

A PARAMETER-ESTIMATION ALGORITHM
FOR SMALL DIGITAL COMPUTERS

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ABSTRACT

An algorithm is developed for performing parameter estimation on a small-size digital computer. First principles of matrix algebra are used to derive a sequential estimator which computes an estimate of a general parameter array \underline{A} from an array of measurements $\underline{Z} = \underline{H}\underline{A} + \underline{V}$ where \underline{V} is a matrix of zero-mean noise terms. At every stage a new row is adjoined to each of \underline{Z} , \underline{H} and \underline{V} and a new estimate of \underline{A} is calculated recursively, with any one of three well-known filtering processes available from the same basic set of recursive equations: a least-squares filter to minimize $J = \frac{1}{2} \text{trace} (\underline{Z} - \underline{H}\hat{\underline{A}})(\underline{Z} - \underline{H}\hat{\underline{A}})'$, a maximum-likelihood filter to maximize $p_{\underline{Z}|\underline{A}}(\underline{Z}|\hat{\underline{A}})$ or a maximum-a-posteriori filter to maximize $p_{\underline{A}|\underline{Z}}(\hat{\underline{A}}|\underline{Z})$. Provision is made for starting the filter either with a-priori means and variances of the parameters or with a deterministic "minimum-norm" composition based on the first s measurement rows, s being the number of rows in the parameter array.

The algorithm is applied to the problem of identifying the parameters of a discrete model for a linear time-invariant control system directly from sequential observations of the inputs and outputs. Results from computer tests are used to demonstrate properties of the algorithm and the important computer programs are included, along with suggestions for further applications.

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I. Introduction

When it is necessary to estimate important parameters of a system from measurements of system variables, the choice of an optimal mathematical procedure depends on the amount of statistical information available concerning the system and measurement process. Unfortunately, not enough information is available in many practical situations to permit using well-known estimators like the Kalman filter, nor is it obvious how these procedures can be adapted for simpler problems. Kishi [8], Sage [13], Young [17] and other authors have indicated how classical least-squares filtering can be useful because of its validity in the absence of statistical information and its similarities with more sophisticated methods, but very little has been written in the way of a unified and complete theory of practical least-squares filtering. Greville [3] presents a derivation of least-squares curve fitting which is mathematically rigorous but unnecessarily complicated by the use of generalized-inverse theory and not directly applicable to the problem of parameter estimation. In an attempt to apply it to the estimation problem, Kishi [8] loses some of the mathematical rigour and neglects some important practical considerations. Young [17] and Sinha and Pille [15] have contributed accurate but very simplified descriptions of the method.

There is considerable advantage to be gained by using a classical least-squares estimator as the basis for on-line filtering algorithms because it is straightforward to imple-

ment, valid under most conditions and easily modified for a-priori statistical information. It is the purpose of this thesis to develop a complete theory for least-squares filtering, leading to an algorithm that can be programmed on a small digital computer and to considerations of how the algorithm can be extended for a number of practical situations. The mathematical approach used by Greville [2,3] was chosen as the most suitable on which to base the derivations for general least-squares filtering equations, although his use of Penrose's pseudo-inverse theory [11, 12] has been abandoned in favour of a more straightforward approach which employs only first principles of matrix algebra. To include the statistical maximum-likelihood and Bayesian filters, some simple modifications of the equations are considered.

In this thesis all symbols representing vectors and matrices are underscored, with upper-case letters denoting matrices and lower-case letters denoting column-vectors wherever possible. A symbol followed by a prime indicates the transpose of the corresponding matrix or column-vector (example: \underline{A}'). Where dimensions of a matrix or vector are given, they are enclosed in parentheses following the symbol (example: $\underline{B}(m \times n)$). The identity matrix is represented by the symbol " \underline{I} " and matrix inverses are denoted by the superscript " -1 ". The symbol for the statistical expected-value operator is " ϵ ".

II. Least-Squares Filtering

An arbitrary but very general representation of the relation between a collection of measurements of system variables and the basic parameters of the system is

$$\underline{Z} = \underline{H}\underline{A} + \underline{V} \quad (1)$$

where \underline{Z} is an array containing all the measured data, \underline{A} is the array of unknown fixed parameters, \underline{H} is the matrix representing the defined relationship between the quantities measured and the parameters, and \underline{V} is an array of measurement noise terms. In a simple example of a body moving with a constant velocity v , it is desired to estimate the velocity and initial position s_0 of the body from measurements of its position s at known times t . The parameters s_0 and v are defined by the equation

$$s = s_0 + vt$$

If the position is measured at times t_1 , t_2 and t_3 and values \bar{s}_1 , \bar{s}_2 and \bar{s}_3 are obtained, then a representation corresponding to equation (1) would be

$$\begin{bmatrix} \bar{s}_1 \\ \bar{s}_2 \\ \bar{s}_3 \end{bmatrix} = \begin{bmatrix} 1 & t_1 \\ 1 & t_2 \\ 1 & t_3 \end{bmatrix} \begin{bmatrix} s_0 \\ v \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ n_3 \end{bmatrix}$$

where n_1 , n_2 and n_3 are measurement noise terms.

The classical method of least squares assumes that for zero-mean noise the estimate $\hat{\underline{A}}$ of the parameter array \underline{A} should

result in a minimum of the sum of the squares of the elements of the matrix $(\underline{Z} - \underline{H}\hat{\underline{A}})$. This corresponds to minimizing the cost function

$$J = \frac{1}{2} \text{trace} (\underline{Z} - \underline{H}\hat{\underline{A}})(\underline{Z} - \underline{H}\hat{\underline{A}})' \quad (2)$$

If the rows of \underline{Z} are labelled successively $\underline{z}_1', \underline{z}_2', \underline{z}_3', \dots$, and the rows of \underline{H} are similarly labelled $\underline{h}_1', \underline{h}_2', \underline{h}_3', \dots$, then the cost function can be written

$$J = \frac{1}{2} \sum_i (\underline{z}_i' - \underline{h}_i' \hat{\underline{A}})(\underline{z}_i' - \underline{h}_i' \hat{\underline{A}})' \quad (3)$$

For a minimum the derivative with respect to $\hat{\underline{A}}$ must be zero:

$$-\sum_i \underline{h}_i' (\underline{z}_i' - \underline{h}_i' \hat{\underline{A}}) = \underline{0}$$

$$\sum_i \underline{h}_i' \underline{z}_i' = \sum_i \underline{h}_i' \underline{h}_i' \hat{\underline{A}}$$

$$\underline{H}' \underline{Z} = \underline{H}' \underline{H} \hat{\underline{A}} \quad (4)$$

If the number of rows in \underline{H} is greater than or equal to the number of columns and the columns are linearly independent then the column vector $\underline{H}\underline{u}$, which is a linear combination of the columns of \underline{H} , is non-zero for all non-zero \underline{u} . Therefore $\underline{u}' \underline{H}' \underline{H} \underline{u}$ is positive for all non-zero \underline{u} which means that $\underline{H}' \underline{H}$ is positive definite and hence non-singular. (4) then gives the unique solution

$$\hat{\underline{A}} = (\underline{H}'\underline{H})^{-1}\underline{H}'\underline{Z} \quad (5)$$

If the number of rows in \underline{H} is less than or equal to the number of columns and the rows are linearly independent then the row vector $\underline{u}'\underline{H}$, which is a linear combination of the rows of \underline{H} , is non-zero for all non-zero \underline{u} . Thus $\underline{u}'\underline{H}\underline{H}'\underline{u}$ is positive for all non-zero \underline{u} and $\underline{H}\underline{H}'$ is positive definite and therefore nonsingular. Pre-multiplying both sides of (4) by \underline{H} gives

$$\begin{aligned} \underline{H}\underline{H}'\underline{Z} &= \underline{H}\underline{H}'\underline{H}\hat{\underline{A}} \\ \underline{Z} &= \underline{H}\hat{\underline{A}} \end{aligned} \quad (6)$$

Except for the case where \underline{H} is square, this equation does not have a unique solution, but although no unique solution can be defined on the basis of the least-squares criterion alone it will nevertheless be desirable to define some arbitrary solution. The most logical choice is that least-squares solution which has a minimum "norm" and is found by minimizing the cost function

$$J_n = \frac{1}{2} \text{trace} (\hat{\underline{A}}\hat{\underline{A}}') \quad (7)$$

subject to equation (6). Using Lagrange's method of undetermined multipliers, an augmented cost function is defined:

$$J_a = \text{trace} \left[\frac{1}{2} \hat{\underline{A}}\hat{\underline{A}}' + \underline{\lambda}(\underline{Z} - \underline{H}\hat{\underline{A}}) \right] \quad (8)$$

where $\underline{\lambda}$ is the array of undetermined multipliers. Now

$$\frac{\partial J_a}{\partial \underline{A}} = \underline{\hat{A}} - \underline{H}' \underline{\lambda}' = \underline{0}$$

$$\underline{\hat{A}} = \underline{H}' \underline{\lambda}' \quad (9)$$

Using (9) in (6),

$$\underline{Z} = \underline{H} \underline{H}' \underline{\lambda}'$$

$$\underline{\lambda}' = (\underline{H} \underline{H}')^{-1} \underline{Z} \quad (10)$$

Using (10) in (9),

$$\underline{\hat{A}} = \underline{H}' (\underline{H} \underline{H}')^{-1} \underline{Z} \quad (11)$$

This equation will define the least-squares estimate of \underline{A} whenever the number of rows of \underline{H} is less than or equal to its number of columns and the rows are linearly independent.

For the many applications where the observations are not available all at once but are received sequentially in time, it is desirable to have a recursive relation which will provide parameter estimates at every stage by updating prior estimates as each new set or block of data arrives. The addition of more data to the \underline{Z} matrix will require that elements be added to the \underline{H} matrix and since the dimensions of \underline{H} will be changing at every stage it is important to establish which of equations (5) and (11) should be used to determine the estimate at each stage.

If the parameter matrix \underline{A} is to have fixed dimensions,

labelled $(s \times r)$, then equation (1) shows that \underline{H} must always have s columns and \underline{Z} must always have r columns. Thus in this scheme, elements adjoined to the \underline{H} and \underline{Z} matrices at sequential stages must take the form of additional rows. If q is the number of rows adjoined to each of \underline{Z} and \underline{H} at every estimation stage, then the total number of rows in each matrix is kq where k is the number of the current estimation stage. To summarize the dimension labels, (1) can be re-written

$$\underline{Z}(kq \times r) = \underline{H}(kq \times s) \underline{A}(s \times r) + \underline{V}(kq \times r) \quad (12)$$

Now, using (5) and (11), the least-squares estimate for \underline{A} at stage k is defined by

$$\hat{\underline{A}}_k = \underline{H}_k' (\underline{H}_k \underline{H}_k')^{-1} \underline{Z}_k, \quad kq \leq s \quad (13)$$

$$\hat{\underline{A}}_k = (\underline{H}_k' \underline{H}_k)^{-1} \underline{H}_k' \underline{Z}_k, \quad kq \geq s \quad (14)$$

where \underline{H}_k and \underline{Z}_k are the matrices \underline{H} and \underline{Z} at stage k . If $q \geq s$ then (14) will apply for all values of k , but if $q < s$ then (13) will apply until k exceeds $\frac{s}{q}$ and (14) will apply for all further stages. In designing a general recursive relation for (13) and (14), advantage can be taken of the fact that both solutions would apply for a stage k where $kq = s$, provided the rows of \underline{H} are linearly independent. \underline{H}_k would be square and nonsingular and (13) and (14) would reduce to

$$\hat{\underline{A}}_k = \underline{H}_k^{-1} \underline{Z}_k, \quad kq = s \quad (15)$$

Thus if the number of rows adjoined to \underline{H}_k at each stage (q) is a factor of its number of columns (s) then there will be a stage where $kq = s$ such that both (13) and (14) are valid and the final solution from the recursive form of (13) can be used as the starting value for the recursive form of (14).

To obtain the recursive forms for equations (13) and (14) it is convenient to introduce new symbols \underline{G}_k and \underline{J}_k defined by

$$\underline{G}_k = \underline{H}_k' (\underline{H}_k \underline{H}_k')^{-1}, \quad kq \leq s \quad (16)$$

$$\underline{J}_k = (\underline{H}_k' \underline{H}_k)^{-1} \underline{H}_k', \quad kq \geq s \quad (17)$$

In the theory of generalized inverses \underline{G}_k would be called the right generalized inverse or right pseudo-inverse of \underline{H}_k and \underline{J}_k would be called the left generalized inverse or left pseudo-inverse of \underline{H}_k . The matrices \underline{Z}_k , \underline{H}_k , \underline{G}_k and \underline{J}_k are partitioned as follows:

$$\underline{Z}_k(kq \times r) = \begin{bmatrix} \underline{Z}_{k-1}([k-1]q \times r) \\ \dots\dots\dots \\ \underline{Z}_k^*(q \times r) \end{bmatrix} \quad (18)$$

$$\underline{H}_k(kq \times s) = \begin{bmatrix} \underline{H}_{k-1}([k-1]q \times s) \\ \dots\dots\dots \\ \underline{H}_k^*(q \times s) \end{bmatrix} \quad (19)$$

$$\underline{G}_k(s \times kq) = \begin{bmatrix} \underline{F}_k(s \times [k-1]q) & \vdots & \underline{E}_k(s \times q) \end{bmatrix} \quad (20)$$

$$\underline{J}_k (s \times kq) = \begin{bmatrix} \underline{D}_k (s \times [k-1] q) & \vdots & \underline{B}_k (s \times q) \end{bmatrix} \quad (21)$$

Equation (13) can now be written

$$\hat{\underline{A}}_k = \underline{G}_k \underline{Z}_k = \underline{F}_{k-k-1} \underline{Z}_{k-1} + \underline{E}_{k-k} \underline{Z}_k^*, \quad kq \leq s \quad (22)$$

To solve for \underline{F}_k and \underline{E}_k , define the matrix

$$\underline{Q}_k = \underline{G}_k \underline{H}_k = \underline{H}_k' (\underline{H}_k \underline{H}_k')^{-1} \underline{H}_k = \underline{F}_{k-k-1} \underline{H}_{k-1} + \underline{E}_{k-k} \underline{H}_k^* \quad (23)$$

Post-multiplying by \underline{H}_k' gives

$$\underline{H}_k' = \underline{F}_{k-k-1} \underline{H}_{k-1} \underline{H}_k' + \underline{E}_{k-k} \underline{H}_k^* \underline{H}_k' \quad (24)$$

Using (19), this can be written as two equations:

$$\underline{H}_{k-1}' = \underline{F}_{k-k-1} \underline{H}_{k-1} \underline{H}_{k-1}' + \underline{E}_{k-k} \underline{H}_k^* \underline{H}_{k-1}' \quad (25)$$

$$\underline{H}_k^{*'} = \underline{F}_{k-k-1} \underline{H}_{k-1} \underline{H}_k^{*'} + \underline{E}_{k-k} \underline{H}_k^* \underline{H}_k^{*'} \quad (26)$$

From (25)

$$\underline{F}_k = \underline{H}_{k-1}' (\underline{H}_{k-1} \underline{H}_{k-1}')^{-1} - \underline{E}_{k-k} \underline{H}_k^* \underline{H}_{k-1}' (\underline{H}_{k-1} \underline{H}_{k-1}')^{-1} \quad (27)$$

Substituting this into (22) gives

$$\hat{\underline{A}}_k = \hat{\underline{A}}_{k-1} - \underline{E}_{k-k} \underline{H}_k^* \hat{\underline{A}}_{k-1} + \underline{E}_{k-k} \underline{Z}_k^*, \quad kq \leq s$$

$$\hat{\underline{A}}_k = \hat{\underline{A}}_{k-1} + \underline{E}_k (\underline{Z}_k^* - \underline{H}_k^* \hat{\underline{A}}_{k-1}), \quad kq \leq s \quad (28)$$

and into (23) gives

$$\underline{Q}_k = \underline{Q}_{k-1} - \underline{E}_k \underline{H}_k^* \underline{Q}_{k-1} + \underline{E}_k \underline{H}_k^*$$

$$\underline{Q}_k = \underline{Q}_{k-1} + \underline{E}_k \underline{H}_k^* (\underline{I} - \underline{Q}_{k-1}) \quad (29)$$

and into (26) gives

$$\underline{H}_k^{*'} = \underline{Q}_{k-1} \underline{H}_k^{*'} - \underline{E}_k \underline{H}_k^* \underline{Q}_{k-1} \underline{H}_k^{*'} + \underline{E}_k \underline{H}_k^* \underline{H}_k^{*}$$

$$\underline{E}_k = (\underline{I} - \underline{Q}_{k-1}) \underline{H}_k^{*'} \left[\underline{H}_k^* (\underline{I} - \underline{Q}_{k-1}) \underline{H}_k^{*'} \right]^{-1} \quad (30)$$

Equations (28), (29) and (30) constitute the recursive relation which corresponds to equation (13). It may be verified from these equations that the correct starting values for $\hat{\underline{A}}$ and \underline{Q} are zero, for then

$$\underline{E}_1 = \underline{H}_1^{*'} (\underline{H}_1^* \underline{H}_1^{*'})^{-1}$$

$$\hat{\underline{A}}_1 = \underline{H}_1^{*'} (\underline{H}_1^* \underline{H}_1^{*'})^{-1} \underline{Z}_1^*$$

$$\underline{Q}_1 = \underline{H}_1^{*'} (\underline{H}_1^* \underline{H}_1^{*'})^{-1} \underline{H}_1^*$$

which are consistent with the definitions of $\hat{\underline{A}}_k$ and \underline{Q}_k in (13) and (23).

Using (18) and (21), equation (14) can be written

$$\hat{A}_k = J_k Z_k = D_k Z_{k-1} + B_k Z_k^*, \quad kq \geq s \quad (31)$$

To solve for D_k and B_k , begin by forming the product $H_k J_k$ using (17), (19) and (21):

$$H_k J_k = H_k (H_k' H_k)^{-1} H_k' = \begin{bmatrix} H_{k-1} D_k & \vdots & H_{k-1} B_k \\ \vdots & \ddots & \vdots \\ H_k^* D_k & \vdots & H_k^* B_k \end{bmatrix} \quad (32)$$

Pre-multiplying by H_k' gives

$$H_k' = H_k' \begin{bmatrix} H_{k-1} D_k & \vdots & H_{k-1} B_k \\ \vdots & \ddots & \vdots \\ H_k^* D_k & \vdots & H_k^* B_k \end{bmatrix} \quad (33)$$

Using (19) this can be written as the two equations

$$H_{k-1}' = H_{k-1}' H_{k-1} D_k + H_k^{*'} H_k^* D_k \quad (34)$$

$$H_k^{*'} = H_{k-1}' H_{k-1} B_k + H_k^{*'} H_k^* B_k \quad (35)$$

From (34)

$$D_k = (H_{k-1}' H_{k-1} + H_k^{*'} H_k^*)^{-1} H_{k-1}' \quad (36)$$

and from (35)

$$B_k = (H_{k-1}' H_{k-1} + H_k^{*'} H_k^*)^{-1} H_k^{*'} \quad (37)$$

If a new matrix is defined by

$$\begin{aligned}
\underline{P}_k &= \underline{J}_k \underline{J}_k' = (\underline{H}_k' \underline{H}_k)^{-1} \underline{H}_k' \underline{H}_k (\underline{H}_k' \underline{H}_k)^{-1} = (\underline{H}_k' \underline{H}_k)^{-1} \\
&= (\underline{H}_{k-1}' \underline{H}_{k-1} + \underline{H}_k^{*'} \underline{H}_k^*)^{-1} \quad (38)
\end{aligned}$$

then (36) and (37) can be written as

$$\underline{D}_k = \underline{P}_k \underline{H}_{k-1}' \quad (39)$$

$$\underline{B}_k = \underline{P}_k \underline{H}_k^{*'} \quad (40)$$

From (38)

$$\begin{aligned}
\underline{P}_k^{-1} &= \underline{H}_{k-1}' \underline{H}_{k-1} + \underline{H}_k^{*'} \underline{H}_k^* \\
&= \underline{P}_{k-1}^{-1} + \underline{H}_k^{*'} \underline{H}_k^* \quad (41)
\end{aligned}$$

Pre-multiplying by \underline{P}_k and post-multiplying by \underline{P}_{k-1} gives

$$\underline{P}_{k-1} = \underline{P}_k + \underline{P}_k \underline{H}_k^{*'} \underline{H}_k^* \underline{P}_{k-1} \quad (42)$$

Using (40) this becomes

$$\underline{P}_{k-1} = \underline{P}_k + \underline{B}_k \underline{H}_k^{*'} \underline{P}_{k-1}$$

$$\underline{P}_k = \underline{P}_{k-1} - \underline{B}_k \underline{H}_k^{*'} \underline{P}_{k-1} \quad (43)$$

and using this result in (39) gives

$$\underline{D}_k = \underline{P}_{k-1} \underline{H}_{k-1}' - \underline{B}_k \underline{H}_k^* \underline{P}_{k-1} \underline{H}_{k-1}' \quad (44)$$

and in (40) gives

$$\begin{aligned} \underline{B}_k &= \underline{P}_{k-1} \underline{H}_k^{*'} - \underline{B}_k \underline{H}_k^* \underline{P}_{k-1} \underline{H}_k^{*'} \\ \underline{B}_k &= \underline{P}_{k-1} \underline{H}_k^{*'} (\underline{I} + \underline{H}_k^* \underline{P}_{k-1} \underline{H}_k^{*'})^{-1} \end{aligned} \quad (45)$$

Using (44) in (31)

$$\hat{\underline{A}}_k = \underline{P}_{k-1} \underline{H}_{k-1}' \underline{Z}_{k-1} - \underline{B}_k \underline{H}_k^* \underline{P}_{k-1} \underline{H}_{k-1}' \underline{Z}_{k-1} + \underline{B}_k \underline{Z}_k, \quad kq \geq s$$

