# A New Block Algorithm for Full-Rank Solution of the Sylvester-Observer Equation 

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#### Abstract

A new block algorithm for computing a full rank solution of the Sylvester-observer equation arising in state estimation is proposed. The major computational kernels of this algorithm are: 1) solutions of standard Sylvester equations, in each case of which one of the matrices is of much smaller order than that of the system matrix and (furthermore, this small matrix can be chosen arbitrarily), and 2) orthogonal reduction of small order matrices. There are numerically stable algorithms for performing these tasks including the Krylov-subspace methods for solving large and sparse Sylvester equations. The proposed algorithm is also rich in Level 3 Basic Linear Algebra Subroutine (BLAS-3) computations and is thus suitable for high performance computing. Furthermore, the results on numerical experiments on some benchmark examples show that the algorithm has better accuracy than that of some of the existing block algorithms for this problem.


Index Terms—Block algorithm Sylvester-observer equation, state estimation.

## I. Introduction

The matrix equation

$$
\begin{equation*}
X A-F X=G C \tag{1}
\end{equation*}
$$

where the matrices $A \in \mathbb{R}^{n \times n}, C \in \mathbb{R}^{r \times n}$ are given and the matrices $X \in \mathbb{R}^{(n-r) \times n}, F \in \mathbb{R}^{(n-r) \times(n-r)}$ and $G \in \mathbb{R}^{(n-r) \times r}$ are to be found, is called the Sylvester-observer matrix equation [7].

The (1) is a variation of the well-known standard Sylvester equation $X A-T X=R$, in which $A, T$, and $R$ are given and $X$ is unknown. This is so called, because it arises in the construction of reduced-order observers [16] for the linear system

$$
\begin{array}{lc}
\dot{x}(t)= & A x(t)+B u(t) \\
y(t)= & C x(t) \tag{2}
\end{array}
$$

in the context of state estimation.
There are two basic approaches for state estimation [7]: Eigenvalue Assignment approach and the Sylvester-equation approach. Since one way of finding feedback matrix for eigenvalue assignment is via Sylvester equation [2], [12], [19], [20]; here we will pursue the Sylvester equation approach and, therefore, consider numerical solution of (1).

It is well known that the solvability of (1) is guaranteed if $\Omega(F) \cap \Omega(A)=\emptyset$, where $\Omega(M)$ denotes the spectrum of the matrix $M$. If $F$ is indeed a stable matrix, then once a solution triple $(X, F, G)$ of (1) is computed, an estimate $\hat{x}(t)$ to the state vector $x(t)$ can be computed by solving the following algebraic system of equations [16]:

$$
\left[\begin{array}{l}
X  \tag{3}\\
C
\end{array}\right] \hat{x}(t)=\left[\begin{array}{l}
z(t) \\
y(t)
\end{array}\right]
$$

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Here, $z(t)$ is the state vector of the observer system

$$
\begin{equation*}
\dot{z}(t)=F z(t)+G y(t)+X B u(t), z(0)=z_{0} \tag{4}
\end{equation*}
$$

The state estimation problem clearly requires that the solution matrix $X$ of (1) has full rank. Necessary conditions for existence of a full-rank solution $X$ of (1) are that $(A, C)$ is observable and $(F, G)$ is controllable [18]. We will assume the observability of $(A, C)$ and the matrices $F$ and $G$ will be constructed in such a way that the controllability of $(F, G)$ will be satisfied.

A well-known method for solving the Sylvester-observer equation, based on the observer-Hessenberg decomposition of the observable pair $(A, C)$ is due to Van Dooren [19]. The method is recursive in nature and computes the solution matrix $X$ and the matrices $F$ and $G$ recursively, one row or column at a time.

Van Dooren's algorithm has been generalized to a block algorithm in [5]. The other block algorithms for this problem have been developed earlier in [3], [6], and [17].

In this paper, we present another block algorithm. A distinguishing feature of this new algorithm, compared to other above existing block algorithm is that it is guaranteed to give a full-rank solution $X$ with a triangular structure. This structure can be exploited in computing the first $(n-r)$ components of the vector $\hat{x}(t)$ during the process of solving the linear algebraic system (3). The algorithm also seems to be more accurate then some of the other block algorithms.

