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ESTIMATION OF PARAMETERS IN SYSTEMS OF
RELATIVELY SLOW TIME VARIATION

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ESTIMATION OF PARAMETERS IN SYSTEMS OF RELATIVELY SLOW TIME VARIATION*

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ABSTRACT

The estimation of parameters for a rather general class of nonlinear, time-varying, causal, bounded memory systems is discussed. A model for such systems is established using the concept that the system variation is unknown, but bounded between observation times. A recursive estimation algorithm is developed for the model, and both upper and lower bounds are found for the guaranteed error of estimation.

DEVELOPMENT OF THE SYSTEM MODEL

In this paper the term system means simply a mapping from an appropriate space of inputs to an appropriate space of outputs. The central purpose of the paper is to obtain estimates on how rapidly causal systems, of a certain rather general class that includes nonlinear as well as linear systems, can vary with time and still allow adequate experimental identification.

A particular kind of system model is especially appropriate for this study and is used here. It has the features that it is linear in the parameters, even though the system itself may be nonlinear, and that it is widely applicable if the only noise to be considered is output observation noise. We briefly and heuristically describe such a model in a special case in what follows, and this is sufficient for this paper. However there is a general theory of such models, and most of the ad hoc assumptions made below can either be shown to be justifiable or not needed (see [1]).

Let \mathcal{X} be an arbitrary input space, \mathcal{Y} a linear output space, and \mathcal{H} a set of mappings from \mathcal{X} into \mathcal{Y} (i.e., \mathcal{H} is a class of "systems"), so that one may write

$$y = h(x), \quad x \in \mathcal{X}, \quad y \in \mathcal{Y}, \quad h \in \mathcal{H}. \quad (1)$$

Each $x \in \mathcal{X}$ determines a function from \mathcal{H} into \mathcal{Y} . If this function is denoted by X , then

$$y = X(h), \quad h \in \mathcal{H}. \quad (2)$$

Let addition and scalar multiplication be defined in \mathcal{H} in the way they usually are for functions and then extend \mathcal{H} , if necessary, so that it is closed under linear combinations. Denote this linear extension by \mathcal{F} . It is now trivial to verify that the mapping X as extended to \mathcal{F} will be linear, even

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though the mapping h may be nonlinear (see e.g., [1]). If additive output noise is present, (1) and (2) are replaced by

$$y = h(x) + v \quad (3)$$

and

$$y = Xh + v, \quad h \in \mathcal{F}, \quad (4)$$

where v is a random variable taking values in \mathcal{Y} and X is linear. Thus the problem of identifying the system has been put in the form of the classical problem of estimating h in the linear model (4). Of course, equation (4) is abstract, so we now need to specialize it so as to have a meaningful estimation problem. Here we simply assume what we need in order to do this easily.

Suppose that a system with vector-valued inputs and outputs can be adequately represented in terms of sampled inputs and outputs. Furthermore, assume that it has bounded memory (this is the only critical assumption). Then an input is a vector sequence $\{x_k\}$, the corresponding output is a vector sequence $\{y_k\}$, and if the system has memory m ,

$$\begin{aligned} \text{or } y_k &= h_k(x_k, x_{k-1}, \dots, x_{k-m}) + v_k \\ \text{where } y_k &= h_k(x_k) + v_k, \quad k = 1, 2, \dots, \\ \underline{x}_k &\stackrel{d}{=} (x_k, x_{k-1}, \dots, x_{k-m}). \end{aligned} \quad (5)$$

If the system is time-invariant each h_k is the same; otherwise, of course, the h_k 's are different. To each \underline{x}_k there corresponds a linear mapping X_k defined, as before, by $X_k \underline{x}_k \stackrel{d}{=} h_k(\underline{x}_k)$, so that

$$y_k = X_k h_k + v_k, \quad k = 1, 2, \dots \quad (6)$$

Let there be imposed the further condition that all the mappings $h_k \in \mathcal{F}$ are fully characterized by a finite set of parameters, say p in number. The $\{h_k\}$ can then be represented by p -vectors, and if the output is an r -vector, the $\{X_k\}$ can be represented by $r \times p$ matrices.