Since $\underline{P}_{k-1} = (\underline{H}_{k-1}' \underline{H}_{k-1})^{-1}$, the last equation becomes

$$\hat{\underline{A}}_k = \hat{\underline{A}}_{k-1} + \underline{B}_k (\underline{Z}_k^* - \underline{H}_k^* \hat{\underline{A}}_{k-1}), \quad kq \geq s \quad (46)$$

Equations (43), (45) and (46) provide the recursive relation corresponding to equation (14) and can be started by applying (14) and (38) directly to the first stage k such that $kq \geq s$, which will require inversion of at least an $s \times s$ matrix. Since matrix inversion requires fairly complex programming on a small computer, it is perhaps better to arrange that the starting value for (46) be taken from the last solution of (28) at a stage k where $kq = s$, as described earlier. Similarly a recursive relation can be found which will provide a starting value for \underline{P}_k in (43) when $kq = s$. From (38) the definition of \underline{P}_k is

$$\underline{P}_k = \underline{J}_k \underline{J}_k'$$

and from equations (16) and (17)

$$\underline{G}_k = \underline{J}_k = \underline{H}_k^{-1}, \quad kq = s$$

Therefore

$$\underline{P}_k = \underline{J}_k \underline{J}_k' = \underline{G}_k \underline{G}_k', \quad kq = s \quad (47)$$

Thus at a stage k where $kq = s$ it is possible to obtain the starting value for \underline{P}_k from a recursive relation for

$$\underline{R}_k = \underline{G}_k \underline{G}_k' = \underline{H}_k' (\underline{H}_k \underline{H}_k')^{-1} (\underline{H}_k \underline{H}_k')^{-1} \underline{H}_k \quad (48)$$

Using (20) this can be written

$$\underline{R}_k = \underline{F}_k \underline{F}_k' + \underline{E}_k \underline{E}_k' \quad (49)$$

From (27)

$$\underline{F}_k = (\underline{I} - \underline{E}_k \underline{H}_k^*) \underline{H}_{k-1}' (\underline{H}_{k-1} \underline{H}_{k-1}')^{-1} \quad (50)$$

Substituting this into (49) gives

$$\underline{R}_k = (\underline{I} - \underline{E}_k \underline{H}_k^*) \underline{H}_{k-1}' (\underline{H}_{k-1} \underline{H}_{k-1}')^{-1} (\underline{H}_{k-1} \underline{H}_{k-1}')^{-1} \underline{H}_{k-1}$$

$$\times (\underline{I} - \underline{E}_k \underline{H}_k^*)' + \underline{E}_k \underline{E}_k'$$

$$= (\underline{I} - \underline{E}_k \underline{H}_k^*) \underline{R}_{k-1} (\underline{I} - \underline{E}_k \underline{H}_k^*)' + \underline{E}_k \underline{E}_k'$$

$$\begin{aligned} \underline{R}_k = \underline{R}_{k-1} - \underline{R}_{k-1} \underline{H}_k^{*'} \underline{E}_k - \underline{E}_k \underline{H}_k^{*'} \underline{R}_{k-1} \\ + \underline{E}_k \underline{H}_k^{*'} \underline{R}_{k-1} \underline{H}_k^{*'} \underline{E}_k + \underline{E}_k \underline{E}_k' \end{aligned} \quad (51)$$

which is in a convenient form to be calculated in conjunction with (28), (29) and (30).

The final general algorithm for least-squares estimation of the parameter matrix \underline{A} would therefore use equations (28), (29), (30) and (51) for all estimation stages k such that $kq \leq s$ and for all subsequent stages would use equations (43), (45) and (46) beginning with the values of $\hat{\underline{A}}_k$ and \underline{P}_k given by (28) and (51) at a stage k where $kq = s$.

The calculations involved in these equations are easily performed on a small computer, apart from the following inverses which appear in (30) and (45) respectively:

$$\left[\underline{H}_k^{*'} (\underline{I} - \underline{Q}_{k-1}) \underline{H}_k^{*'} \right]^{-1} \quad (\underline{I} + \underline{H}_k^{*'} \underline{P}_{k-1} \underline{H}_k^{*'})^{-1}$$

As shown in (19) the dimension of $\underline{H}_k^{*'}$ is $q \times s$ which indicates that both of the matrices being inverted above have dimension $q \times q$, q being the number of rows adjoined to \underline{Z} and \underline{H} at each estimation stage. Thus by choosing $q = 1$, both inverses will involve scalars and the necessary computer programming will be vastly simplified. The number of rows adjoined at each estimation stage need have no effect on the number of rows adjoined at each measurement stage because the measured rows can be stored and adjoined in the estimation algorithm one at

a time. Selecting $q=1$ also has the advantage that q will always be a divisor of s , the number of columns in \underline{H} , which is the requirement for proper linking of the two sets of equations as previously explained.

When $q=1$, the matrices \underline{Z}_k^* and \underline{H}_k^* degenerate to row vectors and \underline{E}_k and \underline{B}_k degenerate to column vectors. For this reason it is desirable to change the notation and replace

$$\begin{array}{ll} \underline{Z}_k^* \text{ by } \underline{z}_k' & \underline{E}_k \text{ by } \underline{e}_k \\ \underline{H}_k^* \text{ by } \underline{h}_k' & \underline{B}_k \text{ by } \underline{b}_k \end{array}$$

Equation (30) now becomes

$$\underline{e}_k = (\underline{I} - \underline{Q}_{k-1}) \underline{h}_k \left[\underline{h}_k' (\underline{I} - \underline{Q}_{k-1}) \underline{h}_k \right]^{-1} \quad (52)$$

If the column vector $(\underline{I} - \underline{Q}_{k-1}) \underline{h}_k$ in this equation is given the symbol \underline{c}_k ,

$$\underline{c}_k = (\underline{I} - \underline{Q}_{k-1}) \underline{h}_k \quad (53)$$

then from the definition of \underline{Q}_k in equation (23), which was

$$\underline{Q}_k = \underline{G}_k \underline{H}_k = \underline{H}_k' (\underline{H}_k \underline{H}_k')^{-1} \underline{H}_k$$

it can be seen that

$$\underline{c}_k' = \underline{h}_k' (\underline{I} - \underline{Q}_{k-1})' = \underline{h}_k' (\underline{I} - \underline{Q}_{k-1}) \quad (54)$$

and

$$\begin{aligned}
\underline{c}_k' \underline{c}_k &= \underline{h}_k' (\underline{I} - \underline{Q}_{k-1}) (\underline{I} - \underline{Q}_{k-1}) \underline{h}_k \\
&= \underline{h}_k' (\underline{I} - \underline{Q}_{k-1} - \underline{Q}_{k-1} + \underline{Q}_{k-1} \underline{Q}_{k-1}) \underline{h}_k \\
&= \underline{h}_k' (\underline{I} - \underline{Q}_{k-1} - \underline{Q}_{k-1} + \underline{Q}_{k-1}) \underline{h}_k \\
&= \underline{h}_k' (\underline{I} - \underline{Q}_{k-1}) \underline{h}_k
\end{aligned} \tag{55}$$

so that equation (52) can now be written

$$\underline{e}_k = \underline{c}_k (\underline{c}_k' \underline{c}_k)^{-1} \tag{56}$$

and equation (29) now becomes

$$\underline{Q}_k = \underline{Q}_{k-1} + \underline{e}_k \underline{h}_k' (\underline{I} - \underline{Q}_{k-1}) = \underline{Q}_{k-1} + \underline{e}_k \underline{c}_k' \tag{57}$$

Following is a summary of the major equations and their starting values for the simplified algorithm where $q=1$:

$$k \leq s \left\{ \begin{aligned} &\underline{c}_k = (\underline{I} - \underline{Q}_{k-1}) \underline{h}_k && (53) \\ &\underline{e}_k = \underline{c}_k (\underline{c}_k' \underline{c}_k)^{-1} && (56) \\ &\underline{Q}_k = \underline{Q}_{k-1} + \underline{e}_k \underline{c}_k' , \quad \underline{Q}_k = \underline{0} \text{ at } k=0 && (57) \end{aligned} \right.$$

$$\left. \begin{array}{l} k \leq s \\ k = s \end{array} \right\} \begin{cases} \underline{R}_k = \underline{R}_{k-1} - \underline{R}_{k-1} \underline{h}_k \underline{e}_k' - \underline{e}_k \underline{h}_k' \underline{R}_{k-1} + \underline{e}_k \underline{h}_k' \underline{R}_{k-1} \underline{h}_k \underline{e}_k' + \underline{e}_k \underline{e}_k' , \\ \underline{R}_k = \underline{0} \text{ at } k = 0 \end{cases} \quad (58)$$

$$\left. \begin{array}{l} k \leq s \\ k = s \end{array} \right\} \begin{cases} \hat{\underline{A}}_k = \hat{\underline{A}}_{k-1} + \underline{e}_k (\underline{z}_k' - \underline{h}_k' \hat{\underline{A}}_{k-1}) , \quad \hat{\underline{A}}_k = \underline{0} \text{ at } k = 0 \end{cases} \quad (59)$$

$$\left. \begin{array}{l} k > s \end{array} \right\} \begin{cases} \underline{b}_k = \underline{P}_{k-1} \underline{h}_k (1 + \underline{h}_k' \underline{P}_{k-1} \underline{h}_k)^{-1} \end{cases} \quad (60)$$

$$\left. \begin{array}{l} k > s \end{array} \right\} \begin{cases} \underline{P}_k = \underline{P}_{k-1} - \underline{b}_k \underline{h}_k' \underline{P}_{k-1} , \quad \underline{P}_k = \underline{R}_k \text{ at } k = s \end{cases} \quad (61)$$

$$\left. \begin{array}{l} k > s \end{array} \right\} \begin{cases} \hat{\underline{A}}_k = \hat{\underline{A}}_{k-1} + \underline{b}_k (\underline{z}_k' - \underline{h}_k' \hat{\underline{A}}_{k-1}) , \end{cases}$$

$$\hat{\underline{A}}_k = \hat{\underline{A}}_k \text{ from (59) at } k = s \quad (62)$$

It has already been shown that when the rows of the matrix \underline{H}_k are linearly independent, the product $\underline{H}_k \underline{H}_k'$ is nonsingular and the matrix

$$\underline{Q}_k = \underline{H}_k' (\underline{H}_k \underline{H}_k')^{-1} \underline{H}_k$$

is a left identity for the matrix \underline{H}_k' because

$$\underline{Q}_k \underline{H}_k' = \underline{H}_k' (\underline{H}_k \underline{H}_k')^{-1} \underline{H}_k \underline{H}_k' = \underline{H}_k'$$

Similarly \underline{Q}_k is a left identity for any other matrix whose columns lie in the transposed row space of \underline{H}_k . Thus if a new

row \underline{h}_k is adjoined to the \underline{H} matrix and is a linear combination of the previous $k-1$ rows, then the vector \underline{h}_k will lie in the transposed row space of \underline{H}_{k-1} and equation (53) will give

$$\underline{c}_k = (\underline{I} - \underline{Q}_{k-1})\underline{h}_k = \underline{0} \quad (63)$$

Since the recursive least-squares procedure requires that \underline{H} have maximum rank at every stage and in particular that the rows be linearly independent for the first s stages, \underline{c}_k , being the first calculation involving a new row of \underline{H} , is an extremely useful indicator of this condition. Depending on the process involved, a measurement which would make the rows of \underline{H} linearly dependent can be rejected in favour of a new measurement or the entire process can be re-started with a minimum of wasted time.

Although at this point all the essential equations for a least-squares filtering algorithm have been developed, a preliminary comparison with statistical methods will lead to minor improvements which make the algorithm much more useful. In the next chapter will be presented a derivation of the statistical maximum-likelihood filter which parallels that of the least-squares filter in this chapter. Chapter IV will then describe the complete mechanics of the final computational algorithm which was used in the research project outlined in Chapter V.

III. Maximum-Likelihood Filtering

A maximum-likelihood procedure gives the optimum minimum-variance parameter estimate when no a-priori statistical information is available concerning the parameters and the noise terms affecting the measurements are zero-mean independent white-Gaussian random variables of known variance.

The development of the maximum-likelihood filtering equations in this chapter follows closely that of the least-squares filter in the previous chapter in order that similarities between the two methods will be apparent. This should facilitate explanation of the general-purpose computational algorithm to be presented in Chapter IV.

As in Chapter II, equation (1) will be the arbitrary representation of the measurement process, where as before the matrix \underline{H} is assumed to have maximum rank. The optimum estimate $\hat{\underline{A}}$ of the parameters \underline{A} is chosen so that the probability density of each measured quantity conditional on $\underline{A} = \hat{\underline{A}}$ has a maximum at the observed value of the measured quantity. The probability density function involved is often given the name "likelihood function" and since the noise terms are statistically independent the likelihood function for a row i of measurements is the product of their individual likelihood functions, which are Gaussian:

$$p_{\underline{z}_i | \underline{A}} = \frac{1}{(2\pi)^{r/2} s_i^{r/2}} \exp \left[- \frac{1}{2s_i} (\underline{z}_i' - \underline{h}_i' \underline{A})(\underline{z}_i' - \underline{h}_i' \underline{A})' \right] \quad (64)$$

where r is the number of measurements in a row or the number

of columns in the measurement array and it has been assumed that the noise on each measurement of a row has the same variance s_i . This latter assumption results in a great simplification to the derivation which follows and does not seriously limit the usefulness of the equations, because measurements having different noise-variances can always be located in separate rows. A product of the likelihood functions of all k rows gives the likelihood function for the entire measurement set at stage k :

$$p_{\underline{Z}|\underline{A}} = \frac{1}{(2\pi)^{kr/2} (\det \underline{S})^{r/2}} \exp \left[-\frac{1}{2} \sum_i s_i^{-1} (\underline{z}_i' - \underline{h}_i' \underline{A}) (\underline{z}_i' - \underline{h}_i' \underline{A})' \right] \quad (65)$$

$$\text{where } \underline{S} = \begin{bmatrix} s_1 & 0 & 0 & \cdot & \cdot & \cdot \\ 0 & s_2 & 0 & \cdot & \cdot & \cdot \\ 0 & 0 & s_3 & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \end{bmatrix}, \text{ a positive-definite matrix.}$$

Maximizing this likelihood function is equivalent to maximizing its logarithm:

$$\begin{aligned} \log p_{\underline{Z}|\underline{A}} = & -\frac{1}{2} \sum_i s_i^{-1} (\underline{z}_i' - \underline{h}_i' \underline{A}) (\underline{z}_i' - \underline{h}_i' \underline{A})' - \frac{kr}{2} \log (2\pi) \\ & - \frac{r}{2} \log (\det S) \end{aligned} \quad (66)$$

and a maximum results when the derivative with respect to \underline{A} is zero:

$$\sum_i s_i^{-1} \underline{h}_i (\underline{z}_i' - \underline{h}_i' \hat{\underline{A}}) = \underline{0}$$

$$\underline{H}' \underline{S}^{-1} \underline{Z} = \underline{H}' \underline{S}^{-1} \underline{H} \hat{\underline{A}} \quad (67)$$

When \underline{H} has fewer rows than columns, $(\underline{H}\underline{H}')^{-1}$ exists and the last equation reduces to

$$\underline{Z} = \underline{H} \hat{\underline{A}} \quad (68)$$

This is identical to the least-squares result of equation (6) and the minimum-norm estimates for the two methods are the same:

$$\hat{\underline{A}} = \underline{H}' (\underline{H}\underline{H}')^{-1} \underline{Z} \quad (69)$$

When \underline{H} has more rows than columns, $\underline{H}'\underline{H}$ is positive definite and so is $\underline{H}'\underline{S}^{-1}\underline{H}$. Thus the maximum-likelihood estimate from equation (67) is

$$\hat{\underline{A}} = (\underline{H}'\underline{S}^{-1}\underline{H})^{-1} \underline{H}'\underline{S}^{-1} \underline{Z} \quad (70)$$

which is the least-squares solution of (5) weighted by the inverse of the noise variance matrix \underline{S} .

A recursive relation for equation (70), unlike the method of least squares, cannot theoretically be started using the minimum-norm result of (69) at stage $k=s$ because (69) does not contain the information regarding the noise variance for stages $k \leq s$ that is required by (70). This problem will be discussed later. It is first necessary to obtain a recursive

form for (70).

Following a procedure similar to that used for the recursive form of (5), the maximum-likelihood estimate at a stage k is written as

$$\hat{\underline{A}}_k = \underline{J}_k \underline{Z}_k \quad (71)$$

where \underline{J}_k is now defined by

$$\underline{J}_k = (\underline{H}_{k-1}' \underline{S}_{k-1}^{-1} \underline{H}_{k-1})^{-1} \underline{H}_{k-1}' \underline{S}_{k-1}^{-1} \quad (72)$$

To make the equations compatible with the algorithm derived near the end of Chapter II, one row only will be adjoined to each of \underline{H}_k and \underline{Z}_k at every stage, and the following partitionings are valid:

$$\underline{Z}_k (k \times r) = \begin{bmatrix} \underline{Z}_{k-1} ([k-1] \times r) \\ \vdots \\ \underline{z}_k (1 \times r) \end{bmatrix} \quad (73)$$

$$\underline{H}_k (k \times s) = \begin{bmatrix} \underline{H}_{k-1} ([k-1] \times s) \\ \vdots \\ \underline{h}_k (1 \times s) \end{bmatrix} \quad (74)$$

$$\underline{J}_k (s \times k) = \begin{bmatrix} \underline{D}_k (s \times [k-1]) & \vdots & \underline{b}_k (s \times 1) \end{bmatrix} \quad (75)$$

$$\underline{S}_k^{-1} = \begin{bmatrix} \underline{S}_{k-1}^{-1} & \vdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \vdots & s_k^{-1} \end{bmatrix} \quad (76)$$

Now

$$\begin{aligned}
\underline{H}_k \underline{J}_k &= \underline{H}_k (\underline{H}_k' \underline{S}_k^{-1} \underline{H}_k)^{-1} \underline{H}_k' \underline{S}_k^{-1} \\
&= \begin{bmatrix} \underline{H}_{k-1} \underline{D}_k & \vdots & \underline{H}_{k-1} \underline{b}_k \\ \vdots & \ddots & \vdots \\ \underline{h}_k' \underline{D}_k & \vdots & \underline{h}_k' \underline{b}_k \end{bmatrix} \quad (77)
\end{aligned}$$

Pre-multiplying by $\underline{H}_k' \underline{S}_k^{-1}$,

$$\underline{H}_k' \underline{S}_k^{-1} = \underline{H}_k' \underline{S}_k^{-1} \begin{bmatrix} \underline{H}_{k-1} \underline{D}_k & \vdots & \underline{H}_{k-1} \underline{b}_k \\ \vdots & \ddots & \vdots \\ \underline{h}_k' \underline{D}_k & \vdots & \underline{h}_k' \underline{b}_k \end{bmatrix} \quad (78)$$

Using (74) and (76) this can be written as the two equations

$$\underline{H}_{k-1}' \underline{S}_{k-1}^{-1} = \underline{H}_{k-1}' \underline{S}_{k-1}^{-1} \underline{H}_{k-1} \underline{D}_k + \underline{h}_k \underline{s}_k^{-1} \underline{h}_k' \underline{D}_k \quad (79)$$

$$\underline{h}_k \underline{s}_k^{-1} = \underline{H}_{k-1}' \underline{S}_{k-1}^{-1} \underline{H}_{k-1} \underline{b}_k + \underline{h}_k \underline{s}_k^{-1} \underline{h}_k' \underline{b}_k \quad (80)$$

From (79)

$$\underline{D}_k = (\underline{H}_{k-1}' \underline{S}_{k-1}^{-1} \underline{H}_{k-1} + \underline{h}_k \underline{s}_k^{-1} \underline{h}_k')^{-1} \underline{H}_{k-1}' \underline{S}_{k-1}^{-1} \quad (81)$$

From (80)

$$\underline{b}_k = (\underline{H}_{k-1}' \underline{S}_{k-1}^{-1} \underline{H}_{k-1} + \underline{h}_k \underline{s}_k^{-1} \underline{h}_k')^{-1} \underline{h}_k \underline{s}_k^{-1} \quad (82)$$

Defining

$$\underline{P}_k = (\underline{H}_k' \underline{S}_k^{-1} \underline{H}_k)^{-1} = (\underline{H}_{k-1}' \underline{S}_{k-1}^{-1} \underline{H}_{k-1} + \underline{h}_k \underline{s}_k^{-1} \underline{h}_k')^{-1} \quad (83)$$

(81) and (82) become

$$\underline{D}_k = \underline{P}_k \underline{H}'_{k-1} \underline{S}_{k-1}^{-1} \quad (84)$$

$$\underline{b}_k = \underline{P}_k \underline{h}_k \underline{s}_k^{-1} \quad (85)$$

From (83)

$$\underline{P}_k^{-1} = \underline{P}_{k-1}^{-1} + \underline{h}_k \underline{s}_k^{-1} \underline{h}'_k \quad (86)$$

Pre-multiplying by \underline{P}_k and post-multiplying by \underline{P}_{k-1} ,

$$\underline{P}_{k-1} = \underline{P}_k + \underline{P}_k \underline{h}_k \underline{s}_k^{-1} \underline{h}'_k \underline{P}_{k-1} \quad (87)$$

Using (85) this becomes

$$\underline{P}_k = \underline{P}_{k-1} - \underline{b}_k \underline{h}'_k \underline{P}_{k-1} \quad (88)$$

and using this result in (84) gives

$$\underline{D}_k = \underline{P}_{k-1} \underline{H}'_{k-1} \underline{S}_{k-1}^{-1} - \underline{b}_k \underline{h}'_k \underline{P}_{k-1} \underline{H}'_{k-1} \underline{S}_{k-1}^{-1} \quad (89)$$

and in (85),

$$\underline{b}_k = \underline{P}_{k-1} \underline{h}_k \underline{s}_k^{-1} - \underline{b}_k \underline{h}'_k \underline{P}_{k-1} \underline{h}_k \underline{s}_k^{-1}$$

$$\underline{b}_k = \underline{P}_{k-1} \underline{h}_k (\underline{s}_k + \underline{h}'_k \underline{P}_{k-1} \underline{h}_k)^{-1} \quad (90)$$

Using (73), (75) and (89), equation (77) can be written

$$\hat{\underline{A}}_k = \hat{\underline{A}}_{k-1} + \underline{b}_k (\underline{z}_k - \underline{h}'_k \hat{\underline{A}}_{k-1}) \quad (91)$$

Comparing equations (90), (88) and (91) with (60), (61) and (62) respectively, it is seen that the maximum-likelihood filtering equations are identical to the least-squares filtering equations except that the "1" in equation (60) has been replaced by the variance term s_k in equation (90). In other words the maximum-likelihood filter degenerates to a least-squares filter if $s_k = 1$.