The block algorithms are composed of Level 3 Basic Linear Algebra Subroutine (BLAS-3) computations. Such computations are ideally suited for achieving high-speed in today's high performance computers [10]. Indeed many traditional numerical linear algebra algorithms for matrix computations have been re-designed or new algorithms have been created for this purpose and a high-quality mathematical software package, called LAPACK [1] have been developed based on those block algorithms. Unfortunately, such algorithms in control are rare.

## II. New Block Algorithm

We propose to solve (1) by imposing some structure on the right-hand side of the equation. This means that (like in the SVD-based method [6]) no reduction is imposed on the system matrix. To be more specific, given matrices $A, C$ and a stable self-conjugate set $\mathcal{S}$, we construct matrices $X, F$ and $R$ satisfying

$$
\begin{equation*}
X A-F X=R \quad \Omega(F)=\mathcal{S} \tag{5}
\end{equation*}
$$

and such that we are able to solve $G C=R$ for $G \in \mathbb{R}^{(n-r) \times r}$ later. As the solution $X$ is being computed, a Householder-QR [13] based strategy will be applied so that at the end of the process, $X$ will be a full-rank upper triangular matrix.

## A. Development of the Algorithm

In this section, we propose our new block algorithm for solving (1). First, we investigate the solution of $G C=R$ for $G$. A solution exists only if the rows of the matrix $R$ belong to the row space of the matrix $C$. Assume that the matrix $C$ has full rank $r$ and let $C=R_{c} Q_{c}$ be the thin RQ factorization of $C$ [13], where $Q_{c} \in \mathbb{R}^{r \times n}$ and $R_{c} \in \mathbb{R}^{r \times r}$. If we choose

$$
R=\left[\begin{array}{l}
N_{1}  \tag{6}\\
\ldots \\
N_{q}
\end{array}\right] Q_{c}=N Q_{c}
$$

where $N_{i} \in \mathbb{R}^{n_{i} \times r}, i=1, \ldots, q$, and $n_{1}+n_{2}+\cdots+n_{q}=n-r=s$, then we can find a solution $G \in \mathbb{R}^{(n-r) \times r}$ of $G C=R$ where $G_{i} R_{c}=$ $N_{i}, i=1, \ldots, q$ and

$$
G=\left[\begin{array}{c}
G_{1}  \tag{7}\\
\ldots \\
G_{q}
\end{array}\right]
$$

In particular, the choice $N_{1}=I_{r}$ ensures that $\operatorname{rank}(R)=$ $\operatorname{rank}(C)=r$.

Second, we partition $X$ and $F$ conformally

$$
X=\left[\begin{array}{c}
X_{1}  \tag{8}\\
\cdots \\
X_{q}
\end{array}\right] \quad F=\left[\begin{array}{cccc}
F_{11} & 0 & \cdots & 0 \\
F_{21} & F_{22} & \ldots & \vdots \\
\vdots & \vdots & \ddots & \vdots \\
F_{q 1} & F_{q, q-1} & & F_{q q}
\end{array}\right]
$$

Note that

$$
\begin{aligned}
& \operatorname{rank}\left[\begin{array}{ll}
G & F G \cdots F^{n-r-1} G
\end{array}\right] \\
= & \operatorname{rank}\left[\begin{array}{ll}
G R_{C} & F G R_{c} \cdot F^{n-r-1} G R_{c}
\end{array}\right]
\end{aligned}
$$

(where $R_{c}$ is a full rank $r \times r$ matrix)

$$
=\operatorname{rank}\left[N F N \cdots F^{n-r-1} N\right]
$$

This shows that if we chose $(F, N)$ as a controllable pair, then automatically $(F, G)$ is controllable. To ensure the controllability of the pair $(F, N)$, we choose $N_{1}=I_{r}, N_{2}=\cdot \cdot=N_{q}=0$, and $F$ as in (8) with full-rank blocks $F_{i, i-1}$ and $F_{i j}=0$ for $j<i-1$. Then, $(F, N)$ is controllable.
Substituting (6) and (8) into (5) and equating corresponding blocks on the right and left-hand sides of (5), we obtain

$$
\begin{align*}
X_{1} A-F_{11} X_{1} & =N_{1} Q_{c}  \tag{9}\\
X_{i} A-F_{i i} X_{i} & =N_{i} Q_{c}+\sum_{j=1}^{i-1} F_{i j} X_{j}, \\
i & =2, \ldots, q \tag{10}
\end{align*}
$$