If the systems in \mathcal{F} are of uniformly bounded time variation for each finite interval, one can write

$$h_{k+1} = h_k + w_k, \quad k = 1, 2, \dots, \quad (7)$$

where each component of w_k is bounded. The system model then becomes

$$\begin{cases} h_{k+1} = h_k + w_k \\ y_k = X_k h_k + v_k, \quad k = 1, 2, \dots, \end{cases} \quad (8)$$

where the $\{w_k\}$ are bounded, unknown elements of R^p and the $\{v_k\}$ are random variables representing output noise. The equations (8) are, of course, in the form of the system equations for a degenerate linear dynamical system, but the interpretation given to them is entirely different.

We wish to consider successive blocks of measurements where each block

consists of tests with the same suitably chosen N inputs (x_1, \dots, x_N) . We make the important simplifying assumption that the system parameters change only between blocks of measurements. Results can be obtained without this assumption (see [3]), but there is not space to go into the additional argument necessary here. This assumption gives an acceptable approximation anyway in many cases where there is only slight variation within the blocks.

With this assumption we have

$$\begin{cases} h^{k+1} = h^k + w^k \\ y^k = Xh^k + v^k, \quad k = 1, 2, \dots, \end{cases} \quad (9)$$

where $h^k \triangleq h_{kN}$ and

$$y^k = \begin{bmatrix} y_{(k-1)N+1} \\ y_{(k-1)N+2} \\ \vdots \\ y_{kN} \end{bmatrix}, \quad X \triangleq \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix}, \quad v^k = \begin{bmatrix} v_{(k-1)N+1} \\ v_{(k-1)N+2} \\ \vdots \\ v_{kN} \end{bmatrix}.$$

The condition to be imposed on the inputs (x_1, \dots, x_N) is that the operator X has zero null space, so that the vector h^k is estimable. The usual assumptions are made about the noise,

$$E v^k = 0, \quad E v^k (v^j)^T = R \delta_{jk}, \quad (10a)$$

where R is strictly definite. The boundedness condition on the w^k is taken to be in the form,

$$|(w^k, \psi_i)| \leq \eta_k, \quad i = 1, \dots, p, \quad (10b)$$

for all $k = 1, 2, \dots$, where $\{\psi_i\}$ is a complete orthonormal basis of eigenvectors of $(X^T R^{-1} X)^{-1}$, i.e.,

$$(X^T R^{-1} X)^{-1} \psi_i = \sigma_i^2 \psi_i, \quad i = 1, \dots, p.$$

The eigenvalues $\{\sigma_i^2\}$ are real and nonnegative.

ESTIMATION OF PARAMETERS

We now derive a recursive estimation algorithm for the parameter vector h^k and obtain a uniform upper bound on the mean-squared error. Since the actual mean-squared error depends on the $\{w^k\}$, which are unknown, an exact expression for mean-squared error cannot be given, of course.

We begin by forming the standard linear, unbiased, minimum variance (LUMV) estimate of h^1

$$\hat{h}^1 = C y^1, \quad (11)$$

where $C \triangleq (X^T R^{-1} X)^{-1} X^T R^{-1}$. The error in this estimate satisfies

$$E\|\hat{h}^1 - h^1\|^2 = \sum_{i=1}^p \sigma_i^2 = \sum_{i=1}^p b_{1i}^2 \quad (12)$$

where $b_{1i}^2 \triangleq \sigma_i^2$, $i = 1, \dots, p$. Now consider the second observation

$$y^2 = Xh^2 + v^2 = Xh^1 + Xw^1 + v^2,$$

which can be rewritten as

$$y^2 - Xh^1 = X[(h^1 - \hat{h}^1) + w^1] + v^2. \quad (13)$$

Define $z^2 \triangleq y^2 - Xh^1$ and $\xi^1 \triangleq (h^1 - \hat{h}^1) + w^1 = h^2 - \hat{h}^1$ so that (13) becomes

$$z^2 = X\xi^1 + v^2. \quad (14)$$

Let $\hat{\xi}^1$ be a linear estimate of ξ^1 that is a function of Cz^2 , but is otherwise arbitrary. Thus,