The starting values for \underline{P}_k and $\hat{\underline{A}}_k$ can be obtained by a direct application of (70) and (83) to the first s measurement stages, which would require inversion of an $s \times s$ matrix. However, since starting values constitute a-priori known statistics of the parameters it is instructive instead to compare the recursive maximum-likelihood filter with a similar filter that is based on such statistics. In the maximum-a-posteriori (MAP) filter, \underline{A} has a normal or Gaussian probability distribution, $\hat{\underline{A}}_0$ is its expected value and \underline{P}_0 is a diagonal matrix such that the i th element on its main diagonal is the variance of every parameter in the i th row of \underline{A} . To obtain this filter it is necessary to maximize the so-called a-posteriori density $p_{\underline{A}|\underline{Z}}$ which is related to the likelihood density $p_{\underline{Z}|\underline{A}}$ by the Bayes rule:

$$p_{\underline{A}|\underline{Z}} = \frac{p_{\underline{Z}|\underline{A}} p_{\underline{A}}}{p_{\underline{Z}}} \quad (92)$$

This is equivalent to finding a maximum of its logarithm:

$$\log p_{\underline{A}|\underline{Z}} = \log p_{\underline{Z}|\underline{A}} + \log p_{\underline{A}} - \log p_{\underline{Z}} \quad (93)$$

Differentiating with respect to \underline{A} results in

$$\frac{d}{d\underline{A}} \log p_{\underline{A}|\underline{Z}} = \underline{H}' \underline{S}^{-1} (\underline{Z} - \underline{H} \underline{A}) + \frac{d}{d\underline{A}} \log p_{\underline{A}} \quad (94)$$

where $\frac{d}{d\underline{A}} \log p_{\underline{Z}}$ is zero because $p_{\underline{Z}}$ is not a function of \underline{A} . The a-priori density $p_{\underline{A}}$ can be written

$$p_{\underline{A}} = \frac{1}{(2\pi)^{rs/2} (\det \underline{P}_O)^{r/2}} \exp \left[-\frac{1}{2} \sum_{i,j} \underline{P}_{O_{ii}}^{-1} (\underline{A}_{ij} - \hat{\underline{A}}_{O_{ij}})^2 \right] \quad (95)$$

and then

$$\frac{d}{d\underline{A}} \log p_{\underline{A}} = -\underline{P}_O^{-1} (\underline{A} - \hat{\underline{A}}_O) \quad (96)$$

The maximum a-posteriori density occurs when $\frac{d}{d\underline{A}} \log p_{\underline{A}|\underline{Z}}$ is zero:

$$\underline{H}' \underline{S}^{-1} (\underline{Z} - \underline{H} \hat{\underline{A}}) - \underline{P}_O^{-1} (\hat{\underline{A}} - \hat{\underline{A}}_O) = \underline{0}$$

$$\hat{\underline{A}} = \underline{P} (\underline{H}' \underline{S}^{-1} \underline{Z} + \underline{P}_O^{-1} \hat{\underline{A}}_O) \quad (97)$$

where

$$\underline{P} = (\underline{H}' \underline{S}^{-1} \underline{H} + \underline{P}_O^{-1})^{-1} \quad (98)$$

Comparison with equation (86) shows that the MAP estimate will in fact be generated by the recursive maximum-likelihood equations when $\hat{\underline{A}}_O$ and \underline{P}_O are the expected value and variance, respectively, of the parameters. The resulting filter is actually a special case of the well-known discrete Kalman filter

but has limited application possibilities because of the need for accurate a-priori statistics of the parameters and because of the restriction that parameters in the same row of \underline{A} must have the same variance. However, the fact that the maximum-likelihood estimate of (70) and (83) is generated by the same recursive relations as the MAP estimate of (97) and (98) and that the MAP estimate degenerates to the maximum-likelihood estimate as \underline{P}_0 becomes infinite, indicates that the maximum-likelihood filter can be started with $\hat{\underline{A}}_0$ equal to zero and \underline{P}_0 a diagonal matrix with large elements on the main diagonal. In this way the recursive maximum-likelihood filter would presuppose \underline{A} to have zero expected value and very large variance, which is consistent with a total lack of a-priori statistics.

IV. General Computational Algorithm

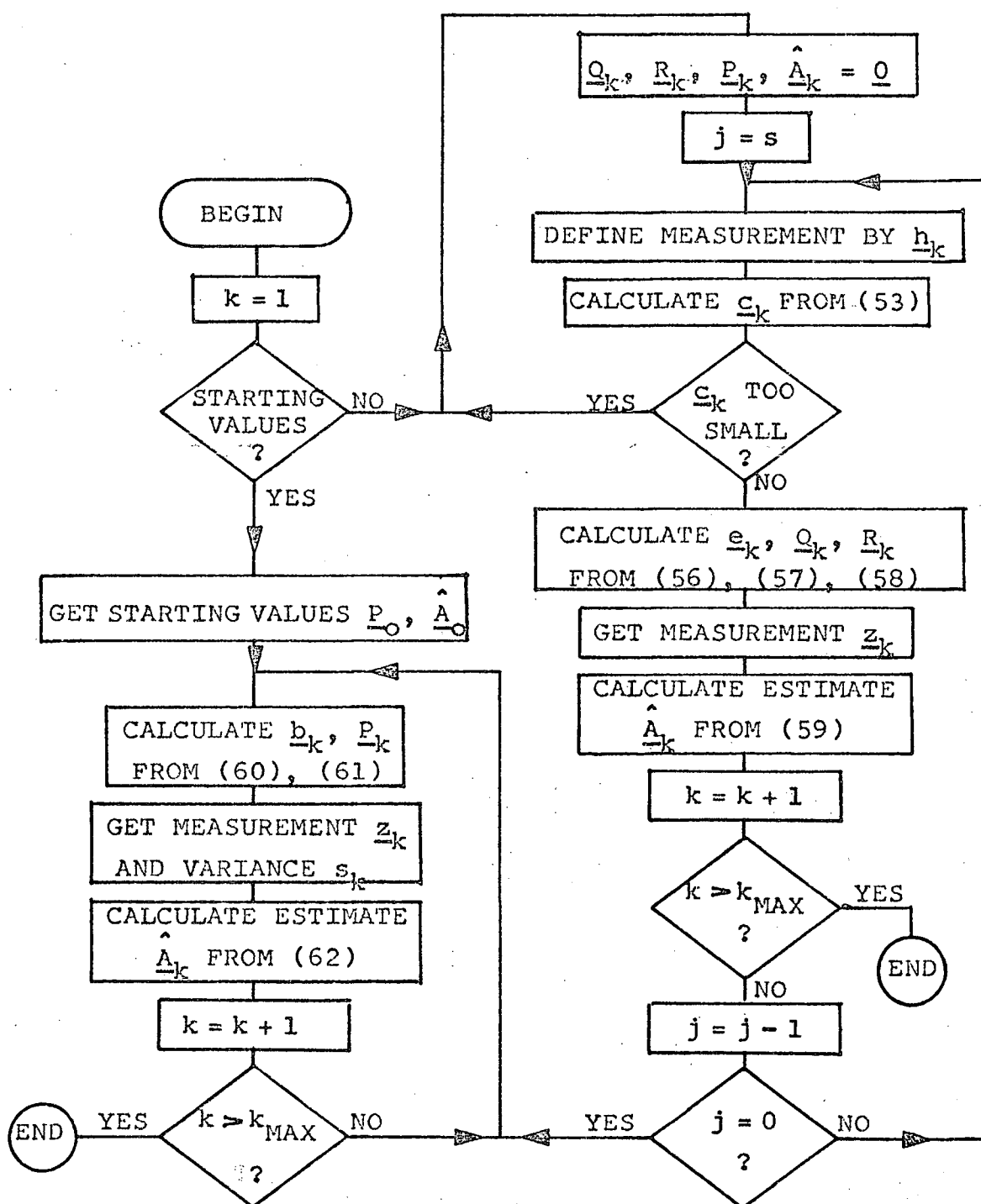
It is now apparent that with very minor alterations the basic least-squares recursive equations of Chapter II (53-62) can perform either maximum-likelihood or Bayesian (maximum-a-posteriori) filtering. By substituting the noise variance s_k in place of the "1" in equation (60) and replacing the minimum-norm equations (53-59) with initial values \hat{A}_0 zero and P_0 very large, a maximum-likelihood filter results. A Bayesian filter is produced by using the expected value and variance of A for \hat{A}_0 and P_0 respectively in the maximum-likelihood filter. The following table summarizes the differences:

TABLE I -- Essential Differences of Least-Squares, Maximum-Likelihood and Bayesian MAP Filters

<u>Filter</u>	<u>s_k</u>	<u>Initial Values</u>
Least-squares	1	minimum-norm composition using equations (53-59)
Maximum-likelihood	noise variance	\hat{A}_0 zero, P_0 very large
Bayesian MAP	noise variance	\hat{A}_0 = expected value of A P_0 = variance of A

On the next page is presented a general computational algorithm which allows for any of the combinations in the above table. It also allows for unclassified combinations such as one in which the noise variance term is "1" and the initial values are \hat{A}_0 zero and P_0 large. This is effectively

FIGURE 1 - General Computational Algorithm for Estimation



a least-squares filter which is begun in the same way as the maximum-likelihood filter, eliminating the need for the "minimum-norm" equations (53) and (56-59). Tests of this filter are described in example 1 of Chapter VI.

In the general algorithm, linear dependence of the rows of \underline{H} in the first s stages of the least-squares filter results in a value of \underline{c}_k which is near zero, re-initializing the entire process. How close to zero \underline{c}_k must come in order for this to occur is a difficult matter to define and depends among other things on the precision of the calculations. While exact linear dependence would theoretically make \underline{c}_k exactly zero, the value determined by the computer will normally contain errors due to truncation and thus be slightly different from zero. In any event, cases of near linear dependence can produce inaccurate estimates, so it is probably best to require that \underline{c}_k remain reasonably large. This can be done by defining a threshold value and causing re-initialization if the magnitude of \underline{c}_k falls less than this threshold during the first s stages.

In choosing which of the various filtering procedures to use it is important to know how the errors of the estimates are expected to compare. A useful matrix which gives an estimate of the error is the error covariance matrix, hereby defined as

$$\text{cov } (\hat{\underline{A}}) = \varepsilon (\hat{\underline{A}} - \underline{A})(\hat{\underline{A}} - \underline{A})' \quad (99)$$

The trace of this matrix is equivalent to the expected value of the sum of the squares of the error matrix ($\underline{A} - \hat{\underline{A}}$).

Using equations (5) and (1) it can be seen that the error covariance of the least-squares filter after s stages is given by

$$\text{cov } (\hat{\underline{A}}_{\text{LS}}) = (\underline{H}'\underline{H})^{-1} \underline{H}' \varepsilon(\underline{V}\underline{V}') \underline{H} (\underline{H}'\underline{H})^{-1} \quad (100)$$

$\varepsilon(\underline{V}\underline{V}')$ can readily be shown to be a diagonal matrix such that the i th element on its main diagonal is the sum of the variances of the measurements in the i th row of \underline{Z} .

The least-squares estimate is always unbiased. That is,

$$\varepsilon(\underline{A} - \hat{\underline{A}}_{\text{LS}}) = \underline{0} \quad (101)$$

The maximum-likelihood estimate (70) has an error covariance given by

$$\text{cov } (\hat{\underline{A}}_{\text{ML}}) = (\underline{H}'\underline{S}^{-1}\underline{H})^{-1} \underline{H}'\underline{S}^{-1} \varepsilon(\underline{V}\underline{V}') \underline{S}^{-1} \underline{H} (\underline{H}'\underline{S}^{-1}\underline{H})^{-1} \quad (102)$$

Because the maximum-likelihood filter requires that measurements in the same row of \underline{Z} have the same variance and since there are r measurements in each row, it is apparent that

$$\varepsilon(\underline{V}\underline{V}') = r \times \underline{S} \quad (103)$$

where \underline{S} is the measurement-noise variance matrix as defined in (65). Therefore, when all measurements in the same row of

\underline{Z} have the same variance, the error covariances of the least-squares and maximum-likelihood estimates become

$$\text{cov } (\hat{\underline{A}}_{\text{LS}}) = r \times (\underline{H}'\underline{H})^{-1} \underline{H}'\underline{S}\underline{H}(\underline{H}'\underline{H})^{-1} \quad (104)$$

$$\text{cov } (\hat{\underline{A}}_{\text{ML}}) = r \times (\underline{H}'\underline{S}^{-1}\underline{H}) \quad (105)$$

The definition of the \underline{P} -matrix for the maximum-likelihood filter as given in equation (83) shows that the error covariance of the maximum-likelihood filter is given simply by

$$\text{cov } (\hat{\underline{A}}_{\text{ML}}) = r \times \underline{P} \quad (106)$$

Using the matrix inequality

$$\underline{M}'\underline{M} \geq (\underline{N}'\underline{M})'(\underline{N}'\underline{N})^{-1}(\underline{N}'\underline{M}) \quad (107)$$

(see Sage and Melsa [14], p. 246) where \underline{M} and \underline{N} are any two $k \times s$ matrices with $k \geq s$ and \underline{N} of rank s , and making the substitutions

$$\underline{M} = \underline{S}^{-\frac{1}{2}} \underline{H}(\underline{H}'\underline{H})^{-1} \quad (108)$$

$$\underline{N} = \underline{S}^{\frac{1}{2}} \underline{H} \quad (109)$$

it is easily shown that

$$\text{cov } (\hat{\underline{A}}_{\text{ML}}) \leq \text{cov } (\hat{\underline{A}}_{\text{LS}}) \quad (110)$$

That is, the maximum-likelihood filter, when applicable, gives an estimate which is as good as or better than that of the least-squares filter.

Like the least-squares estimate, the maximum-likelihood estimate is unbiased:

$$\varepsilon(\hat{\underline{A}}_{\text{ML}} - \underline{A}) = \underline{0} \quad (111)$$

The error covariance of the Bayesian MAP estimate, as defined by equation (97), is

$$\text{cov}(\hat{\underline{A}}_{\text{MAP}}) = \underline{P} (\underline{H}' \underline{S}^{-1} \varepsilon(\underline{V} \underline{V}') \underline{S}^{-1} \underline{H} + \underline{P}_0^{-1} \varepsilon(\underline{A} \underline{A}') \underline{P}_0^{-1}) \underline{P}' \quad (112)$$

Since all measurements in the same row of \underline{Z} must have the same noise variance and the probability distributions of all parameters in the same row of \underline{A} must have the same variance,

$$\varepsilon(\underline{V} \underline{V}') = r \times \underline{S} \quad (113)$$

$$\varepsilon(\underline{A} \underline{A}') = r \times \underline{P}_0 \quad (114)$$

where r is the number of elements in each row of \underline{Z} and \underline{A} . The error covariance therefore becomes

$$\text{cov}(\hat{\underline{A}}_{\text{MAP}}) = r \times \underline{P} (\underline{H}' \underline{S}^{-1} \underline{H} + \underline{P}_0^{-1}) \underline{P} = r \times \underline{P} \quad (115)$$

which can be readily determined from the \underline{P} -matrix. Comparing the values of \underline{P} for the maximum-likelihood and MAP estimates, it is obvious that the MAP estimate, where applicable, has an

error covariance which is less than or equal to that of either the maximum-likelihood or least-squares estimates. In fact, the MAP estimate, when valid, is known to have the least error covariance of any known estimate. Even when the restriction is removed that the noise and parameters be Gaussian the MAP filter still provides the best estimate of all linear filters. The noise must still be random with zero-mean and known variance and the expected value and variance of the parameters must still be known. The filter is then usually called a linear-minimum-variance filter.

In addition to the fact that all parameters in the same row of \underline{A} must have the same variance, the MAP estimate has another major disadvantage. If incorrect prior expected values and variances are used the estimates will be biased, with the bias at a stage k given by

$$\begin{aligned}
 \varepsilon(\hat{\underline{A}}_k - \underline{A}) &= \underline{P}_k (\underline{H}'_k \underline{S}_k^{-1} \underline{H}_k \varepsilon(\underline{A}) + \underline{P}_0^{-1} \hat{\underline{A}}_0 - \underline{P}_k^{-1} \varepsilon(\underline{A})) \\
 &= \underline{P}_k (\underline{P}_0^{-1} \hat{\underline{A}}_0 - \underline{P}_0^{-1} \varepsilon(\underline{A})) \\
 &= (\underline{I} + \underline{H}'_k \underline{S}_k^{-1} \underline{H}_k \underline{P}_0)^{-1} (\hat{\underline{A}}_0 - \varepsilon(\underline{A})) \\
 &= (\underline{I} + \underline{P}_0 \sum_{i=1}^k \underline{h}_i \underline{s}_i^{-1} \underline{h}_i')^{-1} (\hat{\underline{A}}_0 - \varepsilon(\underline{A})) \quad (116)
 \end{aligned}$$

The bias is most noticeable for smaller values of k and decreases as k increases. It is also smaller for higher values of the initial variance \underline{P}_0 and approaches zero as \underline{P}_0 becomes

infinite, the estimate then becoming a maximum-likelihood estimate.

In conclusion it may be said that among the three filters, least-squares, maximum-likelihood and Bayesian MAP, the more extensive the a-priori statistical knowledge of the parameters and measurement noise, the lower is the covariance of estimation error.

