pari

IMAgINART Part



EXECUTION TIME WAS 10.408 SECONDS
\(\qquad\)
```

THE ERRON VECTOR JS:

```




```

*)

```



```

TME |RROR VECTOR 18, -1.2653734127E-02 -4.2539078661E=03 5,2428331290E002 6.2035040435E=02

```


```

TME ERROM VECTOR 18: -9.6099954182E-04 1,4008257652E-02 -4,9370839009E=03 1.5076986457E=01

```



-



NUMBER OF SOLNS. T8ESE COMBGTES :




```

TME APPRUXIMATIUN: TU THE El\&\&f
NUMBER OF STEPS PERFORMED ** 33

```



```

THE ERROK VEETOR IS: 4, 2793994347E-08 4.0457月26760E-08 5.9770306235E=04 5,8691298552E-06

```

```

    Mu(t)
    THE ERROK vector isi
646796506E-09 -1,0570200848E=09 P.2994897273E=05 9,2647140912E-0S

```


\section*{APPENDIX 7}

A RITZ ITERATION PROGRAM FOR GENERAL MATRICES
\begin{tabular}{|c|c|}
\hline  & \begin{tabular}{l}
MASTER DIN: DIMP, P, TYPE,EH:G.H, LINE(60);DATE(3) \\
 \\
 \\
 \\
COMTOH YYPE, HL. EELD \\
DATA LIME/O.j*TH*) ELD, LENGTH,K \\
\(K=1\)
\(M C=E\) ELAPSE (E, DATE, \(2, K\) ) \\
MC \(=\) \\
 \\
 \\
 \\
 \\
 \\
SER'43 \\
 \\
 \\
 \\
CAL GLRE, PR, \\

CA Moinatigitogo to \\
 \\
 \\
COU WRITE (G, 210) H, G, ERS \\
 \\
 \\
 \\
 \\
 1:'? \\
 \\
 \\
311 for"A \\
 \\
 \\
 \\

\[
\text { WAL } H X \text { OP }
\] \\
 HRLTE (s, 5 \\
CRLLEMXPD \\
WRITEHYOS \({ }^{3}\) CAL \\
S40 foritat (iHy \\
ssu WRITF (0:350) \\
SSU FORIAT L \\
CALL HXCP KF, 1 , DIMP, 1, P,FIELD,LENGTH,6,0) \\
S31 FRORET (BATGHT-HANDI) \\
CALL MXAP (MF, 1, DIMP, 1 PR FIELD, LENGTH,6,0) \\
CALLELSOSE (K) DEDATE \\
 \\
 \\
430 FOR'IATM
SUO COHIDHE \\
sou covithale \\
\(949 \underset{\substack{\text { STOP } \\ \text { END }}}{\text { HOIM }}\)
\end{tabular} \\
\hline
\end{tabular}




```

            dOUELE PREGISION SUTIR,SUMS
            OO10 !=1,
            OOLT(1,
    ```



```

            22=0
    ```

20
000
0
0
00
00
```

        GALORABIDGHISATION (YR,DIMN,DIHP,N,N,ZZ)
            00 3n LE{:R
            YR(1,J)=YR(I,J)
            30 X1(1,J)=0:8
    FORM B=Y的SS(KII)
100 Do 740 K=G+1,F
VR(1)=>R(1,'心
1 1 0
1<0
CALL PRDOUCT (VR,VI,WR,W\&,DIMN,N,N1)

```

```

        00130 T=7:0
    ```

```

        &a{J-G,K-G}=sula
    140 8il(J-G.K-G)=SUli
        OO $00 K=0+1,
        DOR{SOYR=? N
        150
        CALl PRDBIGET (VR,VI,WRIWS,DIMN,N,I)
        00 160 =1,品
    c SUGVE{E-VALIE: SNOLEM FOR B !, E, WAV=D
CALGGLJO (SR,BI,LVR,LVI;RVR,RVI,EN,DR,DI,DIMP,PMG,HC,EPSZ,I)
f (G.EO,0) GO T0 200
00980.
180
M,
My0 DI(1)=0., {D{1;1}
<UO DO 230 {=1.:
00 230 j=1;'{,p
SUMR;SUNL=0, 品
SNMR=SIN:R+XE(f,K)*RYR(K-G,J-G)-XI({,K)*RVI{K-G,J=G)
<10 SU"yIS'P!+x
<<0 VR(J)=S'MR
00 230,J=G*1,P
XRR(1,J)=VR(J

```