Therefore, as long as the elements of the given set $\mathcal{S}$ can be successfully distributed in self-conjugate subsets $S_{i} \in \mathbb{C}^{n_{i}}, i=1, \ldots, q$, which are to be assigned as eigenvalues of the block matrices $F_{i i}, i=1, \ldots, q$, we are able to construct matrices $X, F$ and $G$ from their blocks by computing them recursively using (9) and (10).

Let us define

$$
\begin{align*}
X^{i} & =\left[\begin{array}{c}
X_{1} \\
\ldots \\
X_{i}
\end{array}\right] \quad G^{i}=\left[\begin{array}{c}
G_{1} \\
\ldots \\
G_{i}
\end{array}\right]  \tag{11}\\
F^{i} & =\left[\begin{array}{cccc}
F_{11} & \ldots & F_{1, i-1} & 0 \\
\ldots & \ldots & \ldots & 0 \\
F_{i-1,1} & & F_{i-1, i-1} & 0 \\
F_{i 1} & \ldots & \ldots & F_{i i}
\end{array}\right] . \tag{12}
\end{align*}
$$

Next, we now update each $X^{i}$ using QR factorization, so that the matrix $X$ has an uppertriangle structure.

After each block $X_{i}$ of the solution $X$ has been computed, the matrix $X^{i}$ defined previously will have the following structure:

$$
X^{i}=\left[\begin{array}{ccccccc}
* & * & * & * & * & * & * \\
& * & * & * & * & * & * \\
& & \cdot & \cdot & \cdot & \cdot & \cdot \\
& & & & * & * & * \\
* & * & * & * & * & * & * \\
\cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\
* & * & * & * & * & * & *
\end{array}\right] .
$$

The matrix $X^{i}$ is now made upper triangular by premultiplying $X^{i}$ with an appropriate orthogonal matrix $Q_{i}$ (for example, $Q_{i}$ can be product of suitable Householder matrices).

Symbolically, we write: $X^{i} \leftarrow Q_{i}^{T} X^{i}$ where $X^{i}$ is updated to the matrix $Q_{i}^{T} X^{i}$ and the updated matrix $Q_{i}^{T} X^{i}$ is overwritten by $X^{i}$.
The matrix equation

$$
\begin{equation*}
X^{i} A-F^{i} X^{i}=G^{i} C \tag{13}
\end{equation*}
$$

is then updated to

$$
Q_{i}^{T} X^{i} A-Q_{i}^{T} \cdot F^{i} Q_{i} \cdot Q_{i}^{T} X^{i}=Q_{i}^{T} G^{i} C
$$

meaning that it is possible to update the solution matrices, at every step of the orthogonal reduction, simply by computing

$$
\begin{equation*}
X^{i} \leftarrow Q_{i}^{T} X^{i}, F^{i} \leftarrow Q_{i}^{T} F^{i} Q_{i}, G^{i} \leftarrow Q_{i}^{T} G^{i} . \tag{14}
\end{equation*}
$$