V. Identification of A Linear Stationary Process

The computational algorithm of the previous chapter can be used to estimate the parameters of a discrete model for a linear time-invariant process. If measurements of the system variables are available at uniformly-spaced intervals of time, it is possible to develop a model of the form

$$\underline{x}_k = \underline{\phi} \underline{x}_{k-1} + \underline{\Delta} \underline{u}_{k-1} \quad (117)$$

where \underline{x}_k is an n-dimensional vector composed of the system outputs at stage k, \underline{u}_k is an m-dimensional vector composed of the system inputs at stage k and $\underline{\phi}$ and $\underline{\Delta}$ are matrices composed of the constant parameters describing the process. \underline{x}_k is called the state of the system at stage k, \underline{u}_k the control and $\underline{\phi}$ and $\underline{\Delta}$ the state-transition and state-driving matrices respectively. Transposing both sides of the last equation results in

$$\underline{x}'_k = \underline{x}'_{k-1} \underline{\phi}' + \underline{u}'_{k-1} \underline{\Delta}' \quad (118)$$

Because of measurement noise, there will be differences between the observed values of the variables and their true values. Therefore it is convenient to distinguish the observed values with a superscribed bar as follows:

$$\bar{\underline{x}}_k = \underline{x}_k + \underline{\mu}_k \quad (119)$$

$$\bar{\underline{u}}_k = \underline{u}_k + \underline{\omega}_k \quad (120)$$

where $\underline{\mu}_k$ and $\underline{\omega}_k$ are vectors comprised of the noise terms. Combining these two equations with (118) yields the relation between the parameters and the observed values:

$$\bar{\underline{x}}'_k = \bar{\underline{x}}'_{k-1} \underline{\phi}' + \bar{\underline{u}}'_{k-1} \underline{\Delta}' + \underline{\mu}'_k - \underline{\mu}'_{k-1} \underline{\phi}' - \underline{\omega}'_{k-1} \underline{\Delta}'$$

or

$$\bar{\underline{x}}'_k = \begin{bmatrix} \bar{\underline{x}}'_{k-1} \\ \vdots \\ \bar{\underline{u}}'_{k-1} \end{bmatrix} \begin{bmatrix} \underline{\phi}' \\ \vdots \\ \underline{\Delta}' \end{bmatrix} + \underline{\mu}'_k - \underline{\mu}'_{k-1} \underline{\phi}' - \underline{\omega}'_{k-1} \underline{\Delta}' \quad (121)$$

If the measured vectors $\bar{\underline{x}}'_k, k = 1, 2, 3, \dots$ become the successive rows of the \underline{Z} matrix in the computational algorithm:

$$\underline{z}'_k = \bar{\underline{x}}'_k \quad (m) \quad (122)$$

and the corresponding prior measurements become the successive rows of the \underline{H} matrix:

$$\underline{h}'_k = \begin{bmatrix} \bar{\underline{x}}'_{k-1} \\ \vdots \\ \bar{\underline{u}}'_{k-1} \end{bmatrix} \quad (n+m) \quad (123)$$

then in accordance with the representation of equation (1) the unknown parameter will be

$$\underline{A} = \begin{bmatrix} \underline{\phi}' \\ \vdots \\ \underline{\Delta}' \end{bmatrix} \quad (124)$$

and the sequential noise vectors will be

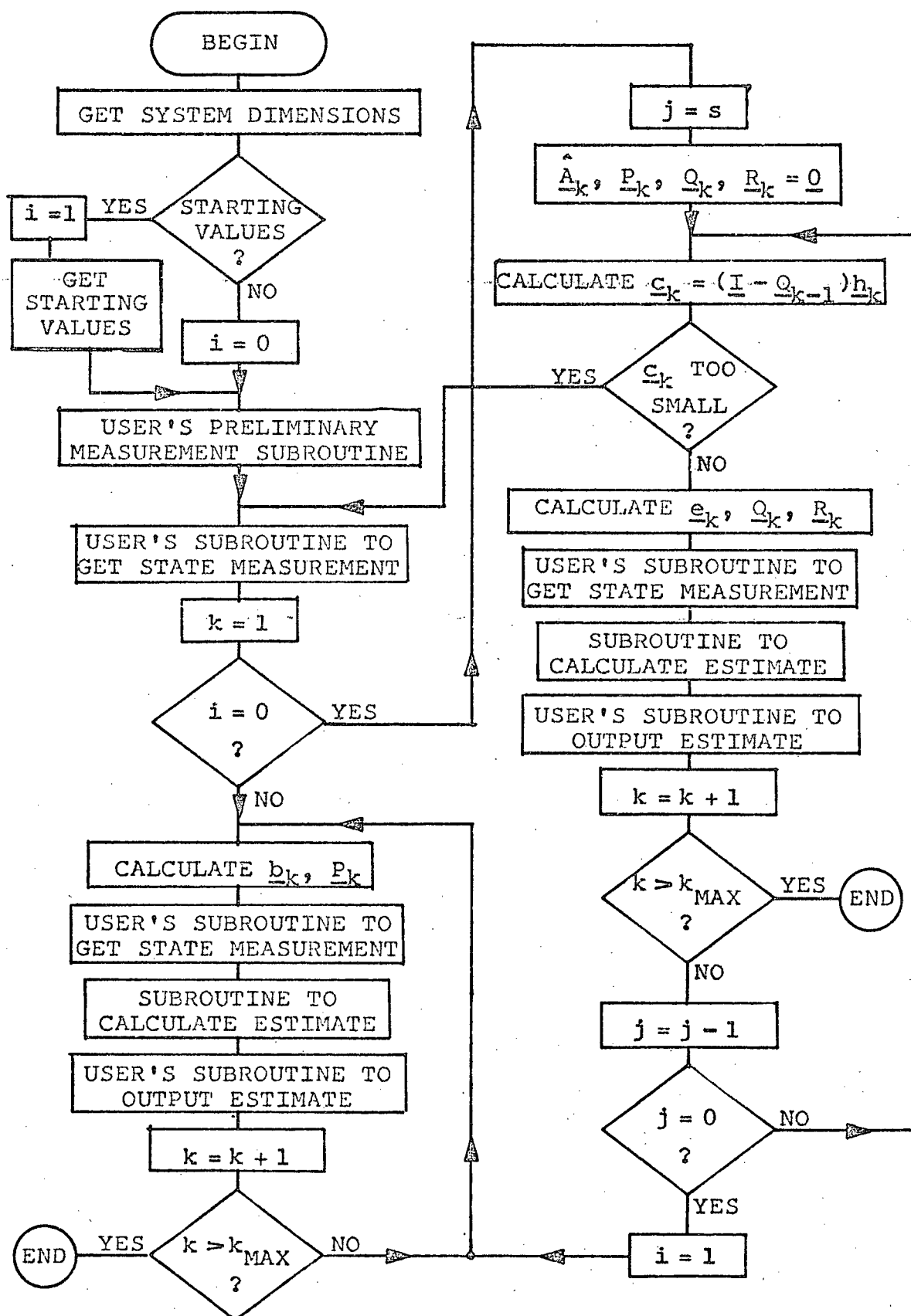
$$\underline{v}_k' = \underline{\mu}_k' - \underline{\mu}_{k-1}' \underline{\phi}' - \underline{\omega}_{k-1}' \underline{\Delta}' \quad (125)$$

In other words, use of the \underline{z}_k' and \underline{h}_k' vectors as defined by (122) and (123) in the general computational algorithm of Chapter IV will produce an estimate of the matrix defined by (124).

If the components of the noise sequences $\underline{\mu}_k$ and $\underline{\omega}_k$ have zero means and are Gaussian, white and independent, then the least-squares filter of Chapter II applies because the overall observation noise \underline{v}_k defined by (125) has zero-mean components. The maximum-likelihood and Bayesian filters, however, are not strictly valid as they have been derived in Chapter III, because the components of \underline{v}_k are not likely to be independent or white. None the less it would seem logical that the hierarchy among the three filters should still exist because of the differing degrees of a-priori information utilized. Thus, although methods exist by which the maximum-likelihood and Bayesian filters can be made optimal (see, for example, Sage and Melsa [14], Chapter 8), they involve such extensive complication of the algorithm that it is convenient in this application to merely ignore the fact that the noise components may be non-white or statistically dependent.

The computational algorithm as applied to the system-identification problem is represented in the flow-chart on the following page. All of the experimental tests described in the next chapter were made using this algorithm on either the

FIGURE 2 - System Identification Algorithm



I.B.M. 360-67 or the Data General Corporation "Nova" digital computer. In the appendix are included the complete programs for the Nova version of the algorithm. Comparison with the flow-chart of Chapter IV will show that the identification algorithm is basically the same except for the addition of certain specialized subroutines for handling the input and output data. These data subroutines can be changed to suit any particular application. There is a preliminary measurement subroutine which is provided in case there are any tasks associated with the measurement process which must be performed before entering the identification cycle. For example, should it be necessary to take samples of the system at a rate faster than the computation cycle would allow, the measurements may all be made in advance and stored by this subroutine. Then on each cycle is a subroutine to get the state measurement from the appropriate source and another to output the calculated estimate.

The algorithm was programmed on the system-360 to allow for more sophisticated analysis using artificial models of known statistics.

In the Nova programs, all the initializing procedures are controlled by the operator using the teletype keyboard in a conversational manner. The system dimensions can be set to estimate any matrix A up to a dimension of 8×8 and the calculations are performed in floating-point arithmetic that is based on a 24-bit mantissa with sign and 7-bit exponent using the standard basic floating-point software provided with the

computer.

Although in the flow-chart the k-counters are separate from the subroutines, in the Nova programs the job of counting stages has been left to the user-supplied subroutines. This allows for counting either at the point where data comes in or at the point of outputting the estimate, whichever is more suitable to the particular application. Also left to the user subroutines is the task of determining the sampling times, which, in the case where data is obtained from an actual system using an analogue-to-digital converter, could require an external real-time clock connected to the input/output bus of the computer.

The programs are thus very versatile, with the permanent software performing identification only, and the user-supplied subroutines having full control over the rest of the process.

VI. Examples

All the examples described in this chapter were used to test the computer programs for the system-identification algorithm and to study various properties of the algorithm. Sequential values of the state were generated for the algorithm in each case using known values of $\underline{\phi}$ and $\underline{\Delta}$ and the estimates were then compared with these known values.

Example 1:

The model parameters were

$$\underline{\phi} = \begin{bmatrix} 0.995 & 0.5 & 0.0 \\ 0.0 & 1.0 & 0.5 \\ 0.0 & -1.13 & 0.9 \end{bmatrix} \quad \underline{\Delta} = \begin{bmatrix} 0.0 \\ 0.0 \\ 1.25 \end{bmatrix}$$

with initial state and control

$$\underline{x}_0 = \begin{bmatrix} 0.0 \\ 1.5 \\ 3.95 \end{bmatrix} \quad u = 1$$

The control was left constant throughout the process, resulting in an open-loop response corresponding to the three curves of Figure 3. The curves are shown to be continuous because it has been assumed that in practice the measurements would result from uniform sampling of this continuous system.

The simulation was performed using the Nova programs and there was no measurement noise added to the model. Table II

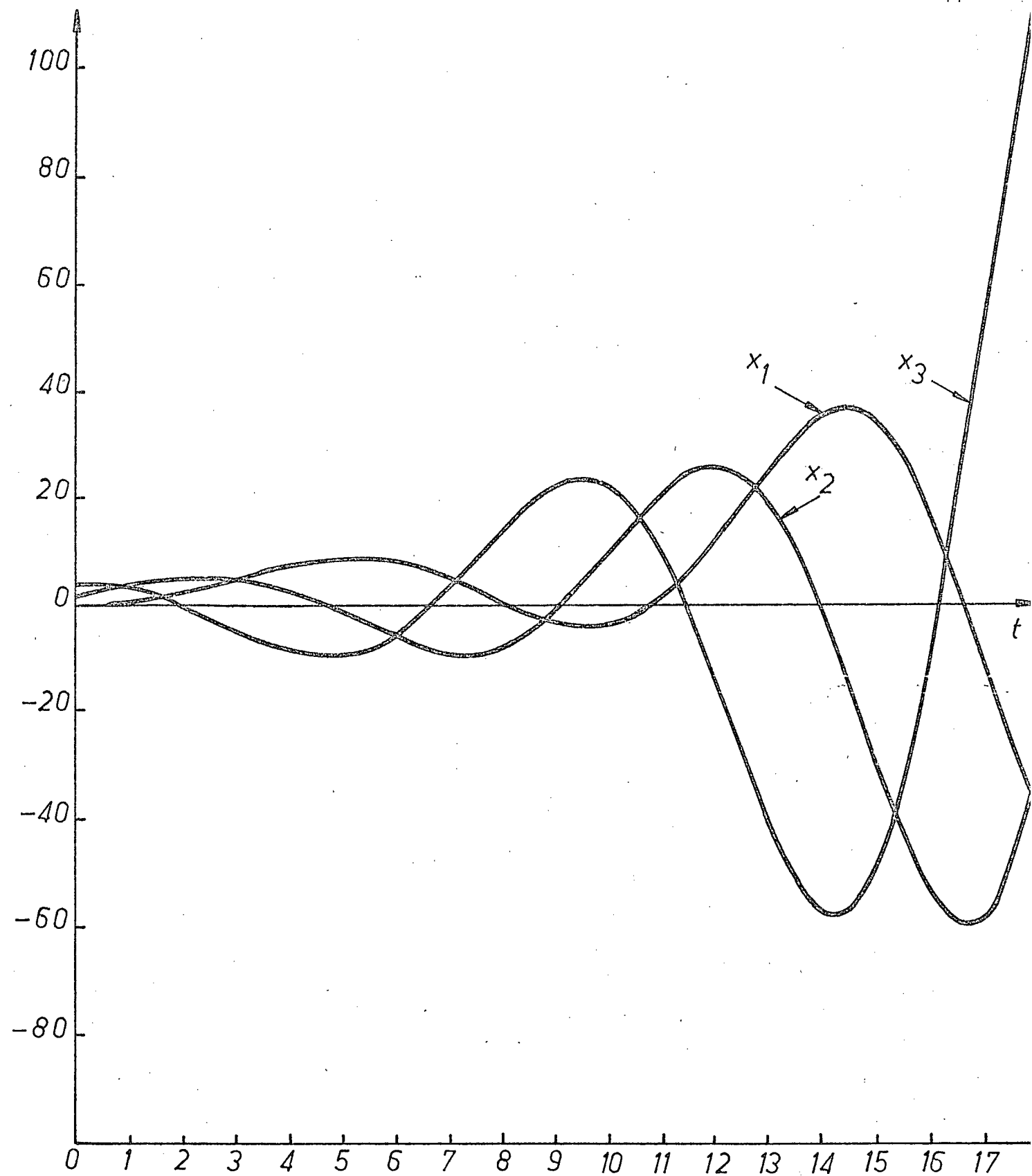


Figure 3 - Time response of continuous system corresponding to Example 1.

TABLE II - Stage-wise Errors of Least-Squares Filter (Example 1)

Figures in each column represent errors at successive stages.

Stage	"minimum norm"	$P_0 = 10 \times I$	$P_0 = 10^2 \times I$	$P_0 = 10^3 \times I$	$P_0 = 10^5 \times I$	$P_0 = 10^7 \times I$	$P_0 = 10^{16} \times I$
1	+ .4956009E+01	+ .4956044E+01	+ .4956009E+01	+ .4956009E+01	+ .4956011E+01	+ .4956009E+01	+ .4956009E+01
2	+ .2193356E+01	+ .2197610E+01	+ .2193400E+01	+ .2193356E+01	+ .2193354E+01	+ .2193356E+01	+ .2193356E+01
3	+ .7292265E+00	+ .1245663E+01	+ .7476390E+00	+ .7294487E+00	+ .7292240E+00	+ .7292260E+00	+ .7292259E+00
4	+ .3315534E-03	+ .8763182E+00	+ .7286461E+00	+ .2720355E+00	+ .2375113E-03	+ .6260436E-05	+ .8251297E-05
5	+ .9723237E-03	+ .8960244E+00	+ .4370673E+00	+ .2738907E-01	+ .8037871E-05	+ .3811357E-06	+ .2695410E-06
6	+ .1147506E-07	+ .8040013E+00	+ .1357909E+00	+ .2873371E-02	+ .8270537E-06	+ .6168898E-07	+ .1110659E-07
7	+ .1032932E-08	+ .5403006E+00	+ .3114320E-01	+ .4229341E-03	+ .1521597E-06	+ .1694626E-07	+ .1032285E-07
8	+ .6331324E-08	+ .2660201E+00	+ .7173627E-02	+ .8230054E-04	+ .4096006E-07	+ .2481867E-08	+ .3086397E-07
9	+ .1174260E-07	+ .1069880E+00	+ .1860306E-02	+ .1993976E-04	+ .1178606E-07	+ .1211445E-09	+ .2235941E-03
10	+ .1237370E-07	+ .4123187E-01	+ .5695862E-03	+ .5937541E-05	+ .3443537E-08	+ .3527151E-09	+ .2407231E-08
11	+ .1113249E-07	+ .1753404E-01	+ .2159944E-03	+ .2214477E-05	+ .5014855E-09	+ .6378680E-09	+ .4007216E-08
12	+ .8576017E-08	+ .9143615E-02	+ .1058297E-03	+ .1067259E-05	+ .2560367E-10	+ .1017675E-03	+ .2451576E-08
13	+ .5819554E-08	+ .5936951E-02	+ .6645077E-04	+ .6555694E-06	+ .9559106E-09	+ .1640657E-08	+ .2018661E-03
14	+ .4588361E-08	+ .4574932E-02	+ .5036433E-04	+ .4924871E-06	+ .3086121E-08	+ .2250708E-08	+ .1039153E-08
15	+ .4319357E-08	+ .3887912E-02	+ .4249783E-04	+ .4198029E-06	+ .1098628E-07	+ .1374427E-07	+ .1718590E-09
16	+ .4324768E-08	+ .3433026E-02	+ .3737925E-04	+ .3787415E-06	+ .1721376E-09	+ .2004652E-03	+ .4943047E-03
17	+ .4286413E-08	+ .3033789E-02	+ .3298429E-04	+ .3446833E-06	+ .3334956E-08	+ .2594733E-08	+ .2070682E-06
18	+ .4066631E-08	+ .2629245E-02	+ .2855703E-04	+ .3090746E-06	+ .7399028E-08	+ .3726839E-08	+ .5057110E-03
19	+ .3959783E-08	+ .2224612E-02	+ .2403805E-04	+ .2663924E-06	+ .3632550E-07	+ .1630333E-07	+ .1006140E-07

shows the actual estimation error as defined by

$$\text{Error } (\hat{\underline{A}}_k) = \text{trace } (\underline{A} - \hat{\underline{A}}_k)(\underline{A} - \hat{\underline{A}}_k)' \quad (126)$$

computed on the Nova at sequential sampling times for the identification algorithm when used as a least-squares filter with a "minimum norm" composition at the start and also when started with $\hat{\underline{A}}_0 = \underline{0}$ and \underline{P}_0 equal to various scalar multiples of the identity matrix \underline{I} . It can be seen that when \underline{P}_0 is fairly large, estimates can be obtained which are as good as, and at some stages marginally better than those obtained when the "minimum norm" procedure is used. Here the filtering problem is a deterministic one because there is no a priori information and the estimates should be based solely on the noise-free observations. \underline{P}_0 must therefore be made large to give minimal weighting of the initial estimates $\hat{\underline{A}}_0$. The resulting filter is then a good approximation to the purely deterministic least-squares filter of Chapter II, with much less computational requirements. However, the pure least-squares filter is subject to minimum initial bias and with it a better estimate results after fewer measurements. Specifically, the estimation error at the fourth stage in this example was lowest with the pure least-squares filter, the estimates being

$$\hat{\underline{\theta}}_4 = \begin{bmatrix} .9949869 & .5000086 & -.0000036 \\ .0000224 & .9999967 & .5000123 \\ -.0000045 & -1.130009 & .8999898 \end{bmatrix} \quad \hat{\underline{A}}_4 = \begin{bmatrix} .0000246 \\ -.0000396 \\ 1.249999 \end{bmatrix}$$

Example 2:

The model was

$$\underline{\phi} = \begin{bmatrix} 0.995 & 0.5 & 0.0 \\ 0.0 & 1.0 & 0.5 \\ 0.0 & -1.13 & -0.9 \end{bmatrix} \quad \underline{\Delta} = \begin{bmatrix} 0.0 \\ 0.0 \\ 1.25 \end{bmatrix}$$

with initial state and initial control

$$\underline{x}_0 = \begin{bmatrix} 0.0 \\ 1.5 \\ -1.45 \end{bmatrix} \quad u_0 = 1$$

and no simulated measurement noise.

In generating the remaining states, the control was left equal to u_0 until stage 1, after which each state was determined using a control chosen to minimize the estimated simple performance function

$$\hat{J}_{k+1} = \hat{\underline{x}}_{k+1}' \underline{W}_1 \hat{\underline{x}}_{k+1} + \underline{u}_k' \underline{W}_2 \underline{u}_k$$

where \underline{W}_1 and \underline{W}_2 are weighting matrices chosen for stability purposes and $\hat{\underline{x}}_{k+1}$ is defined by the equation

$$\hat{\underline{x}}_{k+1} = \hat{\underline{\phi}}_k \underline{x}_k + \hat{\underline{\Delta}}_k \underline{u}_k$$

In this example it is possible to have

$$\underline{W}_1 = \underline{I} \quad \text{and} \quad \underline{W}_2 = 1$$

Setting the derivative of \hat{J}_{k+1} with respect to u_k equal to zero gives

$$\hat{\Delta}_k' \hat{x}_{k+1} + u_k = 0$$

$$u_k = -(\hat{\Delta}_k' \hat{\Delta}_k + 1)^{-1} \hat{\Delta}_k' \hat{\phi}_k x_k$$

Figure 4 shows the variation of the resulting performance function

$$J(t) = \hat{x}_k' \hat{x}_k + u_{k-1}^2, \quad t_k \leq t < t_{k+1}$$

for the open-loop case where the control was left equal to u_0 for all stages and for two cases where u_k was calculated, beginning with u_2 , based on estimates from the least-squares filter using different starting procedures. All calculations were performed on the Nova.

This method might be useful for simple combined identification and control of an actual continuous system by calculating a sub-optimal control based on the discrete model.

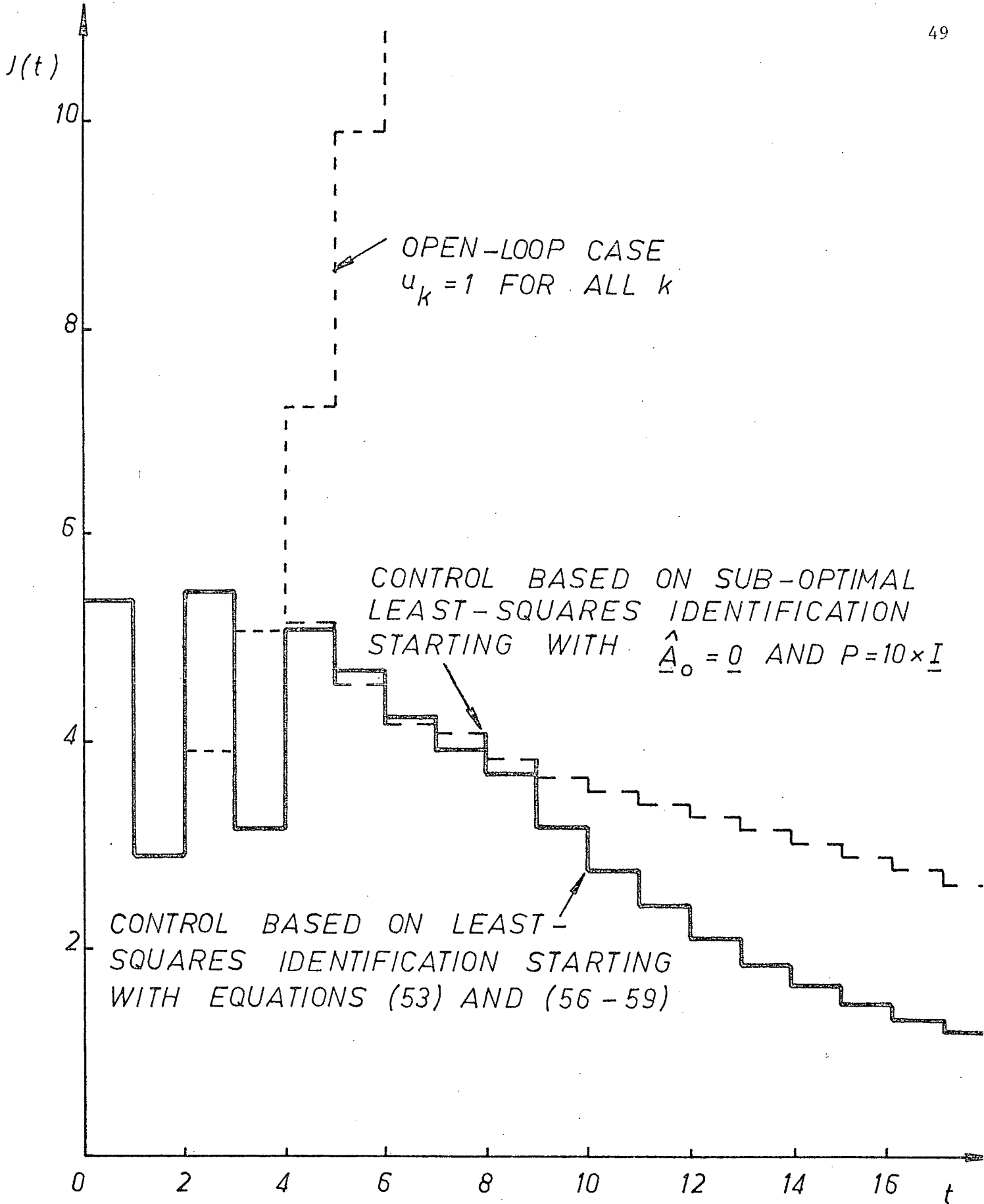


Figure 4 - Plot of performance functions for example 2.

$$J(t) = \underline{x}_k' \underline{x}_k + u_{k-1}^2, \quad t_k \leq t < t_{k+1}$$

Example 3:

The model was

$$\underline{\phi} = \begin{bmatrix} 0.0 & 0.0 & 0.9 \\ 2.0 & 0.0 & 0.0 \\ 0.0 & 0.7 & 0.0 \end{bmatrix} \quad \underline{\Delta} = \begin{bmatrix} 0.0 \\ 0.0 \\ 0.0 \end{bmatrix}$$

with initial state and control

$$\underline{x}_0 = \begin{bmatrix} 2.7 \\ 10.0 \\ 4.9 \end{bmatrix} \quad u = 0.0$$

The simulation was performed on the system-360 with random noise of normal distribution added to the state and control measurements. The standard deviation of the noise was 0.7, the variance 0.49.