```

        SUMR, SU:II=0:O
        SUMR=51P!R+YR(I,K)*LOR(K-G,J-G)+YI(I,K)*LVI(K-G,J-G)
    ```

```

    csu VR(J) SSMMR
    DO 26U J=G*!,P
    <60 YR(1, \J)=VR({J)
    ```
```

END OF SEGMEYT, LENGTH 1798, NAME GLRZ

```
```

    SUBNOITTINEGLJOG(AR,AI,NR,WI,VR,VI,EN,DDR,DDI,DIMN,N,MC,EPS2,ROT)
    INTEGER D!!I!:GNTM),AI(DIMN,DIMM), WR(DI:IN,DIMN),WI(DIMN,DIMN)
    ```

```

        REAL IIAY,HD,HGIISW,HIC
        MARV=O
        ROT=O
        WR(I,I):VR(I,I}=1.0
    ```


```

    WII
    TF (PARK .EG. 1) GO TO 450
    OO TEM=0.0}K=1,
    OD GOG I=q,M
    0
    ```

```

    COMTINAU+TEH
    IF (TAU',LE, EPS) GS TO 450
    lol
    DO 3{0 I=1,H .OR. & EEQ.M) GO TO 300
    AMKIEAI{K'1}
    AR!K=AR}
    AIIK=AI
    ```

```

    HEHI+AJKI* QRMGARKI*AMII-ARIK*AIIM+AIIK*ARIM
    T,
    S00
520
350
ROCTM=SRRT(S*S*C*C
S1G=1.0 (D LT, 0.0) SIG=-1.0
SA=0.0

```

```

    SX,SA=0.0
    CXIC
    MFEE{TSW,GT. 0.0) GOTO 340
    B=-BR
    540
SSU IF (ABS'S).LE.EPS) GO TO 360
CAEC/RONTI
SA=S<RONTV
cotx=coTzx*(SIG*SRRT(q. )\& COT 2x*COT2X))
Sx=SIG/SORT(9:O+COT只COTX)
CX=SX*C^T公
ETA=(ER*BH+nI*E!)/R\capOT
TSE=(DR*Bl-ER*EI)/ROOT\

```
```

40V
CNE-C/R\capOT
TAMH=20.TT (G*2.0*(NC+ND))
CH={.0/SRRT(1:D-TAHH*TANH)
540
TE=S\G*(-RONTY*OE+TSF*D)/RO
ND=ROOTS*ROOT2+TEE\#TEE
TEE=HJ*CX*SK
COS:A=CA*CA-SA+SA
SN:
TEP=HI*CNSA-HR*SNNA
HI=CX*CX*H}+SX*SX*TEP-SA*TEE
B=1SM*TA*CA+ETA*SA
SO
S=HR-SIG*NOT2*E
ROOTESRRT(C*C+S*S) GO TO 380
CB,CH=1.0
G0
SHECH*TSAH(SA*CB-SB*CA)
C1R=CXCH-TEM
C11,C2I=-SX*SH*(CA*CB*SA*SB)
TEP=SX*CH*GA
S1R=TEP-TE!
SN
S1I=TEP+TEI

```

```

    IF (TEM.GT: EPS .AND. TEP .LT, EPS) 60 T0 420
    MARY=0
        {|
    ```


```

    AI(PI,I)=SLS*AIKI+SZI*ARKI+CZR*AIMI+CZJ*ARHI
    WRIK:!IR {I'X
    WRIM=WR
    ```

