# An Analysis of the HR Algorithm for Computing the Eigenvalues of a Matrix 

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#### Abstract

The HR algorithm, a method of computing the eigenvalues of a matrix, is presented. It is based on the fact that almost every complex square matrix $A$ can be decomposed into a product $A=H R$ of a so-called pseudo-Hermitian matrix $H$ and an upper triangular matrix $R$. This algorithm is easily seen to be a generalization of the well-known $Q R$ algorithm. It is shown how it is related to the power method and inverse iteration, and for special matrices the connection between the $L R$ and $H R$ algorithms is indicated.


## 1. INTRODUCTION

A certain class of algorithms for the computation of the eigenvalues of a nonsingular square matrix $A$ is based on the fact that almost every matrix can be decomposed into a product of two matrices of a special form, usually one of them being upper triangular. An algorithm of this kind can be described in the following way: Let $G$ be a subset of the nonsingular square matrices and $T$ be a subset of the nonsingular upper triangular matrices. Starting with the first iterate

$$
A_{1}=A
$$

at the $i$ th step the decomposition

$$
A_{i}=S_{i} R_{i}, \quad S_{i} \in G, \quad R_{i} \in T
$$

is computed. Then the next iterate is

$$
A_{i+1}=R_{i} S_{i}
$$

Among other possibilities of choosing $G$, Della-Dora [5] mentioned the group $\mathrm{O}_{J}$ of the pseudo-orthogonal matrices which are nonsingular real matrices $H$ with the property $H^{T} J H=J$ for a given diagonal matrix $J$ having +1 and -1 entries in the diagonal. Unfortunately this nice group $\mathrm{O}_{J}$ is not suitable for such an algorithm, because the set of real square matrices which split up into a product of an $H \in \mathrm{O}_{J}$ and an upper triangular matrix is too small. Brebner, Grad, and Vrečko [1, 2] proposed the set $G_{J}$ of all real square matrices $H$ with the property that there exists a permutation matrix $P$ such that $H^{T} J H=P^{T} J P$ for a given $J$ as defined above. Elsner [6] has shown that the direct product of $G_{J}$ and the set of real upper triangular matrices with positive diagonal elements is dense in the set of all real square matrices, that is to say, almost every real square matrix $A$ has a decomposition $A=H R$, the so-called $H R$ decomposition with respect to $J$, where $H \in G_{J}$ and $R$ is an upper triangular matrix with positive diagonal elements.

In this paper we study the algorithm which is based on the HR decomposition of an arbitrary complex matrix. The aim is to point out the connection between this algorithm and some well-known methods for the computation of matrix eigenvalues.

In Sec. 2 we briefly discuss the existence, uniquencss, and construction of the $H R$ decomposition of a complex matrix and introduce the $H R$ algorithm with respect to $J$. It is easily seen that for the choice $J$ equal to the identity we get the $Q R$ algorithm as a special case.

In Sec. 3 we give a short proof of convergence for the $H R$ algorithm in its basic form and point out that the algorithm can be interpreted as a modified power method. It is shown that the $H R$ algorithm with shifts contains a modified inverse iteration method.

In Sec. 4 we examine how the $H R$ algorithm acts on the special class of pseudo-Hermitian matrices which are matrices $A$ with the property $A^{*} J=J A$ for a given $J$. The pseudo-Hermitian form is invariant under the $H R$ algorithm. This yields in particular that after a slight modification the tridiagonal form of a real matrix can be preserved throughout the algorithm even for nonsymmetric matrices. Finally we show that for pseudo-Hermitian matrices the $L R$ and $H R$ algorithms are very closely related. The $(2 i+1)$ th iterate of the $L R$ algorithm and the $(i+1)$ th iterate of the $H R$ algorithm differ only by a similarity transformation with a diagonal matrix.

## 2. THE HR ALGORITHM

We denote
by $\mathrm{GL}_{n}(\mathbf{C})$ and $\mathrm{GL}_{n}(\mathbf{R})$ the set of all nonsingular complex and real $n \times n$ matrices respectively,
by $T_{n}(C)$ and $T_{n}(\mathbf{R})$ the set of all nonsingular complex and real upper triangular $n \times n$ matrices respectively, and
by $T_{n}^{+}(\mathbf{C})$ and $T_{n}^{+}(\mathbf{R})$ all matrices of $T_{n}(\mathbf{C})$ and $T_{n}(\mathbf{R})$ respectively which in addition have a real positive diagonal.

By $\operatorname{diag}_{k}^{n}( \pm 1)$ we denote the set of all $n \times n$ diagonal matrices with +1 and -1 entries on the diagonal where $k$ is the exact number of negative entries.

Definition 2.1. Let $J_{1}, J_{2} \in \operatorname{diag}_{k}^{n}( \pm 1)$. Then $H \in \mathrm{GL}_{n}(\mathrm{C})$ is called ( $J_{1}, J_{2}$ )-unitary if $H^{*} J_{1} H=J_{2}$.

By $U_{n}\left(J_{1}, J_{2}\right)$ we denote the set of all $\left(J_{1}, J_{2}\right)$-unitary matrices.
Remark 2.2. If $J_{1} \in \operatorname{diag}_{k}^{n}( \pm 1), J_{2} \in \operatorname{diag}_{m}^{n}( \pm 1)$, and $k \neq m$, then obviously, by a version of Sylvester's law of inertia for Hermitian forms [9], $U_{n}\left(J_{1}, J_{2}\right)$ is empty. For $k=m$ it is easy to verify that $U_{n}\left(J_{1}, J_{2}\right) \cap T_{n}^{+}(\mathrm{C})$ contains only the identity matrix $I$ if $J_{1}=J_{2}$, and that it is empty if $J_{1} \neq J_{2}$. Also, $U_{n}(I, I)=U_{n}(-I,-I)$ is the set of all unitary matrices.

The following theorem shows that for almost every matrix there exists a decomposition into a product $H R$ where $R \in T_{n}(C)$ and $H \in U_{n}\left(J_{1}, J_{2}\right)$ for a given $J_{1}$ and a suitable $J_{2}$. This decomposition is uniquely determined if in addition we demand $R \in T_{n}{ }^{+}(C)$.

Theorem 2.3. Let $A \in G L_{n}(C)$ and $J_{1}, J_{2} \in \operatorname{diag}_{k}^{n}( \pm 1)$.
(i) There exist $H \in U_{n}\left(J_{1}, J_{2}\right)$ and $R \in T_{n}(C)$ with $A=H R$ if and only if no principal minor of $A^{*} I_{1} A$ vanishes and the product of the first $i$ diagonal elements of $J_{2}$ coincides with the sign of the ith principal minor of $A^{*} J_{1} A$ for all $i \in\{1, \ldots, n\}$.
(ii) Let $H_{1}, H_{2} \in U_{n}\left(J_{1}, J_{2}\right), R_{1}, R_{2} \in T_{n}^{+}(\mathrm{C})$. If $A=H_{1} R_{1}=H_{2} R_{2}$, then $H_{1}=H_{2}$ and $R_{1}=R_{2}$.