The identification algorithm was used as a "best case" of the Bayesian MAP filter, with $\hat{\underline{\phi}}_0 = \underline{\phi}$ and $\hat{\underline{\Delta}}_0 = \underline{\Delta}$. s_k at every stage was set equal to the noise variance, 0.49. While in example 1 the initial estimate was inaccurate and the measurements were exact, in this example the initial estimates are exact and the measurements are noisy. Figure 5 shows the computed estimation errors as defined by (126) at each stage. As expected, the results are opposite to those of example 1, with a lower \underline{P}_0 now giving the better estimates because of increased weighting of $\hat{\underline{A}}_0$.

The results of Figure 6 were obtained with this same example and show the effect on the estimation error of using

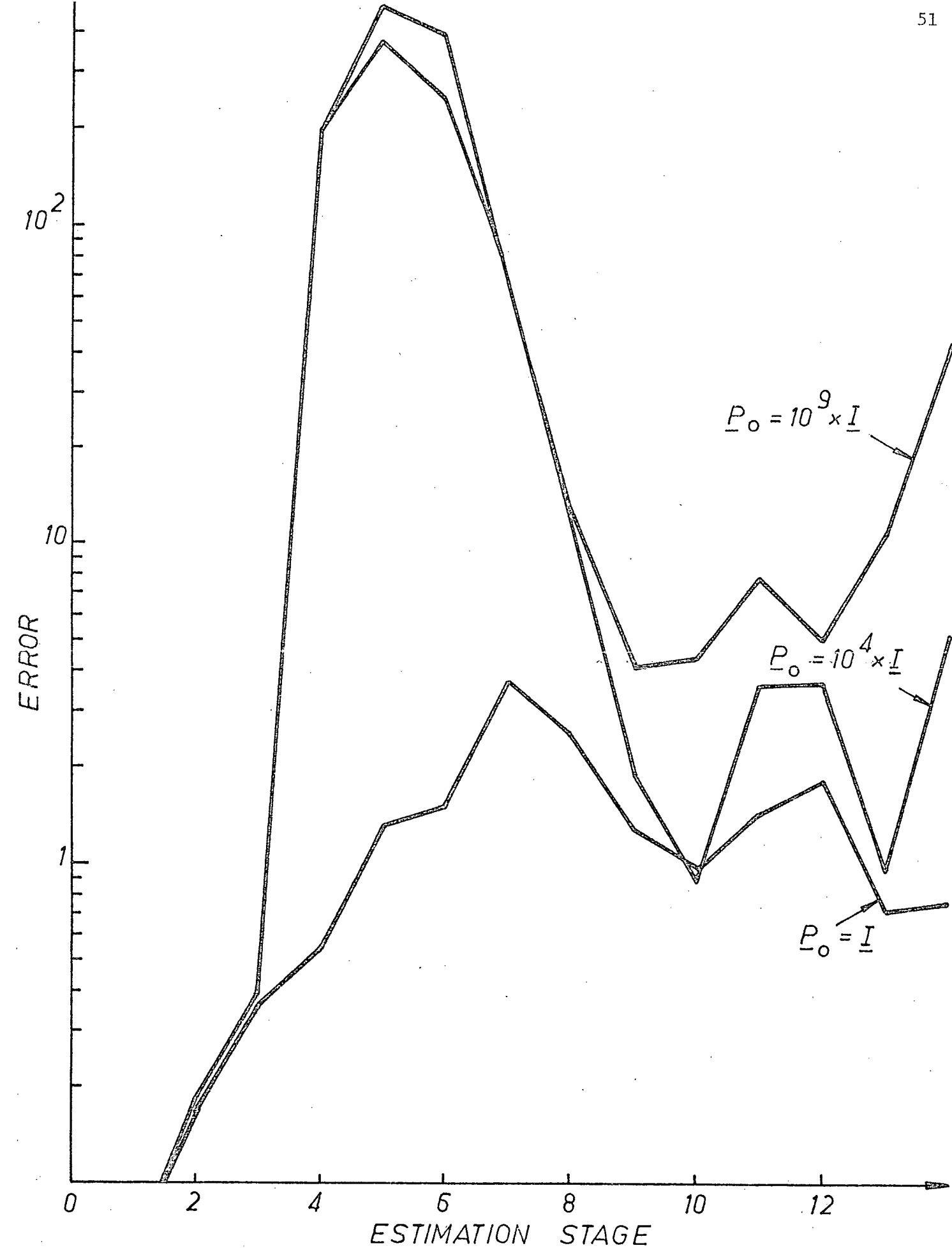
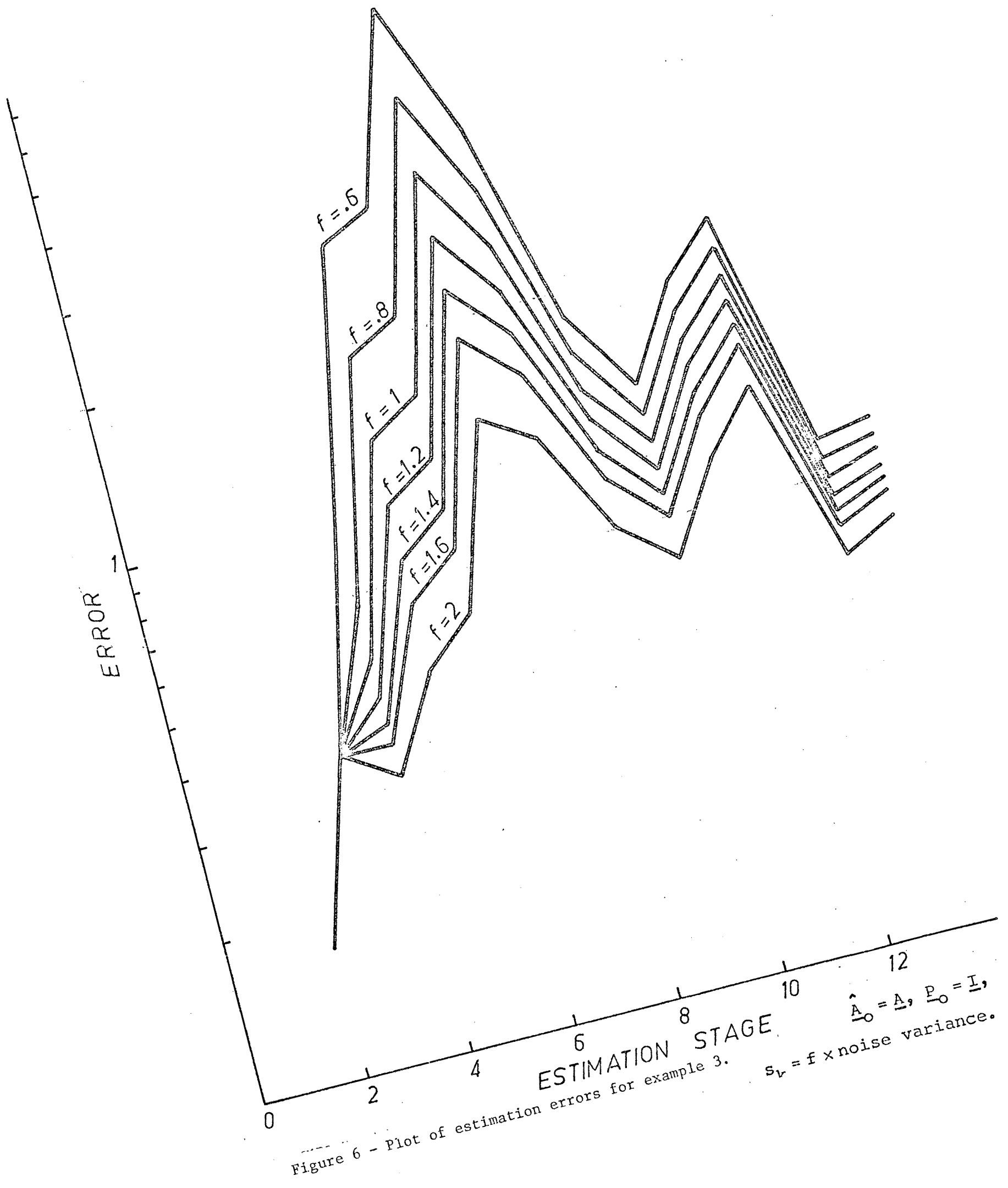


Figure 5 - Plot of estimation errors for example 3. $\hat{\underline{A}}_0 = \underline{A}$, s_k = variance.



different multiples of the noise variance for s_k in the algorithm. When \underline{P}_0 is large the effect is not noticeable but when \underline{P}_0 is small, increasingly higher multiples give increasingly better estimates in the stages following stage 4. A higher value of s_k provides decreased weighting of the noisy measurements and increased weighting of the good initial estimate. s_k has no noticeable effect on the estimates prior to stage 4.

Figure 7 was obtained by the same procedure, except that the minimum-norm composition was used at the start. As is the case when the filter is started with \underline{P}_0 large, there was negligible difference of the errors when values of s_k ranging from 0.5 to 2 times the noise variance were used.

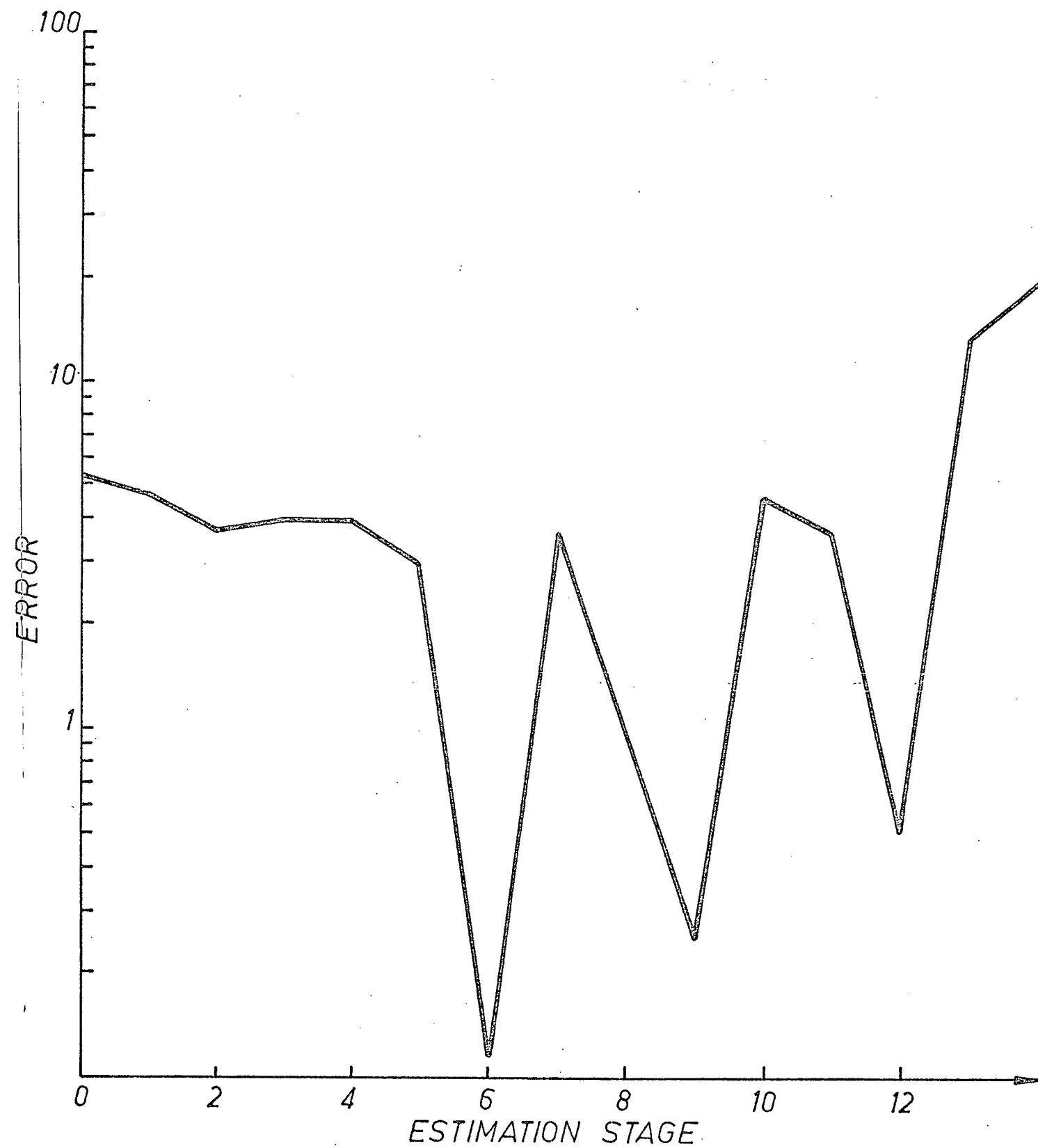


Figure 7 - Plot of estimation errors for example 3. Minimum-norm start.

Example 4:

The model was

$$\underline{\phi} = \begin{bmatrix} 0.995 & 0.5 & 0.0 \\ 0.0 & 1.0 & 0.5 \\ 0.0 & -1.13 & 0.9 \end{bmatrix} \quad \underline{\Delta} = \begin{bmatrix} 0.0 \\ 0.0 \\ 1.25 \end{bmatrix}$$

with initial state and control

$$\underline{x}_0 = \begin{bmatrix} 0.0 \\ 1.5 \\ 3.95 \end{bmatrix} \quad u = 1$$

(see Figure 3 for response curves). The simulation was done on the system-360, introducing Gaussian noise of standard deviation 0.5 and variance 0.25 to the measurements. s_k in the algorithm was set equal to the variance at each stage.

Figure 8 shows the computed estimation errors as defined by (126) at each stage for three different starting procedures: $\hat{\underline{\phi}}_0 = \underline{\phi}$, $\hat{\underline{\Delta}}_0 = \underline{\Delta}$, $\underline{P}_0 = \underline{I}$ for a "best-case" Bayesian MAP filter; a "minimum-norm" composition for a least-squares or maximum-likelihood filter; $\hat{\underline{\phi}}_0 = \underline{0}$, $\hat{\underline{\Delta}}_0 = \underline{0}$, $\underline{P}_0 = 10^6 \times \underline{I}$ for an approximate least-squares or maximum-likelihood filter.

The results still support the hierarchy of filters developed in Chapter IV despite the fact that the overall noise terms defined by (125) are not expected to be statistically independent or white as discussed in Chapter V.

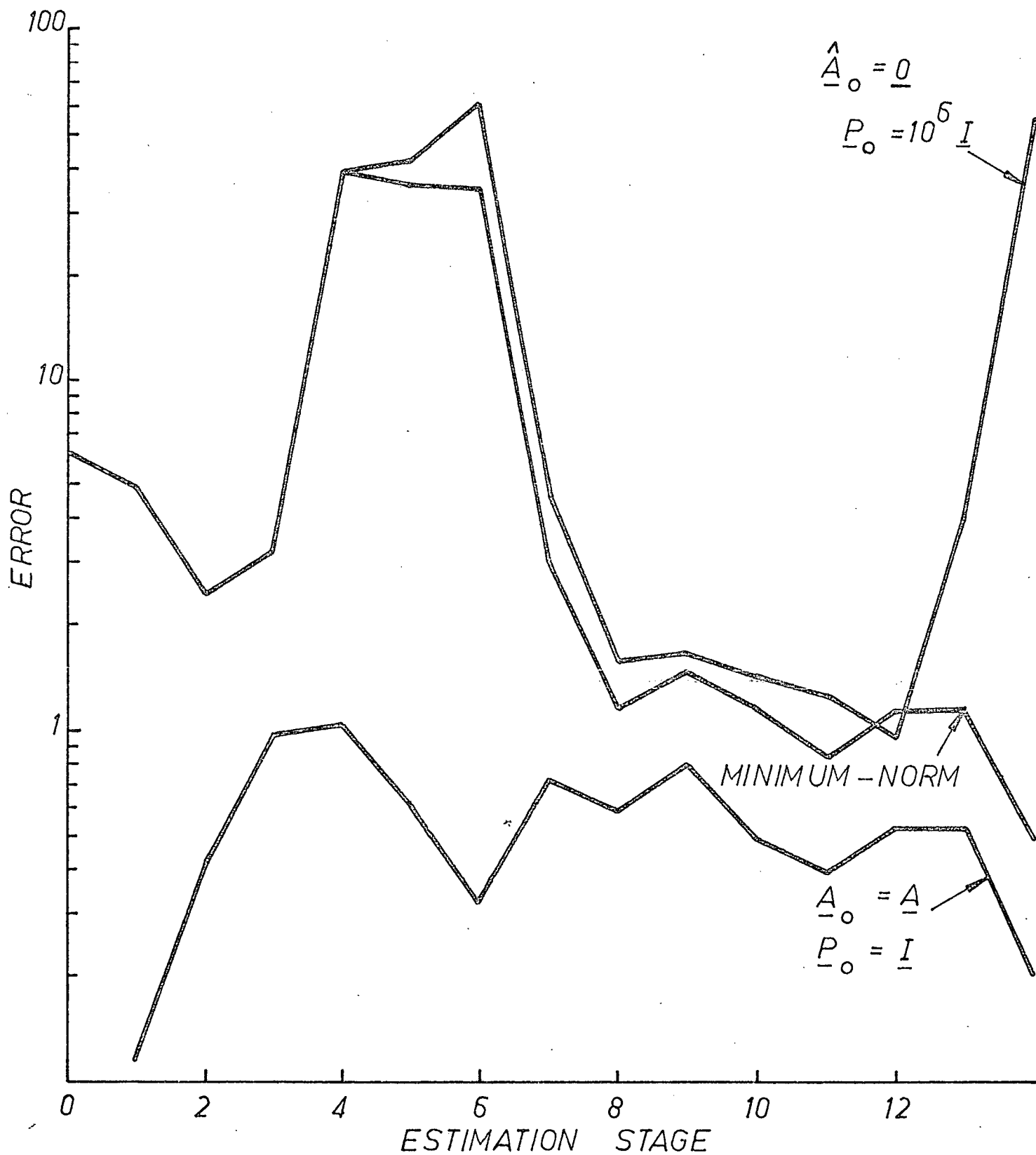


Figure 8 - Plot of errors for estimates in example 4.

VII. Further Applications

What has been presented in this thesis is an algorithm to estimate the parameter matrix \underline{A} in the general measurement process of equation (1):

$$\underline{Z} = \underline{H}\underline{A} + \underline{V} \quad (1)$$

While the accompanying computer programs (see Appendix) have been written for the particular system-identification problem of Chapter V, it is a simple matter to adapt them for any measurement process defined by (1). Specifically, the identification problem of Chapter V requires that each row of \underline{Z} (\underline{z}_k) should be taken from the state measurement which will comprise the next row of \underline{H} (\underline{h}_{k+1}), and thus for the computer programs the vectors \underline{z} and \underline{h} can share the same storage locations. In other applications, separate sets of storage locations may be required. Apart from this, the program, when supplied sequentially (via the user's measurement subroutine) with the rows of \underline{Z} and \underline{H} arrays satisfying the relation of equation (1), will generate a sequential estimate of the parameter array \underline{A} , subject to the following conditions developed in the previous chapters:

The elements of \underline{V} must have zero expected values. If all elements of the same row of \underline{V} (\underline{v}_k) have the same probability distribution and the variance of their distribution is known, it should be supplied for the value of s_k corresponding to that row (maximum-likelihood

filter). If all elements of the same row of \underline{V} do not have the same probability distribution or if the variances of the distributions are not known, s_k should be set equal to 1 at every stage (least-squares filter).