## B. Proposed Block Algorithm for Solving $X A-F X=G C$

The aforementioned discussion leads to the following algorithm.
Input: Matrices $A \in R^{n \times n}$ and $C \in \mathbb{R}^{r \times n}$ of the system (2) and a self-conjugate set $\mathcal{S} \in \mathbb{C}^{n-r}$.
Output: Block matrices $X, F$ and $G$, such that $\Omega(F)=\mathcal{S}$ and $X A-F X=G C$.
Assumption: System (2) is observable, $C$ has full rank and $\Omega(A) \bigcap \mathcal{S}=\emptyset$.
Step 1: Set $s=n-r, \ell=r$ and $N_{1}=I_{r \times r}$, $G_{1}=R_{c}^{-1}$ and $n_{1}=r$.
Step 2: Compute the thin $R Q$ factorization of $C$ [13]: $R_{c} Q_{c}=C$ where $Q_{c} \in \mathbb{R}^{r \times n}$ and $R_{c} \in \mathbb{R}^{r \times r}$.
Step 3: For $i=1,2, \ldots$ do Steps 4 to 10
Step 4: Set $S_{i} \in \mathbb{R}^{\ell}$ to be a self-conjugate subset of the part of $\mathcal{S}$ that was not used yet.
Step 5: Set $F_{i i} \in \mathbb{R}^{\ell \times \ell}$ to be any matrix in upper real Schur form satisfying $\Omega\left(F_{i i}\right)=S_{i}$.
Step 6: Free parameter setup. If $i>1$ set $N_{i} \in \mathbb{R}^{\ell \times n_{i}}$ and $F_{i j} \in \mathbb{R}^{\ell \times n_{j}}, j=1, \ldots, i-1$ to be arbitrary matrices, so that $(F, N)$ is controllable. Compute $G_{i}=N_{i} R_{c}^{-1}$.
Step 7: Solve the Sylvester equation:

$$
X_{i} A-F_{i i} X_{i}=N_{i} Q_{c}+\sum_{j=1}^{i-1} F_{i j} X_{j}
$$

for $X_{i} \in \mathbb{R}^{\ell \times n}$.
Step 8: Form $X^{i}, G^{i}$ and $F^{i}$ as in (11) and (12). If $i>1$, then set $n_{i}$ as the number of rows of $X_{i}$ that are linearly independent of the rows of $X^{i-1}$. If $n_{i}<\ell$, then
set $\ell=n_{i}$, and choose another set $S_{i}$ from $\mathcal{S}$ and repeat Steps 5-8.
Step 9: Find, implicitly, an orthogonal matrix $Q_{i}$ that reduces $X^{i}$ to upper triangular form via left multiplication by $Q_{i}^{T}$, using, say householder matrices , [13]. Then compute the matrix updates

$$
X^{i} \leftarrow Q_{i}^{T} X^{i} \quad G^{i} \leftarrow Q_{i}^{T} G^{i} \quad F^{i} \leftarrow Q_{i}^{T} F^{i} Q_{i}
$$

Step 10: If $n_{1}+\ldots+n_{i}=s$, then let $q=i$ and exit loop.
Step 11: Form the matrices $X=X^{q}, F=F^{q}$ and $G=G^{q}$.

## Remarks:

1) Some compatibility between the structure of the vector $\mathcal{S}$ and the parameters $n_{i}, i=1, \ldots, q$ is required so that Step 4 is always possible to be accomplished.
2) The algorithm does not require reduction of the system matrices $A$ and $C$. This feature is specially attractive when $A$ is large and sparse. There now exist Krylov-subspace based methods for Sylvester equations, suitable for large and sparse computations [8]. If $A$ is small and dense, the standard Hessenberg-Schur method [14] can be used.
3) In Step 6, it is possible to exploit the freedom of assigning $F_{i j}$ to facilitate the solution of the Sylvester equation in Step 7. In particular, the diagonal blocks $F_{i i}$ can be chosen in real-Schur forms, so that if the Hessenberg-Schur algorithm is used, then only the matrix $A$ needs to be decomposed into Hessenberg form and this is to be done once for all the equations in step 7.
4) If matrix $A$ is dense, an orthogonal similarity reduction $A \leftarrow$ $P^{T} A P, C \leftarrow C P$, can be used so to bring Hessenberg structure to the matrix $A$. This will allow Step 7 to be computed efficiently. If $\left(X_{h}, F, G\right)$ is the solution of this reduced problem, then $X=X_{h} P^{T}$ is the solution of the original problem.
5) The algorithm is rich in Level 3-BLAS computations and thus is suitable for high-performance computing using the software LAPACK [1], [10], which is especially designed for such a purpose.
6) The total flop-count of the algorithm is approximately

$$
21 \frac{2}{3} n^{3}+14 \cdot 5 n^{2} r
$$

flops. This amount is smaller than that of Van Dooren's method [19]: $2 r n^{3}+7 n^{3}$, if $r$, the number of columns of the matrix $C$, is grater than 7 .