$$\hat{\xi}^1 = \sum_{i,j=1}^p a_{ij} (Cz^2, \psi_j) \psi_i \quad (15)$$

where the (a_{ij}) are real numbers. The error in this estimate is given by

$$\begin{aligned} \xi^1 - \hat{\xi}^1 &= \sum_{i=1}^p \left[(a_{ii} - 1) (\xi^1, \psi_i) + \sum_{\substack{j=1 \\ (j \neq i)}}^p a_{ij} (\xi^1, \psi_j) \right. \\ &\quad \left. + \sum_{j=1}^p a_{ij} (Cv^2, \psi_j) \right] \psi_i. \end{aligned} \quad (16)$$

Therefore, it follows from (10a) and the properties of the $\{\psi_i\}$ that

$$\begin{aligned} E\|\hat{\xi}^1 - \xi^1\|^2 &= \sum_{i=1}^p E \left[(a_{ii} - 1) (\xi^1, \psi_i) + \sum_{\substack{j=1 \\ (j \neq i)}}^p a_{ij} (\xi^1, \psi_j) \right]^2 \\ &\quad + \sum_{i,j=1}^p a_{ij}^2 \sigma_j^2 \leq 2 \sum_{i=1}^p (a_{ii} - 1)^2 E[(\xi^1, \psi_i)^2] \\ &\quad + 2 \sum_{i=1}^p E \left[\sum_{\substack{j=1 \\ (j \neq i)}}^p a_{ij} (\xi^1, \psi_j) \right]^2 + \sum_{i,j=1}^p a_{ij}^2 \sigma_j^2 \end{aligned} \quad (17)$$

To minimize the upper bound in (17), one should obviously choose $a_{ij} = 0$ for $i \neq j$. Making this choice yields

$$E\|\hat{\xi}^1 - \xi^1\|^2 = \sum_{i=1}^p (a_{ii} - 1)^2 E[(\xi^1, \psi_i)^2] + \sum_{i=1}^p a_{ii}^2 \sigma_i^2 \quad (18)$$

Now

$$\begin{aligned} E[(\xi^1, \psi_i)^2] &= E[(h^1 - \hat{h}^1, \psi_i)^2] + 2E[(h^1 - \hat{h}^1, \psi_i)(w^1, \psi_i)] + E[(w^1, \psi_i)^2] \\ &\leq b_{1i}^2 + 2b_{1i}\eta_i + \eta_i^2 = (b_{1i} + \eta_i)^2, \end{aligned}$$

*Obviously $E[(h^1 - \hat{h}^1, \psi_i)(w^1, \psi_i)] = 0$, but in general $E[(h^n - \hat{h}^n, \psi_i)(w^n, \psi_i)] \neq 0$, $n \geq 2$.

so

$$E\|\xi^1 - \xi^1\|^2 \leq \sum_{i=1}^p \left[(a_{ii} - 1)^2 (b_{1i} + \eta_i)^2 + a_{ii}^2 \sigma_i^2 \right]. \quad (19)$$

The upper bound in (19) is minimized by putting

$$a_{ii} = \frac{(b_{1i} + \eta_i)^2}{(b_{1i} + \eta_i)^2 + \sigma_i^2}, \quad i = 1, \dots, p.$$

The linear estimate that results when these values are used is

$$\hat{\xi}^1 = \sum_{i=1}^p \frac{(b_{1i} + \eta_i)^2}{(b_{1i} + \eta_i)^2 + \sigma_i^2} (Cz^2, \psi_i) \psi_i. \quad (20)$$