```

    WI<I;N1)=S2R*WIIK+S2I I*WRIK+G2R*WIjM+C2J*NRIM
    DO C'11 I =1,N
    ARD位隹{I:G}
    AIIK=A{{I'K}
    AICI, ==CRR*NRIK-C21*AIIK-S2R*ARIM*S2I*AIIM
    ```


```

    VRIV:VR{1,K
    VI!NEVI{
    ```


```

    COMTIM1E
    conT\HUE
    CONTINUE
    ROT&-ROT N N N
    OOR(I)
    R=DDR(I)
    OR=ODR(!
    000
6 1 0
0%0
EN(I)=DR+DR+DI*DI
ENORGO K=DR+DIG
TEH=EN(H=K\&%:N
IF (ARS(TEN) (EE,GSS2) GO TO 6:0
TEPI=DDR(K)=,ODS(1;6SO
{F (ABS{TEM) GEGESS2) GO TO 620
C

```


```

END OF SEGMENT, LENGTH 9766 , NAHE GLJO

```

```

SURROUTINE BIORTHO (YR,YI,XR,XI,DIMN, DIHP,N,P,F,MC)
INTEGER DIII, DIMP, P,F (DIHN, DIMP), XR(DIIN,DIMP),XI(DIMN,DIMP)
REALET,RTEIC DOURLE RECISION LSUM, RSUH
10
RSU'1=0. 5

```

```

CALLCIMP (H,I,K,XR,XI,YR,YI,DIHN,DIMP,SR,SI)

```


```

20
30
DO SOCI: $\mathcal{C}, K-I, K, Y R, Y I, X R, X I, D I M N, D I M P, S R, S I)$

```

```

OSU'i $=$ RS' $\} H+S$ ©
TEMP $\quad=X R(J, K)-S R * X R(J, I)+S I+X I(J, I)$
$X I(J, k)=X I(J, k)-S I=X R(J, I)-S R=X I(J i \xi)$
40

```


```

RSU'I=RS:IM+S
LT=LSUH

```

```

WRITE (iGGGN) GANI:G I IN BIURTHO')
IF (S*!
YZO FOR'领 ( ${ }^{\prime}$ NARNING 2 IN BIORTHO')
$S R=0.0$
$S I=0: 0$
GO To 8
10
CALLCIIP (I,K,K,XR,XI,XR,XI, DIMN,DIMP,SR,SIX
XNOPH=SYRT\{SR) $K, Y R, Y E, Y R, Y I, D I M N, D I M P, S R, S I$

```


```

SR=SR/(XUUR I ( Y NOR11)
SIESIC(XUSN:I*YiNRII)
CALL CSORT (SR,SI,TR,TI)
D1R=XMOTM*
$011=X N O R H+7 I$
$02 R=Y H O R M * T R$

```

```

80
TEMR = SR*XR(J,K) +SI*XI(J,K)
$X I(J, K)=-S I * X R(J, K)+S R * X I(J, K)$
$90 X R(J, K)=T E: T P$
CALLCDIV (1.0,0.0.D2R,O2I,SR, SI)

```

```

$Y I(J, K)=S I * Y R(J, K)+S R * Y\{(J, K)$
$Y G(J)$
110
CONTIASE TEIP
RET'IR
END

```
8589
                                    SURROUTYNE,FIHD {H,K,L,YR,YI,XR,XIMDIMN,DIMP,SR,SI\
                                    REALYR(DI:Q:DI:PP), YI(DIMN,DIHP), XR(DIMN,DIMP), XI(DIMN,DIMP)
                                    DOUFIE RRECISION SUMR,SUHI
                                    Sumr=方.b
                                    SUMI=0.0
10
```



```
SR=SNGL{SUIR}
SETUR
END OF SEGMEMT, LENGTH {69, NAHE CINP
```



```
END OF SEGMEAT, LENGTH 66, NAIIE CABS
```



```
\begin{tabular}{|c|}
\hline \multirow[t]{14}{*}{} \\
\hline \\
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\hline \\
\hline
\end{tabular}
SUBPQUTINE CSQRT (ZR, ZI,YR,YI)
\(X R=2 R\)
\(X I=2 I\)
CALL CARS (XR, XI,H)
\(H=52 R T ?(A B S(X R)+H) / 2.0)\)
XF (XI) 10.20 .10
\(10 \times 1=(1)(2,0 * 1)\)
\(201 F(X R)\)
\(50,30,30\)
\(X F=H\)
\(X 0=T 070\)
40 IF \((x 1)^{0} 60,50,50\)
\(\begin{aligned} & x R \\ & \times I=11\end{aligned}\)
GOTO 70
60 \(\begin{aligned} & X R=-X I \\ & X I \exists-H\end{aligned}\)
70
ENO OF SEGMEIT, LENGTH 88. NAILE GSQRT
```