## III. An Illustrative Numerical Example

To illustrate the implementation of the proposed algorithm, we take matrices $A$ and $C$, and the set $S$ given in (I).

```
Step 1: l=2, N1 = I_.
Step 2: The RQ factorization of C gives
the matrices }\mp@subsup{R}{c}{}\mathrm{ and }\mp@subsup{Q}{c}{}\mathrm{ given in (II) at
the bottom of the page.
Step 3: i=1.
Step 4:
S}={-1.0000+1.0000i-1.0000-1.0000i
Step 5: F
```

$$
F_{11}=\left[\begin{array}{cc}
-1 & -1 \\
1 & -1
\end{array}\right]
$$

Clearly $\Omega\left(F_{11}\right)=S_{1}$.
Step 6: Set

$$
N_{1}=\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right]
$$

for simplicity.
Step 7: Solve $X_{1} A-F_{11} X_{1}=N_{1} Q_{c}$, using MATLAB Command lyap.
$X_{1}=\left[\begin{array}{ccccccc}-.134 & .280 & .067 & -.055 & .103 & -.444 & .235 \\ -.398 & -.104 & .438 & -.124 & .314 & -.027 & .219\end{array}\right]$
Step 8: $n_{1}=2, \quad l=\min \{2,7-2-2\}=2$.
Step 9:After the reduction with an orthogonal matrix, we have the matrix $X_{1}$, as shown in (III) at the bottom of the page.
Step 3: $i=2$.
Step 4: $S_{2}=\{-2.00-1.00 i-2.00+1.00 i\}$.

$$
\begin{align*}
A & =\left[\begin{array}{ccccccc}
0.995 & 2.041 & -3.162 & 3.112 & -2.689 & 0.126 & 2.576 \\
2.694 & 0.815 & 2.552 & 1.953 & 1.438 & -2.547 & 1.255 \\
1.953 & -1.010 & 0.117 & 1.144 & 2.694 & 3.035 & 1.739 \\
-2.231 & -1.635 & 3.101 & 1.437 & -0.956 & -1.430 & 2.340 \\
1.462 & 0.829 & 0.076 & -3.292 & -0.852 & -2.465 & -1.228 \\
3.431 & -2.182 & -1.959 & 2.366 & 3.037 & 0.544 & 3.268 \\
-0.722 & -0.419 & 1.307 & -0.590 & 2.300 & 0.798 & -1.580
\end{array}\right]  \tag{I}\\
C & =\left[\begin{array}{cccccc}
.20 & 5.54 & 5.06 & 4.69 & 4.37 & 6.42 \\
4.79 & 4.51 & 2.68 & 5.56 & .06 & 4.37 \\
4.7 .14
\end{array}\right] \\
S & =\{-1 .-1 .-1 . \mathbf{i}-1 .+1 . \mathbf{i}-2 .-1 . \mathbf{i}-2 .+1 . \mathbf{i}\} .
\end{align*}
$$

$$
\left.\begin{array}{rl}
R_{c} & =\left[\begin{array}{cccccc}
-7.625162 & -9.136243 \\
& -11.264567
\end{array}\right] \\
Q_{c} & =\left[\begin{array}{cccccc}
0.482 & -0.474 & -0.018 & -0.282 & 0.117 & 0.637 \\
-0.425 & 0.458 & 0.314 & -0.561 & 0.063 & 0.308
\end{array} 0.313\right.
\end{array}\right] .
$$