Proof. (i): $A^{*} J_{1} A$ has all principal minors nonzero if and only if it has an $L R$ decomposition $A^{*} J_{1} A=L \tilde{R}$, where $\tilde{R}, L^{*} \in T_{n}(C)$ and $L$ has a unit
diagonal. The product of the first $i$ diagonal elements of $\tilde{R}$ coincides with the $i$ th principal minor of $A^{*} J_{1} A$ for all $i \in\{1, \ldots, n\}$ [14, pp. 201-205].

As $A^{*} J_{1} A$ is Hermitian, all its principal minors are real, and therefore it is easily seen that all diagonal elements of $\tilde{R}$ are real. Let $J_{2}$ be a diagonal matrix with +1 and -1 entries on the diagonal such that for all $i \in\{1, \ldots, n\}$ the product of the first $i$ diagonal elements is just the sign of the $i$ th principal minor of $A^{*} J_{1} A$. Then obviously the $i$ th diagonal element of $J_{2}$ is the sign of the $i$ th diagonal element of $\tilde{R}$, and we can find a real diagonal matrix $D$ such that $\hat{R}=D^{-1} J_{2} D^{-1} \tilde{R}$ has a unit diagonal. As $A^{*} J_{1} A$ is Hermitian, we have

$$
A^{*} J_{1} A=L \tilde{R}=L D J_{2} D \hat{R}=\hat{R}^{*} D J_{2} D L^{*}
$$

and the uniqueness of the $L R$ decomposition of $A^{*} J_{1} A$ implies $L=\hat{R}^{*}$. Defining $R=D \hat{R}$, we have now

$$
\begin{equation*}
A^{*} J_{1} A=R^{*} J_{2} R \tag{2.3.1}
\end{equation*}
$$

[Note that by Sylvester's law of inertia $J_{2} \in \operatorname{diag}_{k}^{n}( \pm 1)$.] From (2.3.1) we get $A=J_{1} A^{-*} R J_{2} R$, and for $H=J_{1} A^{-*} R^{*} J_{2}$ we find $H \in U_{n}\left(J_{1}, J_{2}\right)$.

On the other hand, if $A=H R$ with $R \in T_{n}(C)$ and $H \in U_{n}\left(J_{1}, J_{2}\right)$, then $A^{*} J_{1} A=R^{*} H^{*} J_{1} H R=R^{*} J_{2} R$, which means that $A^{*} J_{1} A$ has an $L R$ decomposition. By examining the principal minors of $R^{*} J_{2} R$ it is easily seen that the $i$ th principal minor of $J_{2}$ is just the sign of the $i$ th principal minor of $A^{*} J_{1}$ A.
(ii): From $H_{1} R_{1}=H_{2} R_{2}$ we get $R_{1} R_{2}^{-1}=H_{1}^{-1} H_{2} \in U_{n}\left(J_{2}, J_{2}\right) \cap T_{n}^{+}(\mathrm{C})$. From Remark 2.2 it follows that $R_{1} R_{2}^{-1}=H_{1}^{-1} H_{2}=I$.

By this theorem we are justified in defining the following.

Definition 2.4. Let $A \in \mathrm{GL}_{n}(\mathbf{C})$ and $J_{1} \in \operatorname{diag}_{k}^{n}( \pm 1)$. Let $A^{*} J_{1} A$ have no vanishing principal minor, and let $J_{2} \in \operatorname{diag}_{k}^{n}( \pm 1)$ such that for all $i \in\{1, \ldots, n\}$ the product of the first $i$ diagonal elements of $J_{2}$ coincides with the sign of the $i$ th principal minor of $A^{*} J_{1} A$. The factorization $A=H R$ with $H \in U_{n}\left(J_{1}, J_{2}\right), R \in T_{n}^{+}(\mathbf{C})$ is called the $H R$ decomposition of $A$ with respect to $J_{1}$.

Remark 2.5.
(i) For $J_{1}=I$ or $J_{1}=-I$ we get the $Q R$ decomposition of $A$. By Theorem 2.3 the condition for this decomposition to exist is that no principal minor of $A^{*} A$ vanishes, which is always true.
(ii) As the $i$ th principal minor of $(A-s I)^{*} J_{1}(A-s I)$ is a polynomial in $s$ of degree $2 i$ there are at most $n(n+1)$ values $\tilde{s}$ for which ( $A-\tilde{s} I$ ) has no $H R$ decomposition with respect to $J_{1}$. Therefore a nondecomposable matrix can always be shifted into a decomposable one even if we confine ourselves to real shifts.
(iii) If $A \in \mathrm{GL}_{n}(\mathbf{R})$ and $A=H R$ is the $H R$ decomposition of $A$ with respect to $J_{1}$, then it can be shown that both matrices $H$ and $R$ are real. This becomes more evident by looking at the construction of such a decomposition.

For given $A \in \mathrm{GL}_{n}(\mathrm{C})$ and $J \in \operatorname{diag}_{k}^{n}( \pm 1)$ the $H R$ decomposition with respect to $J$ can be constructed by computing $H^{-1}$, the matrix which reduces $A$ to upper triangular form, as a product of elementary elimination matrices and permutation matrices. To eliminate an element in position ( $m, i$ ), $i<m$, we can use matrices $H_{1}=\left(h_{l_{t}}\right)$ defined by
and

$$
\left.\begin{array}{c}
h_{i i}=e^{i \alpha} \cosh \phi, \quad h_{i m}=e^{i \beta} \sinh \phi, \\
h_{m i}=e^{-i \beta} \sinh \phi \quad h_{m m}=e^{-i \alpha} \cosh \phi, \\
h_{p p}=1 \quad \text { for } p \neq i, m, \quad h_{p q}=0 \quad \text { otherwise }
\end{array}\right\} \quad \text { if } j_{i}=-j_{m} .
$$

To eliminate all elements of a whole column but the first, we can use matrices $H_{1}$ defined by

$$
H_{1}=I-2 J \mathrm{v}^{*} \quad \text { where } \quad \mathrm{v} \in \mathrm{C}^{n}, \mathrm{v}^{*} J \mathrm{v}=1 .
$$