Since $h^2 = \hat{h}^1 + \hat{\xi}^1$, the estimate of h^2 is taken to be

$$\hat{h}^2 = \hat{h}^1 + \hat{\xi}^1. \quad (21)$$

Then

$$\begin{aligned} E\|\hat{h}^2 - h^2\|^2 &= E\|(\hat{h}^1 + \hat{\xi}^1) - (\hat{h}^1 + \xi^1)\|^2 = E\|\hat{\xi}^1 - \xi^1\|^2 \\ &\leq \sum_{i=1}^p \left\{ \left[\frac{(b_{1i} + \eta_i)^2}{(b_{1i} + \eta_i)^2 + \sigma_i^2} - 1 \right]^2 (b_{1i} + \eta_i)^2 \right. \\ &\quad \left. + \left[\frac{(b_{1i} + \eta_i)^2}{(b_{1i} + \eta_i)^2 + \sigma_i^2} \right]^2 \sigma_i^2 \right\} = \sum_{i=1}^p \frac{(b_{1i} + \eta_i)^2 \sigma_i^2}{(b_{1i} + \eta_i)^2 + \sigma_i^2} = \sum_{i=1}^p b_{2i}^2 \end{aligned} \quad (22)$$

where

$$b_{2i}^2 \triangleq \frac{(b_{1i} + \eta_i)^2 \sigma_i^2}{(b_{1i} + \eta_i)^2 + \sigma_i^2}, \quad i = 1, \dots, p.$$

If this process is continually repeated, we obtain the estimation algorithm

$$\begin{aligned} \hat{h}^k &= \hat{h}^{k-1} + \hat{\xi}^{k-1} \\ \hat{\xi}^{k-1} &= \sum_{i=1}^p \frac{(b_{(k-1)i} + \eta_i)^2 \sigma_i^2}{(b_{(k-1)i} + \eta_i)^2 + \sigma_i^2} (Cy^k - \hat{h}^{k-1}, \psi_i) \psi_i \\ b_{ki}^2 &= \frac{(b_{(k-1)i} + \eta_i)^2 \sigma_i^2}{(b_{(k-1)i} + \eta_i)^2 + \sigma_i^2}, \quad i = 1, \dots, p. \end{aligned} \quad (23)$$

The initial conditions are given by

$$\hat{h}^1 = Cy^1, \quad b_{1i}^2 = \sigma_i^2, \quad i = 1, \dots, p \quad (24)$$

and the error in the estimate of h^k satisfies

$$E\|\hat{h}^k - h^k\|^2 \leq \sum_{i=1}^p b_{ki}^2 \quad (25)$$

Lemma 1. If $f(x)$ is twice continuously differentiable for $x > 0$ and satisfies

$$(i) \quad \lim_{x \rightarrow 0^+} f(x) > 0$$

- (ii) $\lim_{x \rightarrow \infty} f(x) < \infty$
 (iii) $\frac{df(x)}{dx} > 0, x > 0$
 (iv) $\frac{d^2f(x)}{dx^2} < 0, x > 0$

then (a) $f(x) = x$ has a unique solution x^* for $x > 0$.

(b) the sequence $x_n = f(x_{n-1}), x_1 > 0$, converges to x^* .

Proof: Follows from elementary arguments. ||| The limiting upper bound can now be established.

Proposition 1. If x_i^* is the solution of the equation

$$\frac{(x^{1/2} + \eta_i)^2 \sigma_i^2}{(x^{1/2} + \eta_i)^2 + \sigma_i^2} = x,$$

then $\lim_{n \rightarrow \infty} b_{ni}^2 = x_i^*$.

Proof: Define

$$\phi(x) \triangleq \frac{(x^{1/2} + \eta_i)^2 \sigma_i^2}{(x^{1/2} + \eta_i)^2 + \sigma_i^2}$$

and note that $\phi(b_{(n-1)i}^2) = b_{ni}^2$. Result follows directly from application of Lemma 1. ||| Hence, use of the estimation algorithm in (23) yields estimates $\{\hat{h}^k\}$ satisfying $\lim_{k \rightarrow \infty} E \|\hat{h}^k - h^k\|^2 \leq \sum_{i=1}^p x_i^*$.

LOWER BOUNDS ON THE ESTIMATION ERROR

We now derive a lower bound on the attainable mean-squared error, in the sense that with any linear estimator the error can always be as large as this bound if certain parameter changes occur. Of course, in many cases the actual error may be less than this lower bound, but we can never "guarantee" this fact. The basic idea is to construct a problem in which the system variations are random, with known mean and covariance, but bounded as in (10b). Kalman filtering techniques can then be applied in order to find the minimum mean-squared error which is attainable using any linear estimation procedure. This error provides the lower bound of interest.