Step 5: Set $F_{22}$ to be

$$
F_{22}=\left[\begin{array}{cc}
-2 & -1 \\
1 & -2
\end{array}\right]
$$

Then, clearly $\Omega\left(F_{22}\right)=S_{2}$.
Step 6: The free assignment is done via

$$
N_{2}=\left[\begin{array}{ll}
0 & 0 \\
0 & 0
\end{array}\right], \quad F_{21}=\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right]
$$

by simplicity.
Step 7: Solving $X_{2} A-F_{22} X_{1}=N_{2} Q_{c}+F_{21} X_{1}$, we obtain the matrix given by (IV) at the bottom of the page.
Step 8: $n_{2}=2, \quad l=\min \{2,7-2+(2+2)\}=1$.
Step 9: After the reduction, we have the matrix given in (V) at the bottom of the page.
Step 3: $i=3$.
Step 4: $S_{3}=\{-1.0000\}$.
Step 5: We set $F_{33}=-1.0000$.
Step 6: Set $N_{3}=\left[\begin{array}{ll}0 & 0\end{array}\right], \quad F_{32}=\left[\begin{array}{ll}1 & 0\end{array}\right]$.
Step 7: Solving $X_{3} A-F_{33} X_{3}=N_{3} Q_{c}+F_{32} X_{2}$, we obtain $X_{3}$ given in (VI) at the bottom of the page.

Step 8: $n_{3}=1, \quad l=\min \{2,7-2+(2+2+1)\}=0$. Step 9: After the reduction, we have the final solution $X$ given in (VII) at the bottom of the page.
Step 10: Since $n_{1}+n_{2}+n_{3}=7-2$ we set $p=3$ and exit the loop.
Step 11: The algorithm finishes with matrices $X \in \mathbb{R}^{5 \times 7}, F \in \mathbb{R}^{5 \times 5}$ and $G \in \mathbb{R}^{5 \times 2}$.

It can be shown that $\|X A-F X-G C\|_{F}=2.4037 \times 10^{-15}$.

## A. Remark

In order to solve the state estimation problem, system (3) is reduced to upper triangular form by premultiplication by an orthogonal matrix $Q_{4}^{T}$, given by (VIII) at the bottom of the next page. Because of the upper triangular structure of the matrix $X$, the matrix $Q_{4}$ is obtained as the product of six appropriate Householder matrices, (which is not shown here). Therefore, the linear system (3) is reduced to

$$
U \hat{x}(t)=Q_{4}^{T}\left[\begin{array}{l}
z(t) \\
y(t)
\end{array}\right]
$$

where the matrix $U$ is given by (IX) at the top of the page 2228.

$$
X_{1}=\left[\begin{array}{ccccccc}
.420 & -.107 & .271 & .171 & .263 & -.144 & .471 \\
& -.014 & -.198 & -.136 & -.217 & -.079 & .421
\end{array}\right]
$$

(III)

$$
\left[\begin{array}{l}
X_{1}  \tag{IV}\\
X_{2}
\end{array}\right]=\left[\begin{array}{ccccccc}
.420 & -.107 & .271 & .171 & .263 & -.144 & .471 \\
& -.014 & -.198 & -.1359 & -.217 & -.079 & .421 \\
.072 & -.024 & .089 & .068 & .115 & -.032 & .030 \\
.213 & -.138 & .051 & .129 & .217 & -.044 & .235
\end{array}\right]
$$

$$
\left[\begin{array}{l}
X_{1}  \tag{V}\\
X_{2}
\end{array}\right]=\left[\begin{array}{ccccccc}
-.476 & .160 & -.275 & -.218 & -.347 & .151 & -.525 \\
0 & .076 & 0.111 & -0.012 & -.035 & -.011 & -.072 \\
0 & 0 & -.187 & -.145 & -.235 & -.078 & .414 \\
0 & 0 & & .001 & -.003 & .030 & -.056
\end{array}\right]\left[\begin{array}{ll} 
&
\end{array}\right] .
$$

$$
\left[\begin{array}{l}
X_{1}  \tag{VI}\\
X_{2} \\
X_{3}
\end{array}\right]=\left[\begin{array}{ccccccc}
-.476 & .160 & -.275 & -.218 & -.347 & .151 & -.525 \\
0 & .076 & .111 & -.012 & -.035 & -.011 & -.072 \\
0 & 0 & -.187 & -.145 & -.235 & -.078 & .414 \\
0 & 0 & 0 & .001 & -.003 & 0.030 & -.056 \\
.238 & -.156 & .069 & .165 & .270 & -.009 & .256
\end{array}\right]
$$