In any case we have $H_{1} \in U_{n}(J, J)$.
In [1] and [2] these transformations are discussed for real matrices, and in
[3] Brebner and Grad discuss the danger of severe cancellation errors when
calculating elements of these transformation matrices. In the $i$ th step of reduction using the second class of elimination matrices we proceed as follows: Let $A^{(i)}=H_{i-1} \cdots H_{1} A$ already be a matrix for which all elements below the diagonal in the first $i-1$ columns vanish and $H_{i-1} \cdots H_{1} \in$ $U_{n}\left(J, J_{i-1}\right)$. If $J_{i-1}=\operatorname{diag}\left(j_{1}, \ldots, j_{n}\right)$, then we denote $\tilde{J}=\operatorname{diag}\left(j_{i}, \ldots, j_{n}\right)$. Let $a \in C^{n-i+1}$ be the vector formed by the last $n-i+1$ elements of the $i$ th column of $A^{(i)}$, and assume $a^{*} \tilde{J} a \neq 0$. Let $j_{m} \in\left\{j_{i}, \ldots, j_{n}\right\}$ be chosen so that $j_{m} \mathbf{a}^{*} \tilde{J}$ a is positive, and let $P$ be the ( $n-i+1$ )-dimensional permutation matrix which interchanges row 1 and $m-i+1$. Then for $\mathrm{b}=P \mathrm{a}$ and $\hat{J}=P \tilde{J} P=$ $\operatorname{diag}\left(\hat{j}_{1}, \ldots, \hat{\boldsymbol{f}}_{n-i+1}\right)$ we have $\hat{\boldsymbol{j}}_{1} \mathbf{b}^{*} \hat{J} \mathbf{b}>0$.

Now

$$
H^{-1}=I-\frac{i_{1}}{K}\left(\mathbf{b}-z \mathbf{e}_{1}\right)\left(\mathbf{b}-z \mathbf{e}_{1}\right)^{*} \dot{J}
$$

with

$$
z=-\operatorname{sgn}\left(b_{1}\right)\left(\hat{j}_{1} \mathbf{b}^{*} \hat{J} \mathbf{b}\right)^{1 / 2} \quad \text { and } \quad K=z\left(z-b_{1}\right)
$$

[ $b_{1}$ is the first component of $\mathbf{b}$, and $\operatorname{sgn} b_{1}=b_{1} /\left|b_{1}\right| ; \mathbf{e}_{1}$ is the $(n-i+1)$ dimensional first unit vector] is a $(\hat{J}, \hat{J})$-unitary matrix with the property

$$
H^{-1} P a=H^{-1} b=z e_{1}
$$

$H^{-1} P$ is enlarged to give an $n$-dimensional matrix

$$
H_{i}=\left[\begin{array}{c|c}
I & 0 \\
\hline 0 & H^{-1} P
\end{array}\right] .
$$

Defining $J_{i}=H_{i}^{*} J_{i-1} H_{i}$, we get $H_{i} H_{i-1} \cdots H_{1} \in U_{n}\left(J, J_{i}\right)$, and in $A^{(i+1)}=$ $H_{i} A^{(i)}$ we have one more column with zero elements below the diagonal. For the special case $J=I$ the reduction using the first class of elimination matrices is just Givens's method, and the reduction using the second class of elimination matrices is just Householder's method to compute the $Q R$ decomposition of a matrix.

An algorithm based on the $H R$ decomposition can now be defined. Let $A \in \mathrm{GL}_{n}(\mathbf{C})$ and $J \in \operatorname{diag}_{k}^{n}( \pm 1)$. The $H R$ algorithm with respect to $J$ produces a sequence of matrices $\left\{\boldsymbol{A}_{\boldsymbol{i}}\right\}_{i \in \mathrm{~N}}$ in such a way that, starting with

$$
A_{1}=A, \quad J_{1}=J
$$

in the $i$ th step the $H R$ decomposition of $A_{i}$ with respect to $J_{i}$ is computed:

$$
A_{i}=H_{i} R_{i} .
$$

Subsequently $A_{i+1}$ is constructed and $J_{i+1}$ is defined by

$$
A_{i+1}=R_{i} H_{i}, \quad J_{i+1}=H_{i}^{*} J_{i} H_{i} .
$$

Remark 2.6.
(i) For all $i \in \mathbf{N}_{+}$it is easily shown that:
(a) $A_{i+1}=H_{i}^{-1} A_{i} H_{i}=R_{i} A_{i} R_{i}^{-1}$.
(b) $A_{i+1}=\left(H_{1} \cdots H_{i}\right)^{-1} A\left(H_{1} \cdots H_{i}\right)=\left(R_{i} \cdots R_{1}\right) A\left(R_{i} \cdots R_{1}\right)^{-1}$.
(c) $A^{i}=H_{1} \cdots H_{i} R_{i} \cdots R_{1}$.
(d) From the second equality in (b) it follows that for an upper Hessenberg $A$ all $A_{i}$ are upper Hessenberg.
(ii) Obviously we have, for all $i \in \mathbf{N}_{+}$and all $m \in\{1, \ldots, i-1\}$, that $\left(H_{m} \cdots H_{i}\right)^{*} J_{m}\left(H_{m} \cdots H_{i}\right)=J_{i+1}$. Therefore all $J_{i}$ produced in the algorithm are contained in $\operatorname{diag}_{k}^{n}( \pm 1)$.
(iii) For $J=I$ or $J=-I$ this is just the well-known $Q R$ algorithm in its basic form.
(iv) For $J \neq I$ and $J \neq-I$ it may occur that an iterate $A_{i}$ has no $H R$ decomposition with respect to $J_{i}$. Then we say that the $H R$ algorithm with respect to $J$ (without shifts) is not constructible for $A$.
(v) If $A$ is a real matrix, then so are all matrices occurring in the algorithm.

## 3. CONVERGENCE PROPERTIES

For matrices with eigenvalues of distinct moduli we give a proof of convergence for the $H R$ method similar to the proofs known for the $L R$ and $Q R$ algorithms in this case.

Theorem 3.1. Let $A \in \mathrm{GL}_{n}(\mathbf{C}), J \in \operatorname{diag}_{k}^{n}( \pm 1), Y \in \mathrm{GL}_{n}(\mathbf{C})$, and $D=$ $\operatorname{diag}\left(\lambda_{1}, \ldots, \lambda_{n}\right)$, where $\left|\lambda_{1}\right|>\left|\lambda_{2}\right|>\cdots>\left|\lambda_{n}\right|$ and $A=Y D Y^{-1}$. Let $Y^{-1}$ have an LR decomposition, and let $Y$ have an HR decomposition with respect to J. Let the HR algorithm with respect to $J$ be constructible for A. If
$A_{s}=\left(a_{i j}^{(s)}\right)$ denotes the sth iterate in the algorithm, then

$$
\lim _{s \rightarrow \infty} a_{i j}^{(s)}=0 \quad \text { for } \quad i<j, \quad i, j \in\{1, \ldots, n\}
$$

and

$$
\lim _{s \rightarrow \infty} a_{i i}^{(s)}=\lambda_{i} \quad \text { for all } \quad i \in\{1, \ldots, n\}
$$

Proof. Let $Y^{-1}=L_{Y} R_{Y}$ denote the $L R$ decomposition of $Y^{-1}, Y=H_{Y} \tilde{R}$ the $H R$ decomposition of $Y$ with respect to $J$, and $L_{Y}=\left(l_{i i}\right), J^{\prime}=H^{*} J H$. For $s \in \mathbf{N}$ the matrix $D^{s} L_{Y} D^{-s}$ is lower triangular with a unit diagonal. As $\left(\lambda_{i} / \lambda_{j}\right)^{s} l_{i j}$ is the $(i, j)$ th element for $i<j$, there exists a sequence of matrices $\left\{E_{s}\right\}_{s \in N}$ which tends to the zero matrix for $s \rightarrow \infty$ and $D^{s} L_{Y} D^{-s}=I+E_{s}$.