If expected values for the parameters are known then they should be used as the elements of $\hat{\underline{A}}_0$. If in addition the probability distributions of all parameters in the same row of \underline{A} have the same variance and the variances of the distributions of all the parameters are known, then \underline{P}_0 should be a diagonal matrix with the i th element on its main diagonal equal to the variance of the distribution of every parameter in the i th row of \underline{A} . Otherwise \underline{P}_0 should be a diagonal matrix with each element on its main diagonal set large enough to allow for any uncertainty in the corresponding row of $\hat{\underline{A}}_0$.

If expected values for the parameters are not known then no initial values should be supplied for $\hat{\underline{A}}_k$ and \underline{P}_k , but equations (53) and (56 - 59) should be used at the start. However, where the increased computational time required by these equations would be prohibitive, a good approximation can be achieved by using initial values $\hat{\underline{A}}_0 = \underline{0}$ and \underline{P}_0 diagonal with large elements on the main diagonal.

Rapid Identification

A major difficulty with the method of system-identification developed in Chapter V is that the estimated discrete

model cannot be accurate unless the rate of sampling the state is high in relation to the rate at which the state varies. At the same time, such rapid sampling can lead to near linear-dependence in the state measurements and consequent ill-conditioning of the \underline{H} matrix, which makes adequate identification impossible. Hanafy and Bohn [4] have suggested augmenting the state measurement at each sampling time with the measured outputs of integrators cascaded to the inputs and outputs of the continuous system. It is claimed that this additional data is effective in overcoming the problem of ill-conditioning. However, the usual treatment becomes cumbersome because the data and parameters must be structured into lengthy vectors in order to fit the form of conventional estimators, which are derived for a measurement process of the type

$$\underline{z} = \underline{H}\underline{a} + \underline{v}$$

\underline{z} being the data vector, \underline{a} the parameter vector, \underline{H} the measurement matrix and \underline{v} a vector of noise terms. For the identification problem this results in a large \underline{H} matrix of block-diagonal form and containing many zeros.

The algorithm of this thesis can be used quite readily for identification with augmented state measurements. At each sampling time, the inputs and outputs of the system are measured and stored, along with the outputs of the successive integrators. A state measurement is processed as one row in the estimation algorithm, followed by the integrator outputs as subsequent rows. Suppose, for example, that each of the

system inputs and outputs is passed through two integrators. Evidently the integrals

$$\int_0^t \underline{x}'(t) dt \quad \text{and} \quad \int_0^t \left[\int_0^t \underline{x}'(t) dt \right] dt$$

will satisfy the same linear differential equation as does $\underline{x}'(t)$, so uniform samples of their outputs should satisfy the same difference equation:

$$\underline{x}'(t_k) = \begin{bmatrix} \underline{x}'(t_{k-1}) \\ \vdots \\ \underline{u}'(t_{k-1}) \end{bmatrix} \underline{A}$$

$$\int_0^{t_k} \underline{x}'(t) dt = \begin{bmatrix} \int_0^{t_{k-1}} \underline{x}'(t) dt \\ \vdots \\ \int_0^{t_{k-1}} \underline{u}'(t) dt \end{bmatrix} \underline{A}$$

$$\int_0^{t_k} \left[\int_0^t \underline{x}'(t) dt \right] dt = \begin{bmatrix} \int_0^{t_{k-1}} \left[\int_0^t \underline{x}'(t) dt \right] dt \\ \vdots \\ \int_0^{t_{k-1}} \left[\int_0^t \underline{u}'(t) dt \right] dt \end{bmatrix} \underline{A}$$

The beginning rows of data for the estimation algorithm would therefore be

$$\underline{z}_1' = \overline{\underline{x}'(t_1)} \quad \underline{h}_1' = \begin{bmatrix} \overline{\underline{x}'(t_0)} \\ \vdots \\ \overline{\underline{u}'(t_0)} \end{bmatrix}$$

$$\begin{aligned} \underline{z}_2' &= \overline{\int_0^{t_1} \underline{x}'(t) dt} & \underline{h}_2' &= \begin{bmatrix} \overline{\int_0^{t_0} \underline{x}'(t) dt} & \vdots & \overline{\int_0^{t_0} \underline{u}'(t) dt} \\ \overline{\int_0^{t_0} \underline{x}'(t) dt} & \vdots & \overline{\int_0^{t_0} \underline{u}'(t) dt} \\ \vdots & \ddots & \vdots \\ \overline{\int_0^{t_0} \underline{x}'(t) dt} & \vdots & \overline{\int_0^{t_0} \underline{u}'(t) dt} \end{bmatrix} \\ \\ \underline{z}_3' &= \overline{\int_0^{t_1} \left[\int_0^t \underline{x}'(t) dt \right] dt} & \underline{h}_3' &= \begin{bmatrix} \overline{\int_0^{t_0} \left[\int_0^t \underline{x}'(t) dt \right] dt} & \vdots & \overline{\int_0^{t_0} \left[\int_0^t \underline{u}'(t) dt \right] dt} \\ \overline{\int_0^{t_0} \left[\int_0^t \underline{x}'(t) dt \right] dt} & \vdots & \overline{\int_0^{t_0} \left[\int_0^t \underline{u}'(t) dt \right] dt} \\ \vdots & \ddots & \vdots \\ \overline{\int_0^{t_0} \left[\int_0^t \underline{x}'(t) dt \right] dt} & \vdots & \overline{\int_0^{t_0} \left[\int_0^t \underline{u}'(t) dt \right] dt} \end{bmatrix} \\ \\ \underline{z}_4' &= \overline{\underline{x}'(t_2)} & \underline{h}_4' &= \begin{bmatrix} \overline{\underline{x}'(t_1)} & \vdots & \overline{\underline{u}'(t_1)} \\ \overline{\underline{x}'(t_1)} & \vdots & \overline{\underline{u}'(t_1)} \\ \vdots & \ddots & \vdots \\ \overline{\underline{x}'(t_1)} & \vdots & \overline{\underline{u}'(t_1)} \end{bmatrix} \end{aligned}$$

where the superscribed bars indicate that these are the observed values of the variables concerned. With this procedure the state measurement defining \underline{z} at a given stage does not immediately become the \underline{h} vector for the following stage as it does in the simple identification problem. Therefore separate sets of memory locations are needed for the \underline{z} and \underline{h} vectors, as mentioned at the beginning of this chapter.

Identification of Non-Linear Systems

Both the identification methods discussed thus far have assumed a linear model for the system being measured. However, it is equally possible, within the allowable forms of measurement processes, to assume certain non-linear models. Netravali and de Figueiredo [9] have discussed methods of obtaining regression functions for classes of discrete non-linear systems in which the evolution operators can be represented by algebraic

or trigonometric polynomials. Although noise considerations are more involved, the computational requirements are not unlike those of the linear identification problem and are adaptable to the computer programs contained in this thesis. As a very simple example, suppose it is desired to estimate a third-order non-linear algebraic model of the form

$$x_{k+1} = a_0 + a_1 x_k + a_2 x_k^2 + a_3 x_k^3$$

from measurements of the scalar variable x_k , $k = 0, 1, 2, \dots$. The estimation algorithm would begin with the following data:

$$\begin{aligned} \underline{z}'_1 &= \bar{x}_1 & \underline{h}'_1 &= \begin{bmatrix} 1 & \bar{x}_0 & \bar{x}_0^2 & \bar{x}_0^3 \end{bmatrix} \\ \underline{z}'_2 &= \bar{x}_2 & \underline{h}'_2 &= \begin{bmatrix} 1 & \bar{x}_1 & \bar{x}_1^2 & \bar{x}_1^3 \end{bmatrix} \end{aligned}$$

where again the superscribed bar is used to denote measured values.

It is useful to assume non-linear models in some cases involving linear systems where not all of the state variables are measured. For example, although Figure 3 in the previous chapter describes a linear system of 3 outputs and 1 input, a model for any one of the outputs, obtained from measurements of that output alone, would have to be non-linear. Of course, non-linear models are not always necessary to reduce the order of a linear system, because many linear systems can be realized in terms of reduced linear models. A further sophistication of the identification algorithm for linear systems could pro-

vide for appropriate selection of the measured variables to effect such a reduction.

Time-Varying Parameters

Time-varying parameters can be accommodated by modifying the algorithm so that prior estimates are updated at each stage to allow for expected time-variations during the measurement interval. That is, if the parameter array \underline{A} is known to vary according to the difference equation

$$\underline{A}_{k+1} = \underline{\Theta}(k+1, k) \underline{A}_k$$

then $\hat{\underline{A}}_{k-1}$ in the algorithm is replaced by its a priori update:

$$\hat{\underline{A}}_{k|k-1} = \underline{\Theta} \hat{\underline{A}}_{k-1}$$

This is a much-used procedure and forms the basis of the Kalman filter for state estimation. Other methods are available if no model for the parameter variations is known (see, for example, Young [17]).

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APPENDIXProgram-Equivalents of Symbols Appearing in the Text

<u>Programs</u>	<u>Text</u>
A	\hat{A}_k
B	$\underline{b}_k, \underline{e}_k$
C	\underline{c}_k
CSQU	$\underline{c}_k, \underline{c}_k$
CTHR	threshold for $\underline{c}_k, \underline{c}_k$
H	$\underline{h}_k, \underline{z}_k$
I	i
J	j
KØ	k_{MAX}
P	$\underline{p}_k, \underline{r}_k$
Q	\underline{Q}_k
R	r, n
RS	$rs, n(m+n)$
S	$s, m+n$
SS	$s^2, (m+n)^2$
V	s_k

Memory-Allocation for Identification Programs

Labels apply to main-program assembly only. Locations available for user-written programs are marked by asterisks.

<u>Locations</u>	<u>Label:Content</u>	<u>Use</u>
0000-0001		*
0002		starting address of main program
0003		*
0004-0007		required by floating-pt. interpreter
0010-0037		*
0040-0043		required by floating-pt. interpreter
0044-0277		*
0300	KEEP	} pointers, indicators
0301	SAVE	
0302	AMAT	
0303	AMAT0	
0304	BMAT	
0305	BMAT0	
0306		*
0307	ZERO :: 0	} floating-point zero
0310		
0311	ONE : 1	one
0312	R	no. of columns in parameter array (r)
0313	S	number of rows in parameter array (s)
0314	RS	product rs
0315	SS	product ss
0316	I	indicator
0317	J	counter
0320		*
0321	K0	} indicators and counters
0322	L	
0323	L0	
0324	M	
0325	N	
0326	N0	
0327		*
0330	A : 500	} indirect matrix addresses
0331	P : 700	
0332	Q: 1100	
0333	TEMP1: 1300	
0334	TEMP2: 1500	
0335	TEMP3: 1700	
0336	H : 2100	
0337	C : 2120	

Ø34Ø	B :	214Ø	} indirect matrix addresses
Ø341	CSQU :	216Ø	
Ø342	CTHR :	Ø4Ø42Ø	} threshold for $c_k'c_k$, initially 1
Ø343		Ø	
Ø344		27ØØ	contains starting adr. of main prog.
Ø345		3Ø54	contains starting adr. of calc'ns
Ø346	V :	Ø4Ø42Ø	} measurement variance, initially loaded as floating-point "1"
Ø347		Ø	
Ø35Ø	MXADD :	223Ø	} indirect subroutine addresses
Ø351	MXSUB :	2251	
Ø352	MXMPY :	2272	
Ø353	MXDIV :	2355	
Ø354	MXTR :	2374	
Ø355	DATRD :	244Ø	
Ø356	DATPN :	2473	
Ø357	DATRC :	2533	
Ø36Ø	DIGIT :	2572	} indirect addresses for user's subroutines
Ø361	DATWR :	26ØØ	
Ø362	WRITE :	2646	
Ø363	INIT		
Ø364	MEAS		
Ø365	DATIN		
Ø366	DTOUT		
Ø367			*
Ø37Ø	STR1 :	217Ø	} indirect addresses for teleprinter message strings
Ø371	STR2 :	2174	
Ø372	STR3 :	22ØØ	
Ø373	STR4 :	22Ø4	
Ø374	STR5 :	221Ø	
Ø375	STR6 :	2214	
Ø376	STR7 :	222Ø	
Ø377	STR8 :	2224	
Ø4ØØ-Ø477			floating-pt. interpreter work area
Ø5ØØ-2161			matrix storage area (see 33Ø-341)
2162-2167			*
217Ø-2227			teleprinter message strings
223Ø-2431			matrix arith. subr. (see 35Ø-354)
2432-2437			*
244Ø-2666			I/O subroutines (see 355-362)
2667			*
27ØØ-34Ø3	BEGIN		main program
34Ø4-5577			*
56ØØ-6577			basic floating-pt. interpreter

Instructions for Using the Identification Program-Package

First load the program tapes in the following order:

1. Nova Basic Floating-Point Interpreter
2. Data-supply subroutines (INIT, MEAS, DATIN, DTOUT)
3. Identification program-package

The program is self-starting and will begin by printing certain questions which are to be answered by typing numbers into the teletypewriter. Each number will be required in either fixed- or floating-point format. In the case of fixed-point only one decimal digit will be accepted, while floating-point format can be any string of characters in the following order:

1. A + or - sign (optional)
2. A string of decimal digits (optional)
3. A decimal point (optional)
4. A string of decimal digits
5. The letter E, if there is to be an exponent
6. A + or - sign (optional)
7. One or two decimal digits denoting exponent
(optional)
8. A "space"

A character typed in error can be deleted with a "rubout".

Examples of allowed strings are: 500_, +50_, +5.E2_, -2.05E-04_, +.3054E-22_, -2E03_, where _ denotes a "space".

The questions printed and explanations of the required responses are as follows:

1. "R = ____" : A fixed-point integer from 1 to 8 equaling r , the number of columns in the parameter array, or n , the number of system outputs.

2. "S = ____" : A fixed-point integer from 1 to 8 equaling s , the number of rows in the parameter array, or $m+n$, where m is the number of system inputs and n is the number of

system outputs.

3. "SAMPLES?" : A number in floating-point format equal to the number of state-samples to be taken.

4. "COPY? " : A fixed-point integer corresponding to one of the following instructions regarding starting values:

Ø: No starting values are available for A and P.

1: The starting values now in memory are to be used.

2: Copy the starting values from memory onto paper tape.

3: Copy the starting values from memory onto the teleprinter.

4: Read the starting values from the tape in the high-speed reader and enter them into memory (tape must be one which has been produced by response 2).

5: Accept the starting values from the teletype keyboard. (Note that following this response the program will print "PARAMS " after which the elements of the parameter matrix should be typed in floating-point format row by row. A carriage-return and line-feed will occur automatically after each element has been typed and an extra line-feed will occur at the end of each row. When all rows are finished, the program will print "P-MATRIX" and the starting values of the P-matrix elements should then be typed row by row in floating-point format.)

6: Execute the user-written subroutine whose starting address is found in location INIT = 363.

7: Accept new initial values for CTHR and V from the teletype keyboard. (The program will respond by printing "CTHR, V:" after which the values of CTHR and V should be typed in floating-point format one after the other.)

5. "READY? " : A fixed-point integer corresponding to:

Ø: Return for another pass at question 4.

1: Proceed to execute the identification program.

IMPORTANT: The last response to question 4 must be "Ø" or "1"

Instructions for Writing I/O Subroutines

INIT: This subroutine is called if a "6" is typed in response to the question "COPY?" and allows the user to supply starting values with his own subroutine. Starting address should be stored in location 363.

MEAS: This subroutine is called just before the recursive identification process is started and can be used for such tasks as rapid pre-measuring and storing of data. Its starting address should be entered into location 364.

DATIN: Called each time a new sample of the system outputs is required. Starting address should be loaded into location 365.

DTOUT: Called just after a new estimate of the parameters has been calculated and useful for outputting the parameter matrix. The starting address should be loaded into location 366.

The model estimated by the program will be (see Chapter V)

$$\underline{x}_k(n) = \phi(n \times n) \underline{x}_{k-1}(n) + \underline{\Delta}(n \times m) \underline{u}_{k-1}(m) = \underline{A}'(n \times (n+m)) \underline{h}_k(n+m)$$

where

$$\underline{h}_k = \begin{bmatrix} \underline{x}_{k-1} \\ \vdots \\ \underline{u}_{k-1} \end{bmatrix} \quad \underline{A} = \begin{bmatrix} \phi' \\ \vdots \\ \underline{\Delta} \end{bmatrix}$$

The user's data-supply subroutines should store measured values of \underline{x}_k and \underline{u}_k in the \underline{h} -vector locations, which begin at the address found in location H = 336. \underline{x}_k is stored first and then \underline{u}_k , each element to be written in 32-bit hexadecimal floating-point format occupying 2 consecutive locations as provided by the Nova instruction FFLO. The maximum number of elements in

h is 8. The estimated parameter array A will be left row by row starting at the address contained in location $A = 330$, each element in floating-point format and occupying 2 consecutive locations. Output via the teleprinter or paper-tape punch can be achieved using the subroutines which are addressed indirectly through locations $DATWR = 361$ and $DATPN = 356$.

Values of the variance term s_k for a maximum-likelihood filter can be entered in floating-point format into locations $V = 346$ and $V + 1 = 347$.

The total number of state samples measured or estimation cycles performed is controlled by the user's subroutines, using location $K = 320$ as a counter. The initial count, which is typed in response to the question "SAMPLES?", is found in location $K0 = 321$.

Dimension parameters typed in response to "R = " and "S = " and the locations where they are stored are:

R = 312	r, n
S = 313	s, m + n
RS = 314	rs, n(m+n)
SS = 315	s^2 , $(m+n)^2$

Example:

The following set of programs are examples of the subroutines, MEAS, DATIN and DTOUT, required to make and store a rapid set of state-samples of a continuous system via an A/D converter with multiplexed inputs, and under control of an external real-time clock. The stored data is to be processed one row at a time by the identification program, after which the parameter estimate is to be printed, along with a

warning in the case of a minimum-norm composition if an insufficient number of linearly independent measurements were available for the parameters to be observable.

; DATA-SUPPLY SUBROUTINES FOR A/D CONVERTER

```

R      = 312
S      = 313
I      = 316
J      = 317
K      = 320
KØ     = 321
N      = 325
A      = 330
H      = 336
BEGIN  = 344
START  = 345
MXTR   = 354
DATWR  = 361
WRITE  = 362
STR5   = 374

```

```

.LOC 364
MEAS
DATIN
DTOUT

```

```

.LOC 341Ø
111116      ; STRING 11: "INS MEAS"
123Ø4Ø
1151Ø5
1Ø1123

```

```

MAX:      2Ø4Ø      ; MAX NO OF STOR LOC AVAILABLE
STORE:    3537      ; IND ADR FOR 1ST STOR LOC
MEAS:     LDA 3, R
           STA 3, N      ; N = R
           LDA 3, KØ
           STA 3, K      ; PRESET SAMPLE COUNTER
           SUB 2, 2      ; CLEAR AC2
           ADD 3, 2
           DSZ N
           JMP .-2      ; AC2 = KR
           LDA 3, MAX    ; AC3 = MAX
           SUBZ# 2, 3, SNC ; SKIP IF KR NOT EXCEED MAX
           JMP @BEGIN    ; RESTART
           LDA 3, STORE
           STA 3, 21     ; PRESET LOC POINTER
           SUBO 2, 2     ; AC2 = Ø
SMPL:     LDA 3, R
           STA 3, N      ; RESET MEASUREMENT COUNTER

```



```

DOAC 2, 44      ; SET MUX CHANNEL TO 0
NIOS 63         ; ENABLE HARDWARE CLOCK
SKPDN 63
CRRNT: JMP .-1   ; WAIT FOR CLOCK
NIOS 51         ; CLEAR A/D
NIOS 51         ; START A/D
SKPDN 51
JMP .-1         ; WAIT FOR A/D
DIA 0, 51       ; GET RESULT
STA 0, @21      ; STORE RESULT
NIOP 44         ; INC MUX CHANNEL
DSZ N          ; SKIP IF DONE CURRENT SAMPLE
JMP CRRNT
DSZ K           ; SKIP IF DONE ALL SAMPLES
JMP SMPL
LDA 3, K0
STA 3, K
ISZ K           ; PRESET SAMPLE COUNTER
LDA 3, STORE
STA 3, 21
JMP @START

DATIN: STA 3, RETURN ; STORE RETURN ADR
DSZ K          ; SKIP IF NO MORE DATA
JMP .+2
JMP OUT
LDA 2, H       ; PRESET LOC POINTER
LDA 3, R       ; AC3 = R
STA 3, N       ; PRESET MEAS COUNTER
CMPNT: SUB 0, 0 ; AC0 = 0
LDA 1, @21     ; GET DATA WORD
MOVL# 1, 1, SZC ; SKIP IF NON-NEGATIVE
COM 0, 0       ; AC0 = 177777
STA 0, 0, 2
STA 1, 1, 2    ; STORE DATUM IN H
FETR
FFLO 0, 2     ; CONVERT TO FP
FIC2          ; INC LOC POINTER
FEXT
DSZ N         ; SKIP IF HAVE ALL COMPS
JMP CMPNT
JMP @RETURN   ; RETURN

RETURN: 0
STR11: 3410
OUT: LDA 3, I
MOV 3, 3, SZR ; SKIP IF I = 0
JMP PRINT
LDA 3, J      ; AC3 = J
SUBZL 1, 1    ; AC1 = 1
ADCZ# 1, 3, SNC ; SKIP IF J GREATER THAN 1
JMP .+3
LDA 2, STR11
JSR @WRITE    ; TYPE "INS MEAS"

```

```

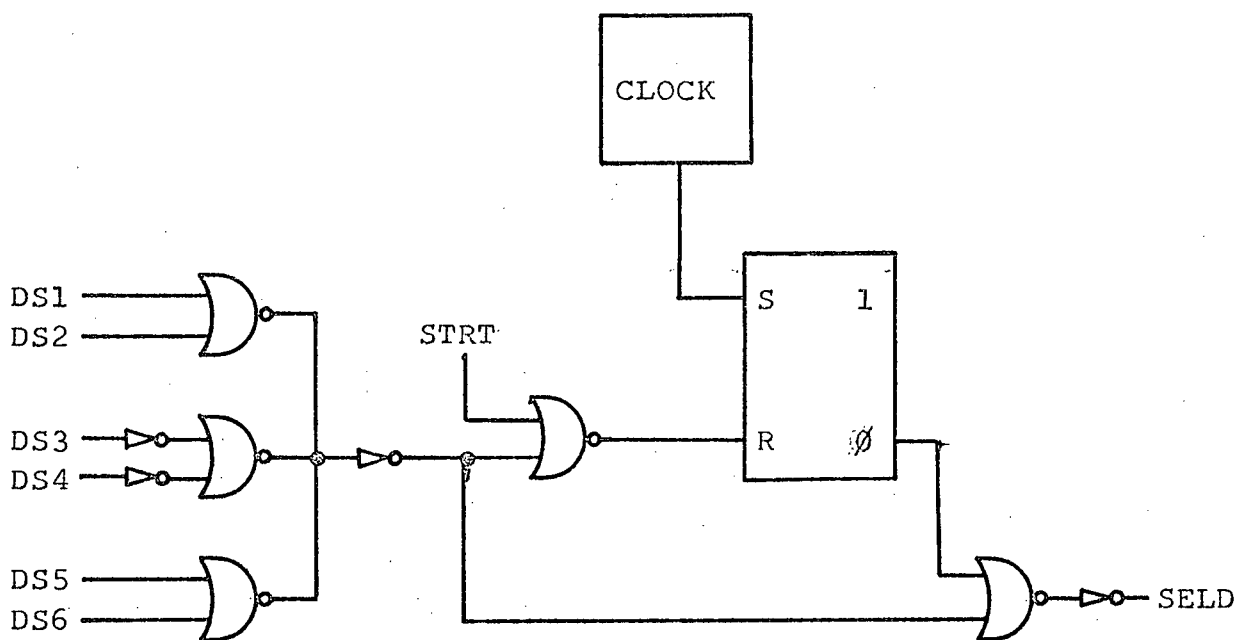
PRINT:  LDA 2, STR5
        JSR @WRITE      ; TYPE "PARAMS  "
        LDA 0, S
        LDA 1, R
        LDA 2, A
        JSR @DATWR      ; PRINT PARAMETERS
        JMP @BEGIN      ; RESTART MAIN PROG

DTOUT:  JMP 0, 3         ; RETURN

        .END

```

INTERFACE FOR REAL-TIME CLOCK



Identification Programs for Nova Computer

On the following pages are found the assembler listings of the basic identification programs for the Nova computer.