$$
\left[\begin{array}{l}
X_{1} \\
X_{2} \\
X_{3}
\end{array}\right]=\left[\begin{array}{ccccccc}
.532 & -.213 & .277 & .269 & .431 & -.140 & .584 \\
0 & -.102 & -.124 & 0.43 & .084 & .047 & .051 \\
0 & 0 & .188 & .148 & 0.239 & .082 & -.417 \\
0 & 0 & 0 & -.007 & -.006 & -.030 & -.001 \\
0 & 0 & 0 & 0 & .004 & -.026 & .057
\end{array}\right]
$$



Fig. 1. Here $n$ is the size of the system matrix $A=\operatorname{Pentoep}(n)$, regarded as pentadiagonal. The dash-dotted line corresponds to the proposed algorithm, the dashed line to the SVD-based algorithm and the solid line to the Hessenberg reduction algorithm.

## IV. Comparison of Efficiency and Accuracy With Existing Block Algorithms on Benchmark Examples

Figs. 1 and 2 show a comparison, in terms of accuracy and speed, of the proposed algorithm with the recent SVD-based [6] and the ob-server-Hessenberg reduction based [5] algorithms. The left-hand side graph of each figure compares the CPU-time and the right-hand side


Fig. 2. Here $n$ is the size of the system matrix $A=\operatorname{Pentoep}(n)$, regarded as toeplitz. The dash-dotted line corresponds to the proposed algorithm, the dashed line to the SVD-based algorithm and the solid line to the Hessenberg reduction algorithm.
compares the accuracy. $n$ is the size of the matrix $A$. The comparison is made on benchmark testing with the family Pentoep and with the family of Riemann matrices [15]. Speed is measured in terms of normalized CPU-time, that is, the required CPU-time is divided by the CPU-time of a call to the LAPACK [1]routine dgemm for multiplying two arbitrary matrices. Accuracy is measured by computing the Frobenius norm $\|X A-F X-G C\|_{F}$. Computations were performed in Matlab 6 in Pentium II 400 MHz environment. The results of our experiment show that the proposed algorithm can achieve a better accuracy with a comparable speed for the problems tested.

$$
Q_{4}=\left[\begin{array}{ccccccc}
-.11 & -.135 & -.942 & -.092 & -.271 & .011 & .001  \tag{VIII}\\
.0 & -.019 & .05 & .886 & -.4593 & -.013 & -.036 \\
.0 & .0 & -.29 & .45 & .844 & -.04 & -.010 \\
.0 & .0 & .0 & -.047 & -.014 & -.641 & -.77 \\
.0 & .0 & .0 & .0 & -.0285 & -.766 & .64 \\
-.042 & .990 & -.1248 & .005 & -.0449 & .001 & -.001 \\
-.99 & -.027 & .110 & .010 & .032 & -.001 & -.0
\end{array}\right] .
$$

$$
U=\left[\begin{array}{ccccccc}
-4.82 & -4.69 & -2.90 & -5.75 & -.29 & -4.6 & -5.24  \tag{IX}\\
-.0 & 5.4 & 4.9 & 4.45 & 4.27 & 6.25 & 1.52 \\
.0 & .0 & -.66 & -.27 & -1.01 & -.209 & -.081 \\
.0 & .0 & -.0 & .16 & .163 & .167 & -.137 \\
.0 & .0 & .0 & -.0 & -.148 & -.061 & -.449 \\
.0 & .0 & .0 & -.0 & -.0 & .036 & -.026 \\
.0 & .0 & .0 & -.0 & -.0 & .0 & .039
\end{array}\right] .
$$

## V. CONCLUSION

A new block algorithm for solving the Sylvester-observer equation is proposed. The algorithm does not require the reduction of the system matrix $A$ and is then ideally suitable for large and sparse computations by using the recently developed Krylov-subspace based methods. This algorithm is well-suited for implementation on high-performance computing using $L A P A C K$ and it seems to be accurate compared with similar ones; however, numerical stability properties have not been studied yet.

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