Because the $H R$ decomposition is unique and continuous and $\lim _{s \rightarrow \infty}$ $\left(I+\tilde{R}_{Y} E_{s} \tilde{R}_{Y}^{-1}\right)=I$, for sufficiently large $s$ there exists the $H R$ decomposition with respect to $J^{\prime}: I+\tilde{R}_{Y} E_{s} \tilde{R}_{Y}^{-1}=\hat{H}_{s} \hat{R}_{s}$ with $\hat{H}_{s}^{*} J^{\prime} \hat{H}_{s}=J_{s}$ and $\lim _{s \rightarrow \infty} \hat{H}_{s}=I$. Therefore for sufficiently large $s$ we have

$$
\begin{aligned}
A^{s} & =Y D^{s} Y^{-1}=Y D^{s} L_{Y} D^{-s} D^{s} R_{Y}=Y\left(I+E_{s}\right) D^{s} R_{Y}=H_{Y} \tilde{R}_{Y}\left(I+E_{s}\right) D^{s} R_{Y} \\
& =H_{Y}\left(I+\tilde{R}_{Y} E_{s} \tilde{R}_{Y}^{-1}\right) \tilde{R}_{Y} D^{s} R_{Y}=H_{Y} \hat{H}_{s} \hat{R}_{s} \tilde{R}_{Y} D^{s} R_{Y}
\end{aligned}
$$

Let $\tilde{D_{s}}$ be a unitary diagonal matrix such that $\tilde{D}_{s} \hat{R}_{s} \tilde{R}_{Y} D^{s} R_{Y} \in T_{n}^{+}(\mathrm{C})$. Now $H_{Y} \hat{H}_{s} \tilde{D}_{s}^{-1} \in U_{n}\left(J, J_{s}\right)$ and with Remark 2.6(i) (c) we find two HR decompositions with respect to $J$ of $A^{s}$ :

$$
A^{s}=H_{Y} \hat{H}_{s} \tilde{D}_{s}^{-1} \tilde{D}_{s} \hat{R}_{s} \tilde{R}_{Y} D^{s} R_{Y} \quad \text { and } \quad A^{s}=H_{1} \cdots H_{s} R_{s} \cdots R_{1}
$$

Because of uniqueness $H_{Y} \hat{H}_{s} \tilde{D}_{s}^{-1}=H_{1} \cdots H_{s}$ must hold, and with Remark 2.6 (i) (b) this yields

$$
\begin{aligned}
A_{s+1} & =\left(H_{Y} \hat{H}_{s} \tilde{D}_{s}^{-1}\right)^{-1} A H_{Y} \hat{H}_{s} \tilde{D}_{s}^{-1} \\
& =\tilde{D}_{s} H_{s}^{-1} \hat{H}_{Y}^{-1} Y D Y^{-1} H_{Y} \hat{H}_{s} \tilde{D}_{s}^{-1}=\tilde{D}_{s}^{-1} \hat{H}_{s}^{-1} \tilde{R}_{Y} D \tilde{R}_{Y}^{-1} \hat{H}_{s} \tilde{D}_{s}^{-1}
\end{aligned}
$$

As $\lim _{s \rightarrow \infty} \hat{H}_{s}=I$ and $\tilde{D}_{s}, \tilde{D}_{s}^{-1}$ are bounded, we get the statement of the theorem by this last equation.

According to this theorem the diagonal elements $a_{i i}^{(s)}$ converge to the eigenvalues $\lambda_{i}$ of $A$ essentially as fast as $\left(\lambda_{i} / \lambda_{i+1}\right)^{s}$ converges to 0 for $s \rightarrow \infty$. But this is just the rate of convergence we get when using the power method for computing $\lambda_{i}$. Parlett and Poole [10] pointed out how the $Q R$ algorithm is connected to the power method. The following lemma proves that the $H R$ algorithm can likewise be interpreted as a nested sequence of $n$ power methods starting with the subspaces spanned by $\left\{\mathbf{e}_{1}\right\},\left\{\mathbf{e}_{1}, e_{2}\right\}, \ldots$, $\left\{\mathbf{e}_{1}, \ldots, \mathbf{e}_{n}\right\}$, where $\mathbf{e}_{i}$ denotes the $i$ th unit vector.

For $A \in \mathrm{GL}_{n}(\mathbf{C})$ let $\mathcal{Q}$ denote the operator on $\mathbf{C}^{n}$ defined by $A$. For an $n \times q$ matrix $X$ let $X$ denote the subspace of $C^{n}$ spanned by the $q$ columns of $X$.

Starting with an $n \times q$ matrix $X_{0}$ corresponding to the subspace $\mathbf{X}_{0}$, the power method creates a sequence of subspaces $\mathbf{X}_{k}=\mathbb{Q} \mathbf{X}_{k-1}$. For each $k \in \mathbf{N}_{+}$the subspace $X_{k}$ is represented by a suitable $n \times q$ matrix $X_{k}$, which means that in each step $X_{k}$ is gained by suitably normalizing $A X_{k-1}$. Under certain conditions the sequence $\left\{\mathbf{X}_{k}\right\}_{k \in N}$ "converges" to the dominant $q$-dimensional invariant subspace of $\mathscr{Q}$ [10].

Now looking at the $H R$ algorithm with respect to $J \in \operatorname{diag}_{k}^{n}( \pm 1)$ applied to $A$, with the usual notation $A_{s}=H_{s} R_{s}, H_{s}^{*} J_{s} H_{s}=J_{s+1}$ for the $s$ th step and with $P_{s}=H_{1} \cdots H_{s}$, the following holds:

Lemma 3.2. For each $s \in \mathbf{N}_{+}$and $q \in\{1, \ldots, n\}$, the first $q$ columns of $P_{s}$ span the subspace $\mathbf{X}_{s}$ of the power method applied to the starting subspace spanned by the first $q$ unit vectors.