END OF SEGMENT, LENGTH 2Z2, NAIIE INFO


END OF SEGMEMT, LENGTH 176. NAIIE NORMALISATION

```
end of segment, lengyh 182, NaME ELAPSE
```



```
SUBROUTIME : 1 XOP (A, DIMP, DIMP, N, P, FIELD, LENGTH, STREAM, IFLAG)
```




```
10 CALL DEFBUF (2,16:BIFFER)
FRHTG (5), FRUTZ SS)=FIELD
```



```
READ \((2,30)\) MIOTH
30 FOR'laT íx 122
IF (P*1HOTK-
Nzarı川1
LAST \(=P_{\text {mill }} *: 12\)
IF (IFLAG) 50.999 .60
N4 \(=1\)
GO TO 70
60
```



```
WRITE \((2,80)\) N3,NT, W4: LAST
FORAA (2, 94\()^{\prime}\) FRMTY(2), FRHT1(4), FRMT2(2), FRMT2(4)
\(F O R T A T{ }^{\top}(4 A 4)\)
100
\(N 2=0\)
\(1 F\)
\(N 3=\{\) (IFLAG) \(110,999,120\)
120 NO TO \(=130\)
```




```
so READ (2, 150 ) FR!IT1(2), FRHT1(4)
150
```



```
suO RETHR!
IF (N-9) 909 400.310
```



```
KK KK K H K K
WRITE (STREAM, 320\() ~ K ~ K K ~\)
```



```
540 URITE (STKEAH, 350 ) P
```



```
WRITE (STREAM,FRMTZ) (A(I,P), \(I=1, N)\)
sou \(K K=15119+1\)
```



```
sTU RETIIR
400 0 \(\quad 490 \quad k=1\), \(\mathrm{H} 2 \mathrm{N1}\); N 1
```



```
\(4 \angle 0\) WRITES (STREAM,FRHTZSA(1, P)
```



```
WRITE (STREAM,FRMT2) (A(1, J), J \(\quad\) KK, P)
444
SETI!R!1!XOP
END


THE METHOD OF "QUICK RITZ" ITERATION FOR AN ARBITRARY MATMIX

THIS PROGRAM HAS RUN ON
ANO EXECUTION STARTED AT
IB/3B/46
EXAMPLE NUMBER 6

4 eigenvalues and 2 eloenvectors have been accepted to an aceuracy of q,ouemb

ThE 6 apphoximatiuns to the eioenvabues are,
\begin{tabular}{|c|c|c|}
\hline al part & \(3.0000000001 E\) OO 3.0000000000E 00 & 1,9099999985E 00 2,0000040007E 00 \\
\hline imagimart part & & \\
\hline & 5.7206765570E-19 =1.4162110052E=11 & 1.0000000002E 00-9.9999949987Es01 \\
\hline
\end{tabular}
the matrix of curbesponding left-hano eigenvecturs is given below
meal part
inagimart palt

 \(-4.4 n\)
-
the matrix of correspondilg righpahano eigenvectors is given belohi
- REAL PARI
thagimary part


TME GOGASETS OF CORRESPONDING ERRORS ARE:
might-mand

\section*{IIMORIATIONAL OUTPUT ON LOGICAL STREAM 4 FOR EXAMPLG NUMAER 6}

```


[^0]:    PR -