; REQUIRE BASIC FLOATING POINT INTERPRETER

```

000300      KEEP      = 300
000301      SAVE      = 301
000302      AMAT      = 302
000303      AMAT0     = 303
000304      BMAT      = 304
000305      BMAT0     = 305
000322      L        = 322
000323      L0       = 323
000324      M        = 324
000325      N        = 325
000326      N0       = 326

```

```

000307      .LOC 307
00307 000000  ZERO:  0
00310 000000      0

```

```

000350      .LOC 350
00350 002230  MXADD      ; THESE ARE THE PAGE-0
00351 002251  MXSUB      ; ADDRESSES IN WHICH THE
00352 002272  MXMPY      ; STARTING ADDRESSES OF
00353 002355  MXDIV      ; THE SUBROUTINES CAN BE
00354 002374  MXTR       ; FOUND.

```

```

002230      .LOC 2230

```

; SUBR TO ADD TWO MATRICES (C = A + B)

```

; ENTER WITH:  LOC N   = NO. OF ELTS IN EACH MATRIX
;              AC0     = ADR OF A
;              AC1     = ADR OF B
;              AC2     = ADR OF C

```

```

02230 040302  MXADD:  STA 0, AMAT      ; PRESET A-MATRIX POINTER
02231 044304      STA 1, BMAT      ; PRESET B-MATRIX POINTER
02232 054301      STA 3, SAVE      ; STORE RETURN ADR
02233 006004  XADD:   FETR          ; ENTER FP MODE
02234 022302      FLDA 0, @AMAT    ; GET ELT OF A
02235 026304      FLDA 1, @BMAT    ; GET ELT OF B
02236 123000      FADD 1, 0        ; ADD ELTS
02237 041000      FSTA 0, 0, 2     ; STORE RESULT IN C
02240 104000      FIC2            ; INC C-MATRIX POINTER
02241 100000      FEXT            ; EXIT FP MODE
02242 010302      ISZ AMAT
02243 010302      ISZ AMAT      ; INC A-MATRIX POINTER
02244 010304      ISZ BMAT
02245 010304      ISZ BMAT      ; INC B-MATRIX POINTER
02246 014325      DSE N          ; SKIP IF ALL ELTS ADDED
02247 000764      JMP XADD       ; ADD NEXT PAIR OF ELTS
02250 002301      JMP @SAVE      ; RETURN

```

; SUBR TO SUBTRACT ONE MATRIX FROM ANOTHER (C = A - B)

; ENTER WITH: LOC N = NO. OF ELTS IN EACH MATRIX

;	AC0	= ADR OF A	
;	AC1	= ADR OF B	
;	AC2	= ADR OF C	80

02251	040302	MXSUB:	STA 0, AMAT	; PRESET A-MATRIX POINTER
02252	044304		STA 1, BMAT	; PRESET B-MATRIX POINTER
02253	054301		STA 3, SAVE	; STORE RETURN ADR
02254	006004	XSUB:	FETR	; ENTER FP MODE
02255	022302		FLDA 0, @AMAT	; GET ELT OF A
02256	026304		FLDA 1, @BMAT	; GET ELT OF B
02257	122400		FSUB 1, 0	; SUBTRACT ELT OF B FROM ELT OF A
02260	041000		FSTA 0, 0, 2	; STORE RESULT IN C
02261	104000		FIC2	; INC C-MATRIX POINTER
02262	100000		FEXT	; EXIT FP MODE
02263	010302		ISZ AMAT	
02264	010302		ISZ AMAT	; INC A-MATRIX POINTER
02265	010304		ISZ BMAT	
02266	010304		ISZ BMAT	; INC B-MATRIX POINTER
02267	014325		DSZ N	; SKIP IF DONE
02270	000764		JMP XSUB	; DO ANOTHER SUBTRACTION
02271	002301		JMP @SAVE	; RETURN

; SUBR TO MULTIPLY TWO MATRICES (C = AB)

;	ENTER WITH:	LOC L	= NO. OF COLUMNS IN A/ROWS IN B
;		LOC M	= NO. OF ROWS IN A
;		LOC N	= NO. OF COLUMNS IN B
;		AC0	= ADR OF A
;		AC1	= ADR OF B
;		AC2	= ADR OF C

02272	040302	MXMPY:	STA 0, AMAT	
02273	040303		STA 0, AMAT0	; PRESET A-MATRIX POINTERS
02274	044304		STA 1, BMAT	
02275	044305		STA 1, BMAT0	; PRESET B-MATRIX POINTERS
02276	054301		STA 3, SAVE	; STORE RETURN ADR
02277	034322		LDA 3, L	
02300	054323		STA 3, L0	; LOC L0 = NO. OF COLUMNS IN A
02301	024325		LDA 1, N	
02302	044326		STA 1, N0	; LOC N0 = NO. OF COLUMNS IN B
02303	127000		ADD 1, 1	; AC1 = TWICE NO. COLS IN B
02304	000420		JMP XMPY+2	
02305	034302	MRET:	LDA 3, AMAT	
02306	054303		STA 3, AMAT0	; BEGIN NEXT ROW OF A
02307	034305		LDA 3, BMAT0	
02310	054304		STA 3, BMAT	; GO TO FIRST COLUMN OF B
02311	034326		LDA 3, N0	
02312	054325		STA 3, N	; RESET COLUMN-COUNTER
02313	000407		JMP XMPY	
02314	034300	NRET:	LDA 3, KEEP	
02315	054304		STA 3, BMAT	
02316	010304		ISZ BMAT	
02317	010304		ISZ BMAT	; BEGIN NEXT COLUMN OF B
02320	034303		LDA 3, AMAT0	
02321	054302		STA 3, AMAT	; REPEAT SAME ROW OF A
02322	034323	XMPY:	LDA 3, L0	
02323	054322		STA 3, L	; RESET PRODUCT-COUNTER
02324	034304		LDA 3, BMAT	
02325	054300		STA 3, KEEP	; STORE COLUMN-POINTER

02326	006004	FETR	; ENTER FP MODE
02327	030307	FLDA 2, ZERO	; ZERO CUMULATIVE SUM
02330	022302	LRET: FLDA 0, @AMAT	; GET ELT OF A 81
02331	026304	FLDA 1, @BMAT	; GET ELT OF B
02332	120100	FMPY 1, 0	; MULTIPLY ELTS
02333	113000	FADD 0, 2	; ADD PROD TO CUMULATIVE SUM
02334	100000	FEXT	; EXIT FP MODE
02335	010302	ISZ AMAT	
02336	010302	ISZ AMAT	; MOVE ALONG ROW OF A
02337	034304	LDA 3, BMAT	
02340	137000	ADD 1, 3	
02341	054304	STA 3, BMAT	; MOVE DOWN COLUMN OF B
02342	006004	FETR	; ENTER FP MODE
02343	014322	FDSZ L	; SKIP IF ALL PRODUCTS DONE
02344	000764	FJMP LRET	; FORM NEXT PRODUCT
02345	051000	FSTA 2, 0, 2	; STORE RESULT IN C
02346	104000	FIC2	; MOVE ALONG ROW OF C
02347	100000	FEXT	; EXIT FP MODE
02350	014325	DSZ N	; SKIP IF DONE ALL COLS OF B
02351	000743	JMP NRET	
02352	014324	DSZ M	; SKIP IF DONE ALL ROWS OF A
02353	000732	JMP MRET	
02354	002301	JMP @SAVE	; RETURN

; SUBR TO DIVIDE A MATRIX BY A SCALAR (C = A/B)

; ENTER WITH: LOC N = NO. OF ELTS IN A
 ; AC0 = ADR OF A
 ; AC1 = ADR OF B
 ; AC2 = ADR OF C

02355 040302 MXDIV: STA 0, AMAT ; PRESET A-MATRIX POINTER
 02356 044304 STA 1, BMAT ; PRESET B-MATRIX POINTER
 02357 054301 STA 3, SAVE ; STORE RETURN ADR

02360 006004 XDIV: FETR ; ENTER FP MODE
 02361 022302 FLDA 0, @AMAT ; GET ELT OF A
 02362 026304 FLDA 1, @BMAT ; GET ELT OF B
 02363 120200 FDIV 1, 0 ; DIVIDE ELT OF A
 02364 041000 FSTA 0, 0, 2 ; STORE RESULT IN C
 02365 104000 FIC2 ; INC C-MATRIX POINTER
 02366 100000 FEXT ; EXIT FP MODE
 02367 010302 ISZ AMAT
 02370 010302 ISZ AMAT ; INC A-MATRIX POINTER
 02371 014325 DSZ N ; SKIP IF ALL ELTS DIVIDED
 02372 000766 JMP XDIV
 02373 002301 JMP @SAVE ; RETURN

; SUBR TO TRANSPOSE A SQUARE MATRIX (A = A')

; ENTER WITH: AC1 = NO. OF ROWS OR COLUMNS OF A
 ; AC2 = ADR OF A

02374 044324 MXTR: STA 1, M
 02375 014324 DSZ M ; LOC M = 1 LESS THAN NO. ROWS
 02376 000402 JMP +2
 02377 001400 JMP 0, 3
 02400 054301 STA 3, SAVE ; STORE RETURN ADR
 02401 127000 ADD 1, 1 ; AC1 = TWICE NO. OF ROWS
 02402 121400 INC 1, 0
 02403 101400 INC 0, 0 ; AC0 = TWICE NO. ROWS + 2
 02404 000403 JMP +3
 02405 030303 TRRET: LDA 2, AMAT0
 02406 113000 ADD 0, 2 ; MOVE DOWN DIAGONAL
 02407 050303 STA 2, AMAT0 ; STORE ELT POINTER
 02410 050302 STA 2, AMAT ; PRESET FIRST ELT POINTER
 02411 034324 LDA 3, M
 02412 054325 STA 3, N ; PRESET COUNTER
 02413 034302 XTR: LDA 3, AMAT
 02414 137000 ADD 1, 3
 02415 054302 STA 3, AMAT ; SET FIRST ELT-POINTER
 02416 006004 FETR ; ENTER FP MODE
 02417 104000 FIC2 ; SET SECOND ELT-POINTER
 02420 026302 FLDA 1, @AMAT
 02421 031000 FLDA 2, 0, 2 ; GET ELTS
 02422 045000 FSTA 1, 0, 2
 02423 052302 FSTA 2, @AMAT ; SWAP ELTS
 02424 100000 FEXT ; EXIT FP MODE
 02425 014325 DSZ N ; SKIP IF DONE ROW
 02426 000765 JMP XTR
 02427 014324 DSZ M ; SKIP IF DONE MATRIX
 02430 000755 JMP TRRET

JMP @ SAVE

RETURN

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•END 7777

AMAT	000302
AMAT0	000303
BMAT	000304
BMAT0	000305
KEEP	000300
L	000322
L0	000323
LRET	002330
M	000324
MRET	002305
MXADD	002230
MXDIV	002355
MXMPY	002272
MXSUB	002251
MXTR	002374
N	000325
N0	000326
NRET	002314
SAVE	000301
TRRET	002405
XADD	002233
XDIV	002360
XMPY	002322
XSUB	002254
XTR	002413
ZERO	000307

; INPUT-OUTPUT SUBROUTINES FOR TTY AND PTP

; REQUIRE BASIC FLOATING-POINT INTERPRETER

```

000040      .LOC 40      ; THESE ARE THE SUBROUTINES
00040 002560      RECV    ; TO BE USED BY FP INSTRUCTIONS
00041 002637      TYPE    ; FDFC AND FFDC, RESPECTIVELY

```

```

000300      KEEP      = 300
000301      SAVE      = 301
000324      M          = 324
000325      N          = 325
000326      NO         = 326

```

```

000355      .LOC 355    ; THESE ARE THE PAGE-0
00355 002440      DATRD  ; ADDRESSES IN WHICH THE
00356 002473      DATPN  ; STARTING ADDRESSES OF
00357 002533      DATRC  ; THE SUBROUTINES CAN BE
00360 002572      DIGIT  ; FOUND.
00361 002600      DATWR
00362 002646      WRITE

```

```

002440      .LOC 2440

```

; SUBR TO STORE DATA FROM PAPER TAPE

```

; ENTER WITH:  AC1      = NO. OF FLOATING-POINT DATA
;               AC2      = STARTING ADR OF STORAGE LOC

```

```

02440 127000  DATRD:  ADD 1, 1      ; DOUBLE AC1
02441 044325      STA 1, N          ; N = NO. OF DATA WORDS
02442 050020      STA 2, 20
02443 014020      DSZ 20            ; SET LOC POINTER
02444 054301      STA 3, SAVE        ; STORE RETURN ADR
02445 060112      NIOS PTR          ; READ A LINE FROM TAPE
02446 063612      SKPDN PTR
02447 000777      JMP --1
02450 060512      DIAS 0, PTR        ; GET RESULT, READ AGAIN
02451 063612      SKPDN PTR
02452 000777      JMP --1
02453 101005      MOV 0, 0, SNR      ; SKIP IF RESULT NON-ZERO
02454 000774      JMP --4
02455 004405      JSR READ           ; GET DATA WORD
02456 042020      STA 0, 020         ; STORE DATA WORD
02457 014325      DSZ N              ; SKIP IF ALL WORDS READ
02460 000775      JMP --3
02461 002301      JMP 0SAVE          ; RETURN

```

```

02462 064512  READ:  DIAS 1, PTR      ; GET RESULT, READ AGAIN
02463 063612      SKPDN PTR
02464 000777      JMP --1
02465 125300      MOVS 1, 1          ; LEFT-JUSTIFY IN AC1
02466 060512      DIAS 0, PTR        ; GET RESULT, READ AGAIN
02467 063612      SKPDN PTR
02470 000777      JMP --1
02471 123000      ADD 1, 0           ; COMBINE HALVES
02472 001400      JMP 0, 3          ; RETURN

```

; SUBR TO PUNCH DATA ON PAPER TAPE

; ENTER WITH: AC1 = NO. OF FLOATING-POINT DATA
 ; AC2 = STARTING ADR OF STORAGE LOC

```

02473 127000 DATPN: ADD 1, 1 ; DOUBLE AC1
02474 044325 STA 1, N ; N = NO. OF DATA WORDS
02475 050020 STA 2, 20
02476 014020 DSZ 20 ; SET LOC POINTER
02477 054301 STA 3, SAVE ; STORE RETURN ADR
02500 102400 SUB 0, 0 ; ZERO AC0
02501 152420 SUBZ 2, 2 ; ZERO AC2, SET CARRY
02502 004421 JSR PUNCH ; PUNCH A ZERO
02503 151103 MOVL 2, 2, SNC ; COUNT OF 17
02504 000776 JMP --2
02505 100000 COM 0, 0 ; SET AC0
02506 061113 DOAS 0, PTP ; PUNCH A 377
02507 063613 SKPDN PTP
02510 000777 JMP --1
02511 022020 LDA 0, 020 ; GET DATA WORD
02512 004411 JSR PUNCH ; PUNCH DATA WORD
02513 014325 DSZ N ; SKIP IF ALL WORDS PUNCHED
02514 000775 JMP --3
02515 102400 SUB 0, 0 ; ZERO AC0
02516 152420 SUBZ 2, 2 ; ZERO AC2, SET CARRY
02517 004404 JSR PUNCH ; PUNCH A ZERO
02520 151103 MOVL 2, 2, SNC ; COUNT OF 17
02521 000776 JMP --2
02522 002301 JMP 0SAVE ; RETURN

02523 105300 PUNCH: MOVS 0, 1 ; RIGHT-JUSTIFY FIRST HALF
02524 065113 DOAS 1, PTP ; PUNCH FIRST HALF
02525 063613 SKPDN PTP
02526 000777 JMP --1
02527 061113 DOAS 0, PTP ; PUNCH SECOND HALF
02530 063613 SKPDN PTP
02531 000777 JMP --1
02532 001400 JMP 0, 3 ; RETURN

```

; SUBR TO STORE DATA FROM KEYBOARD

; ENTER WITH: AC0 = NO. OF ROWS OF FP DATA
 ; AC1 = NO. OF COLUMNS
 ; AC2 = STARTING ADR OF STORAGE LOC

```

02533 040324 DATRC: STA 0, M ; M = NO. OF ROWS
02534 044326 STA 1, N0 ; N0 = NO. OF COLUMNS
02535 054301 STA 3, SAVE ; STORE RETURN ADR
02536 034326 NXTRW: LDA 3, N0
02537 054325 STA 3, N ; N = NO. OF COLUMNS
02540 020503 LDA 0, LF
02541 004476 JSR TYPE ; LINE-FEED
02542 020502 NXTEL: LDA 0, CR
02543 004474 JSR TYPE ; CARRIAGE-RETURN
02544 020477 LDA 0, LF
02545 004472 JSR TYPE ; LINE-FEED
02546 006004 FETR ; ENTER FLOATING-POINT MODE
02547 124000 FDFC 1 ; ACCEPT DEC NO., CONVERT

```

```

02550 045000      FSTA 1, 0, 2      ; STORE HEXADECIMAL NO.
02551 104000      FIC2              ; INC STORAGE-LOC POINTER
02552 100000      FEXT              ; EXIT FP MODE
02553 014325      DSZ N              ; SKIP IF HAVE ALL ELTS OF ROW
02554 000766      JMP NXTEL         ;
02555 014324      DSZ M              ; SKIP IF HAVE ALL ROWS
02556 000760      JMP NXTRW         ;
02557 002301      JMP @SAVE         ; RETURN

```

```

02560 054300  RECV: STA 3, KEEP      ; STORE RETURN ADR
02561 060110      NIOS TTI          ; ENABLE KEYBOARD
02562 063610      SKPDN TTI
02563 000777      JMP -1            ; WAIT FOR CHARACTER
02564 060410      DIA 0, TTI        ; GET CHARACTER
02565 024404      LDA 1, MASK       ; AC1 = 177
02566 123400      AND 1, 0          ; MASK TO 7 BITS
02567 004450      JSR TYPE          ; ECHO CHARACTER
02570 002300      JMP @KEEP         ; RETURN
02571 000177  MASK: 177

```

; SUBR TO ACCEPT A DIGIT FROM KEYBOARD

; BINARY VALUE OF DIGIT IS LEFT IN AC0

```

02572 054301  DIGIT: STA 3, SAVE     ; STORE RETURN ADR
02573 004765      JSR RECV          ; RETURN DIGIT IN AC0
02574 024403      LDA 1, DTMSK      ; AC1 = 17
02575 123400      AND 1, 0          ; MASK TO 4 BITS
02576 002301      JMP @SAVE         ; RETURN
02577 000017  DTMSK: 17