Proof. According to Remark 2.6(i) (b) we have $A_{s+1}=P_{s}^{-1} A P_{s}$ or $A P_{s}=$ $P_{s} A_{s+1}$, which leads to

$$
\begin{equation*}
A P_{s} R_{s+1}^{-1}=P_{s} A_{s+1} R_{s+1}^{-1}=P_{s} H_{s+1} R_{s+1} R_{s+1}^{-1}=P_{s+1} \tag{3.2.1}
\end{equation*}
$$

Therefore the first $q$ columns of $P_{s+1}$ are linear combinations of the first $q$ columns of $A P_{s}$. If $\mathbf{P}_{s, q}$ denotes the subspace spanned by the first $q$ columns of $P_{s}$, then

$$
\mathbb{Q} \mathbf{P}_{s, q}=\mathbf{P}_{s+1, q} \text { for all } s \in \mathbf{N}_{+}
$$

with $P_{1}=H_{1}=A R_{1}^{-1}=A I R_{1}^{-1}$.
In particular, for $q=1$ the $H R$ algorithm in its basic form contains the modified power method:

Theorem 3.3. Let $\mathbf{p}_{s}$ denote the first column of $P_{s}$. The sequence $\left\{\mathbf{p}_{s}\right\}_{s \in \mathbf{N}}$ is then created by the modified power method: $\mathbf{p}_{0}=\mathbf{e}_{1}, \mathbf{p}_{s+1}=$ $\left(\mathbf{1} / r_{s+1}\right) A \mathbf{p}_{s}$ with $r_{s+1}=\left(\left|\mathbf{p}_{s}^{*} A^{*} J A \mathbf{p}_{s}\right|\right)^{1 / 2}$ for all $s \in \mathbf{N}_{+}$. The scalar $r_{s+1}$ can be considered as an approximation at the $(s+1)$ th step to the modulus of the dominant eigenvalue of $A$.

Proof. If we denote by $r$ the first diagonal element of $\boldsymbol{R}_{s+1}$, then (3.2.1) yields

$$
\mathbf{p}_{s+1}=\frac{1}{r} A \mathbf{p}_{s}
$$

Let $\mathbf{a}_{s+1}$ be the first column of $A_{s+1}$. Then $A_{s+1}=H_{s+1} R_{s+1}$ and $H_{s+1}^{*} J_{s+1} H_{s+1}=J_{s+2}$ imply

$$
\left|\left(\frac{1}{r} \mathbf{a}_{s+1}\right) * I_{s+1}\left(\frac{1}{r} \mathbf{a}_{s+1}\right)\right|=1
$$

and therefore $r^{2}=\left|\mathbf{a}_{s+1}^{*} J_{s+1} \mathbf{a}_{s+1}\right|$. In addition, we see from $A_{s+1}=P_{s}^{-1} A P_{s}$ and $P_{s}^{*} J P_{s}=J_{s+1}$ that

$$
\mathbf{a}_{s+1}^{*} J_{s+1} \mathbf{a}_{s+1}=\left(P_{s}^{-1} A \mathbf{p}_{s}\right)^{*} J_{s+1}\left(P_{s}^{-1} A \mathbf{p}_{s}\right)=\mathbf{p}_{s}^{*} A^{*} J A \mathbf{p}_{s}
$$

Therefore $r=r_{s+1}$ holds.
According to Theorem 3.1, under suitable conditions $\mathbf{a}_{s+1}$ tends to $\lambda \mathbf{e}_{1}, \lambda$ being the dominant eigenvalue of $A$. Hence $\left.\left(\mid \mathbf{a}_{s+1}^{*} J_{s+1} \mathbf{a}_{s+1}\right) \mid\right)^{1 / 2}$ can be considered as an approximation to $|\lambda|$ at the $(s+1)$ th step, since $\lim _{s \rightarrow \infty}\left(\left|\mathbf{a}_{s+1}^{*} J_{s+1} \mathbf{a}_{s+1}\right|\right)^{1 / 2}=\lim _{s \rightarrow \infty} r_{s+1}=|\lambda|$ holds for strictly dominant $\lambda$.

To accelerate convergence, shifts can be used in the algorithm. The $H R$ algorithm with respect to $J \in \operatorname{diag}_{k}^{n}( \pm 1)$ and the sequence $\left\{k_{i}\right\}_{i \in \mathbf{N}_{+}}$of shift parameters reads:

$$
\begin{aligned}
A_{1} & =A, \quad J_{1}=J, \\
\left(A_{i}-k_{i} I\right) & =H_{i} R_{i} \quad \text { with } \quad H_{i}^{*} J_{i} H_{i}=J_{i+1} \text { and } R_{i} \in T_{n}^{+}(\mathrm{C}), \\
A_{i+1} & =R_{i} H_{i}+k_{i} I .
\end{aligned}
$$

For these $A_{i}, H_{i}, R_{i}$ and $J_{i}$ the statements of Remark 2.6 except $2.6(i)$ (c) remain valid.

Allowing shifts, we can also assure that the algorithm is constructible, because a nondecomposable or almost nondecomposable matrix can always be shifted away from this dangerous region.

Stewart [12] demonstrated that the $Q R$ algorithm contains a modified inverse iteration method. We shall see how this carries over to its generalization. If in the $H R$ algorithm with respect to $J$ we take the last diagonal element of $A_{i}$ as shift parameter $k_{i}$, with the abovementioned notation and defining $P_{i}=H_{1}, \cdots, H_{i}$, we have

Theorem 3.4. Let $\mathrm{p}_{s}$ denote the last column of $P_{s}$. The sequence $\left\{\mathbf{p}_{s}\right\}_{s \in \mathbf{N}}$ is then created by the modified inverse iteration method:

$$
\mathbf{p}_{0}=\mathbf{e}_{\mathrm{n}}, \quad k_{1}=\mathbf{p}_{0}^{T} A \mathbf{p}_{0}, \quad j_{1}=\operatorname{sgn}\left(\mathbf{p}_{0}^{*} J \mathbf{p}_{0}\right)
$$

and for all $s \in \mathbf{N}$,
$\mathbf{p}_{s+1}=\hat{\mathbf{p}}_{s+1} i_{s+1} i_{s+2} r_{s+1}, \quad k_{s+2}=j_{s+2} \mathbf{p}_{s+1}^{*} J A \mathbf{p}_{s+1} \quad j_{s+2}=\operatorname{sgn}\left(\hat{\mathbf{p}}_{s+1}^{*} J \hat{\mathbf{p}}_{s+1}\right)$.
with

$$
\hat{\mathbf{p}}_{s+1}=J\left(\mathrm{~A}-k_{s+1} I\right)^{-*} J \mathbf{p}_{s}, \quad r_{s+1}=\left(\left|\hat{\mathbf{p}}_{s+1}^{*} J \hat{\mathbf{p}}_{s+1}\right|\right)^{-1 / 2}
$$

Proof. $A P_{s}=P_{s} A_{s+1}$ implies $P_{s+1}=P_{s} H_{s+1} R_{s+1} R_{s+1}^{-1}=P_{s}\left(A_{s+1}-\right.$ $\left.k_{s+1} I\right) R_{s+1}^{-1}=\left(A-k_{s+1} I\right) P_{s} R_{s+1}^{-1}$ and therefore $P_{s+1}^{-*}=\left(A-k_{s+1} I\right)^{-*}$ $P_{s}{ }^{-*} R_{s+1}^{*}$. Together with $P_{s+1}^{*} J P_{s+1}=J_{s+2}$, this yields $P_{s+1}=J\left(A-k_{s+1}\right.$ $I)^{-*} J P_{s} J_{s+1} R_{s+1}^{*} J_{s+2}$. If we denote by $r$ the last diagonal element of $R_{s+1}$ and by $j$ and $j$ the last diagonal elements of $J_{s+1}$ and $J_{s+2}$ respectively, then $\mathbf{p}_{s+1}=J\left(A-k_{s+1} I\right)^{-*} J_{p_{s}} r j$ follows. From $\left(A_{s+1}-k_{s+1} I\right)^{-*} R_{s+1}^{*}=H_{s+1}^{-}{ }^{*}$ we find, with an argument similar to the one used for Theorem 3.3, that $r=r_{s+1}$. That $j=j_{s+1}$ and $\tilde{j}=j_{s+2}$ is a trivial consequence of $P_{i} J P_{i}=J_{i+1}$ for all $i \in N$.

For real upper Hessenberg $A$ two successive steps of the $H R$ algorithm can be performed together, avoiding complex arithmetic if two real or complex conjugate shifts are used for such a two-step iteration. This is possible because the transformation of a matrix to upper Hessenberg form using ( $J, J^{\prime}$ )-unitary matrices is essentially unique:

Lemma 3.5. Let $A \in \mathrm{GL}_{n}(\mathrm{C}), J_{1}, J_{2}, J_{3} \in \operatorname{diag}_{k}^{n}( \pm 1)$, and $H_{1} \in U_{n}\left(J_{1}, J_{2}\right)$, $H_{2} \in U_{n}\left(J_{1}, J_{3}\right)$. Let $H_{1}^{-1} A H_{1}$ and $H_{2}^{-1} A H_{2}$ be upper Hessenberg with at least
one having all subdiagonal elements nonzero. If $H_{1}$ and $H_{2}$ have the same first column, then there exists a unitary diagonal matrix $D$ such that $H_{1}=D H_{2}$.

Proof. Let $B=H_{1}^{-1} A H_{1}=\left(b_{i j}\right)$ have all subdiagonal elements nonzero. With $C=H_{2}^{-1} A H_{2}=\left(c_{i j}\right)$ and $H=H_{2}^{-1} H_{1}$, we have

$$
\begin{equation*}
C H=H B . \tag{3.5.1}
\end{equation*}
$$

If $h_{m}$ denotes the $m$ th column of $H$, then $h_{1}=e_{1}$. It can now be shown by induction using (3.5.1) and

$$
\begin{equation*}
H^{*} J_{2} H=J_{3} \tag{3.5.2}
\end{equation*}
$$

that $h_{i}=z_{i} \mathrm{e}_{i}$ with $\left|z_{i}\right|=1$.
From (3.5.2), $0=h_{2}^{*} J \mathbf{h}_{1}=\mathbf{h}_{2}^{*} J_{2} \mathbf{e}_{1}$ follows, which means that the first component of $\mathbf{h}_{2}$ vanishes. Now (3.5.1) yields $C e_{1}=b_{11} \mathbf{e}_{1}+b_{21} \mathbf{h}_{2}$ or $\mathbf{h}_{2}=$ $\left(1 / b_{21}\right)\left[\left(c_{11}-b_{11}, c_{21}, 0, \ldots, 0\right)^{\mathrm{T}}\right]$, which leads to $b_{11}=c_{11}, \mathbf{h}_{2}=\left(c_{21} / b_{21}\right) \mathbf{e}_{2}$. For $z_{1}:=c_{21} / b_{21}$ we find from (3.5.2) that $\left|z_{1}\right|=1$. Proceeding in the same way we get the statement.

The two-step iteration technique with complex conjugate shifts or two real shifts is very well known for the $Q R$ algorithm, and with the foregoing lemma the arguments there carry over to the $H R$ algorithm. Therefore we shall not go into further details.

Usually the shifts $k_{2 i+1}, k_{2 i+2}$ are taken to be the two eigenvalues of the $2 \times 2$ matrix in the bottom right-hand corner of the current $A_{2 i+1}$. The first column of $H \in U_{n}\left(J_{2 i+1}, J_{2 i+3}\right)$ is computed, where $H R$ is the $H R$ decomposition with respect to $J_{2 i+1}$ of the real matrix $\left(A_{2 i+1}-k_{2 i+1} I\right)\left(A_{2 i+1}-\right.$ $k_{2 i+2} I$ ). Then a ( $J_{2 i+1}, J_{2 i+3}$ )-unitary matrix is constructed which has just this first column and transforms $A_{2 i+1}$ into an upper Hessenberg $A_{2 i+3}$. In the following small examples the eigenvalues were computed using the $H R$ algorithm with respect to $J$ in this form.

Example 3.6. We give the results computed by the $H R$ algorithm with respect to $J$ for several $J$. For each $J$ we list the computed eigenvalues, the total number of two-step iterations, and the actual computing time on the TR 440 at the University of Bielefeld.

$$
\left[\begin{array}{lll}
4 & 1 & 1  \tag{i}\\
2 & 4 & 1 \\
0 & 1 & 4
\end{array}\right] \quad \text { Eigenvalues: } \begin{gathered}
6 \\
3
\end{gathered}
$$

Computed Eigenvalues
Iterations
Time $\left(10^{-5} \mathrm{sec}\right)$
(a) $J=I$
6.00000000012
3.00000894629

4
37.03
2.99999105372
(b) $\quad J=\operatorname{diag}(-1,-1,1)$
6.00000000064
$3.00000000018+i 0.00000190734$
4
41.09
$3.00000000018-i 0.00000190734$
(c) $\quad J=\operatorname{diag}(1,-1,1)$
6.00000000006
3.00000000006

1
11.12
3.00000000000
(ii) $\left[\begin{array}{rrrr}0.00 & 0.07 & 0.27 & -0.33 \\ 1.31 & -0.36 & 1.21 & 0.41 \\ 1.06 & 2.86 & 1.49 & -1.34 \\ -2.64 & -1.84 & -0.24 & -2.01\end{array}\right] \quad$ Eigenvalues: $\begin{gathered}0.03 \\ -1.93+i \\ \\ -1.97-i\end{gathered}$

Before applying the $H R$ algorithm the matrix was transformed into upper Hessenberg form.