```

; SUBR TO TYPE DATA ON TELEPRINTER

; ENTER WITH: AC0 = NO. OF ROWS OF FP DATA
 ; AC1 = NO. OF COLUMNS
 ; AC2 = FIRST ADR WHERE DATA STORED

```

02600 040324 DATWR: STA 0, M      ; LOC M = NO. OF ROWS
02601 044326      STA 1, N0     ; N0 = NO. OF COLUMNS
02602 054301      STA 3, SAVE    ; STORE RETURN ADR
02603 125112 ROW:  MOVL# 1, 1, SZC ; SKIP IF 2 LINES TYPED
02604 000403      JMP .+3        ; NO LINE-FEED
02605 020436      LDA 0, LF      ;
02606 004431      JSR TYPE       ; LINE-FEED
02607 024427      LDA 1, COLS    ; AC1 = -4
02610 034326      LDA 3, N0     ;
02611 054325      STA 3, N      ; N = NO. OF COLUMNS
02612 020432 LINE: LDA 0, CR     ;
02613 004424      JSR TYPE       ; CARRIAGE-RETURN
02614 020427      LDA 0, LF      ;
02615 004422      JSR TYPE       ; LINE-FEED
02616 020427 ELT:  LDA 0, SP     ;
02617 004420      JSR TYPE       ; SPACE
02620 004417      JSR TYPE       ; SPACE
02621 006004      FETR          ; ENTER FP MODE
02622 021000      FLDA 0, 0, 2   ; LOAD HEX FP NO. IN FAC0
02623 140000      FFDC 0         ; TYPE NO. IN DEC FP
02624 104000      FIC2          ; INC STORAGE-LOC POINTER
02625 100000      FEXT          ; EXIT FP MODE
02626 014325      DSZ N          ; SKIP IF DONE ALL ELTS OF ROW
02627 000404      JMP .+4        ;
02630 014324      DSZ M          ; SKIP IF DONE ALL ROWS
02631 000752      JMP ROW       ;
02632 002301      JMP @SAVE      ; RETURN
02633 125404      INC 1, 1, SZR  ; SKIP IF FINISHED LINE
02634 000762      JMP ELT       ;
02635 000755      JMP LINE      ;
02636 177774 COLS: -4           ;

02637 061111 TYPE: DOAS 0, TTO   ; TYPE CHARACTER
02640 063611      SKPDN TTO      ;
02641 000777      JMP .-1        ;
02642 001400      JMP 0, 3       ; RETURN
02643 000012 LF:   12           ;
02644 000015 CR:   15           ;
02645 000040 SP:   40           ;

```

; SUBR TO TYPE A STRING OF 8 CHARACTERS

; ENTER WITH AC2 = STARTING ADR OF STRING

```

02646 054301 WRITE: STA 3, SAVE   ; STORE RETURN ADR
02647 020775      LDA 0, CR       ;
02650 004767      JSR TYPE        ; CARRIAGE RETURN
02651 020772      LDA 0, LF       ;
02652 004765      JSR TYPE        ;
02653 004764      JSR TYPE        ; DOUBLE-SPACE
02654 024762      LDA 1, COLS     ; AC1 = -4
02655 021000 CHAR: LDA 0, 0, 2   ; GET WORD

```

```
02656 101300      MOVS 0, 0      ; SWAP HALVES
02657 101200      MOVR 0, 0      ; SHIFT RIGHT
02660 004757      JSR TYPE      ; PRINT 1ST CHARACTER
02661 021000      LDA 0, 0, 2    ; GET WORD AGAIN
02662 004755      JSR TYPE      ; PRINT 2ND CHARACTER
02663 151400      INC 2, 2      ; INC LOC POINTER
02664 125404      INC 1, 1, SZR  ; SKIP IF DONE
02665 000770      JMP CHAR
02666 002301      JMP @SAVE      ; RETURN
```

007777

•END 7777

CHAR 002655
COLS 002636
CR 002644
DATPN 002473
DATRC 002533
DATRD 002440
DATWR 002600
DIGIT 002572
DTMSK 002577
ELT 002616
KEEP 000300
LF 002643
LINE 002612
M 000324
MASK 002571
N 000325
NØ 000326
NXTEL 002542
NXTRW 002536
PUNCH 002523
READ 002462
RECV 002560
ROW 002603
SAVE 000301
SP 002645
TYPE 002637
WRITE 002646

; RECURSIVE LEAST-SQUARES IDENTIFICATION

; REQUIRES: BASIC FP INTERPRETER
 ; MATRIX ARITHMETIC SUBROUTINES
 ; I/O SUBROUTINES FOR TTY, TAPE
 ; DATA-SUPPLY PROGRAMMES

; THIS PROGRAMME USES THE MAXIMUM
 ; NO. OF SYMBOLS ALLOWED BY THE
 ; RELOCATABLE ASSEMBLER. DO NOT ADD ANY MORE.

000312	R	= 312
000313	S	= 313
000314	RS	= 314
000315	SS	= 315
000316	I	= 316
000317	J	= 317
000321	K2	= 321
000322	L	= 322
000324	M	= 324
000325	N	= 325
000350	MXADD	= 350
000351	MXSUB	= 351
000352	MXMPY	= 352
000353	MXDIV	= 353
000354	MXIR	= 354
000355	DATRD	= 355
000356	DATPN	= 356
000357	DATRC	= 357
000360	DIGIT	= 360
000361	DATNR	= 361
000362	WRITE	= 362
000363	INIT	= 363
000364	MEAS	= 364
000365	DATIM	= 365
000366	DTOUT	= 366

000002 000002 .LOC 2
 000002 000344 JMP 0344

000007 000007 .LOC 7
 000007 000400 400 ; WORK AREA FOR FP INTERPRETER

000311 000001 ONE: .LOC 311
 1

000330	000500	A:	500	; MATRIX ADDRESSES
000331	000700	P:	700	
000332	001100	Q:	1100	
000333	001300	TEMP1:	1300	
000334	001500	TEMP2:	1500	
000335	001700	TEMP3:	1700	
000336	002100	H:	2100	
000337	002120	C:	2120	
000340	002140	R:	2140	
000341	002160	CSQU:	2160	
000342			.LOC 342	


```

00342 040420 CTHR: 040420
00343 000000 0
000344 .LOC 344
00344 002700 BEGIN
00345 003054 START
00346 040420 V: 040420
00347 000000 0
000370 .LOC 370
00370 002170 STR1: 2170 ; ADDRESSES OF STRINGS
00371 002174 STR2: 2174
00372 002200 STR3: 2200
00373 002204 STR4: 2204
00374 002210 STR5: 2210
00375 002214 STR6: 2214
00376 002220 STR7: 2220
00377 002224 STR8: 2224

002170 .LOC 2170 ; MESSAGE STRINGS IN ASCII
00170 122040 ; STRING 1: "R = "
02171 075040 075040
02172 040040 040040
02173 040040 040040
02174 123040 ; STRING 2: "S = "
02175 075040 075040
02176 040040 040040
02177 040040 040040
02200 123101 ; STRING 3: "SAMPLES?"
02201 115120 115120
02202 114105 114105
02203 123077 123077
02204 103117 ; STRING 4: "COPY?"
02205 120131 120131
02206 077040 077040
02207 040040 040040
02210 120101 ; STRING 5: "PARAMS"
02211 122101 122101
02212 115123 115123
02213 040040 040040
02214 120055 ; STRING 6: "P-MATRIX"
02215 115101 115101
02216 124122 124122
02217 111130 111130
02220 122105 ; STRING 7: "READY?"
02221 101104 101104
02222 131077 131077
02223 040040 040040
02224 103124 ; STRING 8: "CTHR, V:"
02225 110122 110122
02226 054040 054040
02227 126072 126072

```

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002700 .LOC 2700 ; PROGRAMME BEGINS

```

```

02700 006305 BEGIN: FINI
02701 030370 LDA 2, STR1
02702 006362 JSR @WRITE ; PRINT "R = ?"
02703 006362 JSR @DIGIT ; GET R
02704 040312 STA 0, R

```

```

0003 .MAIN
02705 030371 LDA 2, STR2
02706 006362 JSR @WRITE ; PRINT "S = ?"
02707 006362 JSR @DIGIT ; GET S
02710 040313 STA 0, S
02711 040325 STA 0, N
02712 126400 SUB 1, 1
02713 107000 ADD 0, 1
02714 014325 DSZ N
02715 000776 JMP .-2
02716 044315 STA 1, SS ; SS = SQUARE OF S
02717 034312 LDA 3, R
02720 054325 STA 3, N
02721 126400 SUB 1, 1
02722 107000 ADD 0, 1
02723 014325 DSZ N
02724 000776 JMP .-2
02725 044314 STA 1, RS ; LOC RS = PRODUCT OF R AND S
02726 030372 LDA 2, STR3
02727 006362 JSR @WRITE ; PRINT "SAMPLES?"
02730 102520 SUBZL 2, 0
02731 126520 SUBZL 1, 1
02732 030333 LDA 2, TEMP1
02733 006357 JSR @DATRC ; GET K0
02734 030333 LDA 2, TEMP1
02735 006004 FETR
02736 075000 FFIX 0, 2
02737 100000 FEXT
02740 035001 LDA 3, 1, 2
02741 054321 STA 3, K0 ; K0 = NO. OF RAPID SAMPLES
02742 030373 COPY: LDA 2, STR4
02743 006362 JSR @WRITE ; PRINT "COPY?"
02744 006362 JSR @DIGIT ; GET I
02745 040316 STA 0, I
02746 101005 MOV 0, 0, SNR ; SKIP IF I = 0
02747 000476 JMP READY ; NO STARTING VALUES
02750 040317 STA 0, J
02751 014317 OPT1: DSZ J ; SAME STARTING VALUES
02752 000402 JMP OPT2
02753 000472 JMP READY
02754 014317 OPT2: DSZ J ; PAPER-TAPE COPY
02755 000407 JMP OPT3
02756 024314 LDA 1, RS
02757 030333 LDA 2, A
02760 006356 JSR @DATPN
02761 024315 LDA 1, SS
02762 030331 LDA 2, P
02763 006356 JSR @DATPN
02764 014317 OPT3: DSZ J ; TELETYPE COPY
02765 000415 JMP OPT4
02766 030374 LDA 2, STR5
02767 006362 JSR @WRITE
02770 020313 LDA 0, S
02771 024312 LDA 1, R
02772 030330 LDA 2, A
02773 006361 JSR @DATWR
02774 030375 LDA 2, STR6
02775 006362 JSR @WRITE
02776 020313 LDA 0, S
02777 024313 LDA 1, S

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03000 030331 LDA 2, P
03001 006361 JSR @DATWR
03002 014317 OPT4: DSZ J ; STARTING VALUES FROM TAPE
03003 000427 JMP OPT5
03004 024314 LDA 1, RS
03005 030330 LDA 2, A
03006 006355 JSR @DATRD
03007 024315 LDA 1, SS
03010 030331 LDA 2, P
03011 006355 JSR @DATRD
03012 014317 OPT5: DSZ J ; STARTING VALUES FROM KBD
03013 000415 JMP OPT6
03014 030374 LDA 2, STR5
03015 006362 JSR @WRITE ; PRINT "PARAMS"
03016 020313 LDA 0, S
03017 024312 LDA 1, R
03020 030330 LDA 2, A
03021 006357 JSR @DATRC
03022 030375 LDA 2, STR6
03023 006362 JSR @WRITE ; PRINT "P-MATRIX"
03024 020313 LDA 0, S
03025 024313 LDA 1, S
03026 030331 LDA 2, P
03027 006357 JSR @DATRC
03030 014317 OPT6: DSZ J ; STARTING VALUES SUPPLIED
03031 000402 JMP .+2 ; BY USER SUBROUTINE
03032 006363 JSR @INIT
03033 014317 OPT7: DSZ J ; CHANGE CTHR AND V
03034 000411 JMP READY
03035 030377 LDA 2, STR3
03036 006362 JSR @WRITE ; PRINT "CTHR, V:"
03037 006004 FETR
03040 120000 FDRC 0 ; GET CTHR
03041 124000 FDRC 1 ; GET V
03042 040342 FSTA 0, CTHR ; STORE CTHR
03043 044346 FSTA 1, V ; STORE V
03044 100000 FEXT
03045 030376 READY: LDA 2, STR7
03046 006362 JSR @WRITE ; PRINT "READY?"
03047 006360 JSR @DIGIT
03050 101005 MOV 0, 0, SNR
03051 000671 JMP COPY
03052 002364 JMP @MEAS ; USER PROGRAMME
03053 003260 SEQ2

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03054 006365 START: JSR @DATIN ; USER PROGRAMME
03055 034316 LDA 3, I
03056 175004 MOV 3, 3, SZR ; SKIP IF I = 0
03057 002774 JMP @START-1
03060 034313 LDA 3, S
03061 054317 STA 3, J ; SET COUNTER: J = S
03062 102400 SUB 0, 2 ; A, P, 0 = 0
03063 030333 LDA 2, TEMPI
03064 034330 LDA 3, A
03065 041400 STA 0, 0, 3
03066 175400 INC 3, 3
03067 172414 SUB# 3, 2, SZR
03070 000775 JMP .-3
03071 000332 LOOP: LDA 0, 0 ; 1. QH
03072 024336 LDA 1, H
03073 030337 LDA 2, C
03074 034313 LDA 3, S
03075 054322 STA 3, L
03076 054324 STA 3, M
03077 034311 LDA 3, ONE
03100 054325 STA 3, N
03101 006352 JSR @XMPY
03102 000336 LDA 0, H ; 2. C = H - QH
03103 024337 LDA 1, C
03104 030337 LDA 2, C
03105 034313 LDA 3, S
03106 054325 STA 3, N
03107 006351 JSR @XSUB
03110 000337 LDA 0, C ; 3. C/C
03111 024337 LDA 1, C
03112 030341 LDA 2, CSQU
03113 034313 LDA 3, S
03114 054322 STA 3, L
03115 034311 LDA 3, ONE
03116 054324 STA 3, M
03117 054325 STA 3, N
03120 006352 JSR @XMPY
03121 006004 FETR ; 4. C TOO SMALL?
03122 000342 FLDA 0, CTHR
03123 006341 FLDA 1, @CSQU
03124 106406 FSUB 0, 1, FSLE
03125 000403 FJMP .+3
03126 102000 FEXT
03127 000725 JMP START
03130 100000 FEXT
03131 000337 SEQ1: LDA 0, C ; 5. B = C/C'C
03132 024341 LDA 1, CSQU
03133 030340 LDA 2, B
03134 034313 LDA 3, S
03135 054325 STA 3, N
03136 006353 JSR @XDIV
03137 000336 LDA 0, H ; 6. HB'
03140 024340 LDA 1, B
03141 030333 LDA 2, TEMPI
03142 034311 LDA 3, ONE
03143 054322 STA 3, L
03144 034313 LDA 3, S
03145 054324 STA 3, M
03146 054325 STA 3, N

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03147 006352 JSR @MXMPY
03150 020331 LDA 0, P ; 7. PHB'
03151 024333 LDA 1, TEMP1
03152 030334 LDA 2, TEMP2
03153 034313 LDA 3, S
03154 054322 STA 3, L
03155 054324 STA 3, M
03156 054325 STA 3, N
03157 006352 JSR @MXMPY
03160 020331 LDA 0, P ; 8. P - PHB'
03161 024334 LDA 1, TEMP2
03162 030331 LDA 2, P
03163 034315 LDA 3, SS
03164 054325 STA 3, N
03165 006351 JSR @MXSUB
03166 024313 LDA 1, S ; 9. (BH'P)(HB')
03167 030334 LDA 2, TEMP2
03170 006354 JSR @MXTR
03171 020334 LDA 0, TEMP2
03172 024333 LDA 1, TEMP1
03173 030335 LDA 2, TEMP3
03174 034313 LDA 3, S
03175 054322 STA 3, L
03176 054324 STA 3, M
03177 054325 STA 3, N
03200 006352 JSR @MXMPY
03201 020340 LDA 0, B ; 10. BB'
03202 024342 LDA 1, B
03203 030333 LDA 2, TEMP1
03204 034311 LDA 3, ONE
03205 054322 STA 3, L
03206 034313 LDA 3, S
03207 054324 STA 3, M
03210 054325 STA 3, N
03211 006352 JSR @MXMPY
03212 020331 LDA 0, P ; 11. (P - PHB') - BH'P
03213 024334 LDA 1, TEMP2
03214 030331 LDA 2, P
03215 034315 LDA 3, SS
03216 054325 STA 3, N
03217 006351 JSR @MXSUB
03220 020331 LDA 0, P ; 12. (P-PHB'-BH'P)+BH'PHB'
03221 024335 LDA 1, TEMP3
03222 030331 LDA 2, P
03223 034315 LDA 3, SS
03224 054325 STA 3, N
03225 006350 JSR @MXADD
03226 020331 LDA 0, P ; 13. P=(P-PHB'-BH'P
03227 024333 LDA 1, TEMP1 ; +BH'PHB')+BB'
03230 030331 LDA 2, P
03231 034315 LDA 3, SS
03232 054325 STA 3, N
03233 006350 JSR @MXADD
03234 020340 LDA 0, B ; 14. BC'
03235 024337 LDA 1, C
03236 030333 LDA 2, TEMP1
03237 034311 LDA 3, ONE
03240 054322 STA 3, L
03241 034313 LDA 3, S

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03242 054324 STA 3, M
03243 054325 STA 3, N
03244 006352 JSR @XMPY
03245 020332 LDA 0, Q ; 15. Q = Q +, BC'
03246 024333 LDA 1, TEMP1
03247 030332 LDA 2, Q
03250 034315 LDA 3, SS
03251 054325 STA 3, N
03252 026350 JSR @XADD
03253 004465 JSR EST
03254 014317 DSZ J
03255 000614 JMP LOOP
03256 034311 LDA 3, ONE
03257 054316 STA 3, I
03260 020331 SEQ2: LDA 0, P ; 16. PH
03261 024336 LDA 1, H
03262 030333 LDA 2, TEMP1
03263 034313 LDA 3, S
03264 054322 STA 3, L
03265 054324 STA 3, M
03266 034311 LDA 3, ONE
03267 054325 STA 3, N
03270 026352 JSR @XMPY
03271 020336 LDA 0, H ; 17. H'PH
03272 024333 LDA 1, TEMP1
03273 030334 LDA 2, TEMP2
03274 034313 LDA 3, S
03275 054322 STA 3, L
03276 034311 LDA 3, ONE
03277 054324 STA 3, M
03300 054325 STA 3, N
03301 006352 JSR @XMPY
03302 026204 FEIR ; 18. V + H'PH
03303 020346 FLDA 0, V
03304 026334 FLDA 1, @TEMP2
03305 107000 FADD 0, 1
03306 046334 FSTA 1, @TEMP2
03307 100000 FEXT
03310 020333 LDA 0, TEMP1 ; 19. B = PH/(V+H'PH)
03311 024334 LDA 1, TEMP2
03312 030340 LDA 2, B
03313 034313 LDA 3, S
03314 054325 STA 3, N
03315 006353 JSR @XDIV
03316 020333 LDA 0, TEMP1 ; 20. (PH)3'
03317 024340 LDA 1, B
03320 030335 LDA 2, TEMP3
03321 034311 LDA 3, ONE
03322 054322 STA 3, L
03323 034313 LDA 3, S
03324 054324 STA 3, M
03325 054325 STA 3, N
03326 006352 JSR @XMPY
03327 020331 LDA 0, P ; 21. P = P - PH3'
03330 024335 LDA 1, TEMP3
03331 030331 LDA 2, P
03332 034315 LDA 3, SS
03333 054325 STA 3, N
03334 026351 JSR @XSUB

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03335 004403 JSR EST
03336 000722 JMP SEQ2
03337 000000 0
03340 054777 EST: STA 3, .-1
03341 020336 LDA 0, H ; 22. H'A
03342 024330 LDA 1, A
03343 030334 LDA 2, TEMP2
03344 034313 LDA 3, S
03345 054322 STA 3, L
03346 034311 LDA 3, ONE
03347 054324 STA 3, M
03350 034312 LDA 3, R
03351 054325 STA 3, N
03352 006352 JSR @MXPY
03353 006365 JSR @DATIN ; 23. Z' - H'A
03354 020336 LDA 0, H
03355 024334 LDA 1, TEMP2
03356 030335 LDA 2, TEMP3
03357 034312 LDA 3, R
03360 054325 STA 3, N
03361 006351 JSR @MXSUB
03362 020340 LDA 0, B ; 24. B(Z'-H'A)
03363 024335 LDA 1, TEMP3
03364 030333 LDA 2, TEMP1
03365 034311 LDA 3, ONE
03366 054322 STA 3, L
03367 034313 LDA 3, S
03370 054324 STA 3, M
03371 034312 LDA 3, R
03372 054325 STA 3, N
03373 006352 JSR @MXPY
03374 020330 LDA 0, A ; 25. A=A+B(Z'-H'A)
03375 024333 LDA 1, TEMP1
03376 030330 LDA 2, A
03377 034314 LDA 3, RS
03400 054325 STA 3, N
03401 006350 JSR @MXADD
03402 006366 JSR @DIOUT ; USER PROGRAMME
03403 002734 JMP @EST-1

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002700

.END 2700

A	000330
B	000340
BEGIN	002700
C	000337
COPY	002742
CSQU	000341
CTHR	000342
DATIN	000355
DATPN	000356
DATRC	000357
DATRD	000355
DATWR	000361
DIGIT	000360
DTOUT	000366
EST	000342
H	000336
I	000315
INIT	000363
J	000317
K0	000321
L	000322
LOOP	000371
M	000324
MEAS	000354
MXADD	000350
MXDIV	000353
MXMPY	000352
MXSUB	000351
MXTR	000354
N	000325
ONE	000311
OPT1	002751
OPT2	002754
OPT3	002764
OPT4	003002
OPT5	003012
OPT6	003030
OPT7	003033
P	000331
Q	000332
R	000312
READY	003045
RS	000314
S	000313
SEQ1	003131
SEQ2	003260
SS	000315
START	003054
STR1	000370
STR2	000371
STR3	000372
STR4	000373
STR5	000374
STR6	000375
STR7	000376
STR8	000377
TEMP1	000333
TEMP2	000334
TEMP3	000335

0010 .MAIN
V 000346
WRITE 000362

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