Computed Eigenvalues
Iterations

> Time $\left(10^{-5} \mathrm{sec}\right)$
(a) $J=I$
3.03000000009
$-1.96999999991 \pm i 1.00000000006$ 12
74.79 0.02999999989
(b) $\quad J=\operatorname{diag}(1,-1,-1,1)$
3.03000000044
0.03000000113

16
209.19
$-1.97000000143 \pm i 1.00000000087$
(c) $\quad J=\operatorname{diag}(-1,1,-1,-1)$
3.03000000073
$-1.97000000032 \pm i 1.00000000023$
14
187.19 0.02999999995

Note that for both cases (a) the method is just the $Q R$ algorithm.

## 4. PSEUDO-HERMITIAN MATRICES

The Hermitian form of a matrix is preserved under similarity transformations with unitary matrices. It is well known that advantage can be taken of this fact for an economical application of the $Q R$ algorithm to Hermitian or symmetric matrices. For the generalization studied here we can observe that the so-called pseudo-Hermitian form of a matrix is invariant under similarity transformations with $\left(J, J^{\prime}\right)$-unitary matrices.

Definition 4.1. Let $A \in \mathrm{GL}_{n}(C)$ and $J \in \operatorname{diag}_{k}^{n}( \pm 1)$. $A$ is called
$J$-Hermitian if $A^{*} J=J A$, and
$J$-symmetric if in addition $A$ is real.
$A$ is called pseudo-Hermitian (pseudo-symmetric) if there exist a $k \in\{1, \ldots, n\}$ and a $J \in \operatorname{diag}_{k}^{n}( \pm 1)$ such that $A$ is $J$-Hermitian ( $J$-symmetric).

## Example 4.2.

(i) For a Hermitian or symmetric nonsingular matrix $B$ we can find a nonsingular matrix $M$ and a $J \in \operatorname{diag}_{k}^{n}( \pm 1)$ such that $B=M^{*} J M$, where $J$ contains the signs of the eigenvalues of $B$. If we have to solve the problem $A x=\lambda B x$ where $A$ too is Hermitian or symmetric, then we may transform this equation to $J M^{-*} A M^{-1} M x=\lambda M x$ or $C y=\lambda y$, where $y=M x$, and $C=J M^{-*} A M^{-1}$ is a $J$-Hermitian or $J$-symmetric matrix. Some examples for the symmetric case are given in [1].
(ii) Specifically, for real matrices $A$ each eigenvalue problem $A x=\lambda \mathbf{x}$ can be transformed into problems $T y=\lambda y$ with $T$ pseudosymmetric and tridiagonal. For it is known [11] that any real matrix $A$ is similar to a real tridiagonal matrix $\tilde{T}$, which may be obtained from $A$ by the Lanczos method [8] with suitable starting vectors for instance. It is easily seen that by similarity transformation with a diagonal matrix, each $\tilde{T}$ with all codiagonal elements nonzero can be transformed into a tridiagonal $T$ for which corresponding codiagonal elements have the same absolute value. Such a $T$ is $J$-symmetric with

$$
J=\operatorname{diag}\left(1, \operatorname{sgn} \frac{t_{12}}{t_{21}}, \ldots, \operatorname{sgn}\left(\frac{t_{12}}{t_{21}} \cdots \frac{t_{n-1, n}}{t_{n, n-1}}\right)\right)
$$

Note that for complex matrices we have no analogous transformation into a pseudo-Hermitian tridiagonal matrix, because $A=M^{-1} T M$ for a $J$-Hermitian $T$ would imply $A=M^{-1} J J T M=M^{-1} J M^{-*} M^{*} J T M$. So $A$ has to be a product of two Hermitian matrices, namely $M^{-1} J M^{-*}$ and $M^{*} J T M$, which is not true for arbitrary $A \in \mathrm{GL}_{n}(\mathbf{C})$ but holds for arbitrary real matrices (see [7], [13]).

Now if $J, J^{\prime} \in \operatorname{diag}_{k}^{n}( \pm 1)$ and $\hbar \in U_{n}\left(J, J^{\prime}\right)$, then for a $J$-Hermitian $A$ the matrix $H^{-1} A H$ is $J^{\prime}$-Hermitian, because

$$
\left(H^{-1} A H\right)^{*} J^{\prime}=H^{*} A^{*} H^{-*} J^{\prime}=H^{*} A^{*} J H=I^{*} J A I I=J^{\prime} I^{-1} A H
$$

In particular, if we apply the $H R$ algorithm with respect to $J$ to a $J$-Hermitian matrix $A$, then because

$$
A_{i}=H_{i-1}^{-1} \cdots H_{1}^{-1} A H_{1} \cdots H_{i-1} \quad \text { and } \quad H_{1} \cdots H_{i-1} \in U_{n}\left(J, J_{i}\right)
$$

each iterate $A_{i}$ is $J_{i}$-Hermitian.
A pseudo-Hermitian upper Hessenberg matrix is obviously tridiagonal. Therefore, because of the invariance of the upper Hessenberg form under the $H R$ algorithm, we find that starting with a tridiagonal $J$-Hermitian or $J$-symmetric matrix $\Lambda$, in the $H R$ algorithm with respect to $J$ all iterates are tridiagonal.

This is of special interest in the case of real matrices which are tridiagonal but not symmetric or which can be transformed into such a matrix in a stable manner. According to Example 4.2(ii) this tridiagonal matrix can be easily modified to a $J$-symmetric tridiagonal matrix, and unlike the $Q R$ algorithm, the $H R$ algorithm with respect to $J$ preserves this tridiagonal form even if this starting matrix is not symmetric.

In the special case of tridiagonal pseudosymmetric matrices convergence can be proved [4] under much weaker conditions than in Theorem 3.1.

Finally, for $J$-Hermitian matrices it can be shown that the $H R$ algorithm with respect to $J$ converges twice as fast as the $L R$ algorithm if no shifts are used, because we find:

Theorem 4.3. For $J \in \operatorname{diag}_{k}^{n}( \pm 1)$ let $A \in \mathrm{GL}_{n}(\mathbf{C})$ be J-Hermitian. Let the HR algorithm with respect to $J$ be denoted by

$$
\begin{aligned}
A_{1} & =A, & J_{1}=J, \\
A_{i} & =H_{i} R_{i}, & \\
A_{i+1} & =R_{i} H_{i}, & J_{i+1}=H_{i}^{*} J_{i} H_{i},
\end{aligned}
$$

and the LR algorithm by

$$
\begin{gathered}
\tilde{A}_{1}=A \\
\tilde{A}_{i}=L_{i} \tilde{R}_{i} \\
\tilde{A}_{i+1}=\tilde{R}_{i} L_{i}
\end{gathered}
$$

If the LR algorithm is constructible, then so is the HR algorithm with respect to J, and for each $i \in \mathbf{N}$ there exists a diagonal matrix $D_{i} \in \mathrm{GL}_{n}(\mathrm{C})$ such that

$$
\Lambda_{i+1}=D_{i}^{-1} \tilde{A}_{2 i+1} D_{i}
$$

Proof. If the $L R$ algorithm is constructible, which means that for each iterate the $L R$ decomposition exists, then there also exists the $L R$ decomposition of $A^{m}$ for all $m \in \mathbf{N}_{+}$, namely

$$
\begin{equation*}
A^{m}=L_{1} \cdots L_{m} \tilde{R}_{m} \cdots \tilde{R}_{1} \tag{4.3.1}
\end{equation*}
$$

We prove the statement by induction taking advantage of the fact that for all $m \in \mathbf{N}, A^{m}$ is J-Hermitian.

By (4.3.1) the $L R$ decomposition of $A^{*} J A=J A^{2}$ exists, which according to Theorem 2.3 yields that the $H R$ decomposition of $A_{1}=A$ with respect to $J_{1}=J$ exists. Now assume that for $i_{0} \in \mathbf{N}$ we have the following; for all $i \in\left\{1, \ldots, i_{0}\right\}$ the $H R$ decomposition of $A_{i}$ with respect to $J_{i}$ exists. Then for $i \in\left\{1, \ldots, i_{0}\right\}$, by (4.3.1) we find

$$
A^{2 i}=L_{1} \cdots L_{2 i} \tilde{R}_{2 i} \cdots \tilde{R}_{1}
$$

and further

$$
A^{i}=H_{1} \cdots H_{i} R_{i} \cdots R_{1}
$$

Because $A^{i}$ is $J$-Hermitian and $H_{1} \cdots H_{i} \in U_{n}\left(J, J_{i+1}\right)$,

$$
J A^{2 i}=A^{i *} J A^{i}=R_{1}^{*} \cdots R_{i}^{*} J_{i+1} R_{i} \cdots R_{1}
$$

Hence $A^{2 i}$ has a decomposition

$$
A^{2 i}=J R_{1}^{*} \cdots R_{i}^{*} J_{i+1} R_{i} \cdots R_{1}
$$

into a product of a lower and an upper triangular matrix.
Now if $D_{i}$ is the diagonal matrix for which $J R_{1}^{*} \cdots R_{i}^{*} J_{i+1} D_{i}^{-1}$ has a unit diagonal, then

$$
A^{2 i}=J R_{1}^{*} \cdots R_{i}^{*} J_{i+1} D_{i}^{-1} D_{i} R_{i} \cdots R_{1}
$$

or

$$
A^{2 i}=L_{1} \cdots L_{2 i} \tilde{R}_{2 i} \cdots \tilde{R_{1}}
$$

is the $L R$ decomposition of $A^{2 i}$. Because the $L R$ decomposition is unique, this yields

$$
J R_{1}^{*} \cdots R_{i}^{*} J_{i+1} D_{i}^{-1}=L_{1} \cdots L_{2 i}
$$

Therefore we have

$$
\begin{aligned}
D_{i}^{-1} \tilde{A}_{2 i+1} D_{i} & =D_{i}^{-1} L_{2 i}^{-1} \cdots L_{1}^{-1} A L_{1} \cdots L_{2 i} D_{i} \\
& =J_{i+1} R_{i}^{-*} \cdots R_{1}^{-*} J A J R_{1}^{*} \cdots R_{i}^{*} J_{i+1} \\
& =J_{i+1} R_{i}^{-*} \cdots R_{1}^{-*} A^{*} R_{1}^{*} \cdots R_{i}^{*} J_{i+1} \\
& =J_{i+1} A_{i+1}^{*} J_{i+1}=A_{i+1}
\end{aligned}
$$

It remains to prove that the $H R$ decomposition of $A_{i_{0}+1}$ with respect to $J_{i_{0}+1}$ exists. From the last equality we get in particular $A_{i_{0}+1}=D_{i_{0}}^{-1} \tilde{A}_{2 i_{0}+1} D_{i_{0}}$. Now $A_{i_{0}+1}^{*} J_{i_{0}+1} A_{i_{0}+1}=J_{i_{0}+1} A_{i_{0}+1}^{2}=J_{i_{0}+1} D_{i_{0}}^{-1} \tilde{A}_{2 i_{0}+1}^{2} D_{i_{0}}$, and because

$$
\begin{aligned}
\tilde{A}_{2 i_{0}+1}^{2} & =L_{2 i_{0}+1} \tilde{R}_{2 i_{0}+1} L_{2 i_{0}+1} \tilde{R}_{2 i_{0}+1}=L_{2 i_{0}+1} \tilde{A}_{2 i_{0}+2} R_{2 i_{0}+1} \\
& =L_{2 i_{0}+1} L_{2 i_{0}+2} \tilde{R}_{2 i_{0}+2} R_{2 i_{0}+1}
\end{aligned}
$$

we find that the $L R$ decomposition of $A_{i_{0}+1}^{*} J_{i_{0}+1} A_{i_{0}+1}$ exists. According to Theorem 2.3 this completes the proof.

In particular, for $J=I$ or $J=-I$, i.e. for the $Q R$ algorithm applied to Hermitian matrices, this theorem gives a generalization of the relationship between the $Q R$ and the Cholesky $L R$ algorithm pointed out by Wilkinson [14, p. 545].

It is easy to construct $J$-Hermitian matrices for which the $H R$ algorithm with respect to $J$ is constructible but the $L R$ algorithm is not, even if $J \neq \pm I$. If for example we apply the $L R$ algorithm to the $\left[\begin{array}{rr}1 & 0 \\ 0 & -1\end{array}\right]$-symmetric matrix

$$
A=\left[\begin{array}{rr}
3 & -1 \\
1 & 21
\end{array}\right]
$$

we see that the third iterate

$$
A_{3}=\left[\begin{array}{rr}
0 & -1 \\
64 & 24
\end{array}\right]
$$

has no $L R$ decomposition.

Now if we examine how the $H R$ algorithm with respect to $\left[\begin{array}{rr}1 & 0 \\ 0 & -1\end{array}\right]$ works on $A$, we find that the first diagonal element $a_{i+1}$ of the $(i+1)$ th iterate $A_{i+1}$ satisfies

$$
a_{i+1}=a_{i}-\frac{24\left(a_{i}^{2}-24 a_{i}+64\right)}{24 a_{i}-64}
$$

The quantity $\left|24 a_{i}-64\right|$ is the absolute value of the first principal minor of $A_{i}^{T} J_{i} A_{i}$, and because $a_{1}=3$ it can be shown by studying the recurrence relation for $a_{i}$ that this value does not vanish. According to Theorem 2.3 this means that the algorithm is constructible.

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Received 3 August 1979; revised 19 December 1979