Suppose that the w^k 's are random vectors, independent of the v^k 's, which satisfy (10b) and are described by

$$\text{and } P[(w^k, \psi_i) = \eta_i] = \frac{1}{2} = P[(w^k, \psi_i) = -\eta_i], \quad (26)$$

$$\text{Then } E[(w^k, \psi_i)(w^l, \psi_j)] = \eta_i^2 \delta_{ij} \delta_{kl}.$$

$$E w^k = 0, \quad E w^k (w^j)^T = Q \delta_{kj}, \quad (27)$$

where Q can be found from knowledge of the $\{\psi_i\}$ and (26). Suppose also that h^1 is a random vector with, say, mean zero and covariance matrix $P_1 =$

$(X^T R^{-1} X)^{-1}$. The error covariance matrix for the Kalman estimate \hat{h}^k of h^k is given by the recursive equation (see e.g., [4])

$$P_k = (P_{k-1} + Q)(I - X^T[X(P_{k-1} + Q)X^T + R]^{-1} \cdot X(P_{k-1} + Q)), \quad k = 2, 3, \dots \quad (29)$$

We then have:

Proposition 2. The upper bound on the attainable mean-squared error of any linear estimate of the system parameters $\{h^n\}$, in the model described by (9) and (10), cannot be less than $\inf_k \text{Tr } P_k \triangleq e$, where P_k ($k \geq 2$) is given by (29) and $P_1 = (X^T R^{-1} X)^{-1}$.

Proof: Suppose the $\{w^k\}$ are random vectors satisfying (26) and h^1 is a random vector with mean zero and covariance P_1 . First we observe that if only y^1 is available, there is no linear estimator that will yield uniformly smaller mean-squared error than P_1 . This is because P_1 was chosen to be the variance of the LUMV estimate for h^1 in the equation $y^1 = Xh^1 + v^1$, and no biased estimate gives a mean-squared error bounded for all h^1 . Next, suppose that for $m \geq 2$ there exists a linear estimator \hat{h}^m such that

$$E(\|\hat{h}^m - h^m\|^2 \mid w^1, \dots, w^{m-1}) < e$$

for every sequence $\{w^1, \dots, w^{m-1}\}$. Then

$$E\|\hat{h}^m - h^m\|^2 = E\{E(\|\hat{h}^m - h^m\|^2 \mid w^1, \dots, w^{m-1})\} < e.$$

But this contradicts the minimum mean-squared error property of the Kalman estimate \hat{h}^m . Consequently, for any m , there is a sequence w^1, \dots, w^{m-1} such that $\inf_k \text{Tr } P_k \geq e$. Since $\{w^1, \dots, w^{m-1}\}$ satisfies (10b), this proves the assertion. |||

It is of interest to interpret this result in the special case of (9) and (10) where X is the identity and R is diagonal. The eigenvectors $\{\psi_i\}$ then become the standard unit vectors in R^p and $Q = \text{diag}(\eta_1^2, \eta_2^2, \dots, \eta_p^2)$. Also, with a little algebraic manipulation (29) becomes

$$P_k = (P_{k-1} + Q)(P_{k-1} + Q + R)^{-1}R.$$

Since $P_1 = R$ is diagonal, all the P_k will be diagonal. In particular, if $P_{k-1} = \text{diag}(\alpha_{(k-1)1}^2, \alpha_{(k-1)2}^2, \dots, \alpha_{(k-1)p}^2)$ then $P_k = \text{diag}(\alpha_{k1}^2, \alpha_{k2}^2, \dots, \alpha_{kp}^2)$ where

$$\alpha_{ki}^2 = \frac{(\alpha_{(k-1)i}^2 + \eta_i^2)\sigma_i^2}{\alpha_{(k-1)i}^2 + \eta_i^2 + \sigma_i^2}, \quad i = 1, \dots, p. \quad (30)$$

Corollary. If for the system described by (9) and (10), X is the identity and R is diagonal, then there exists a sequence $\{w^k\}$ satisfying (10b) such that

$$E\|\hat{h}^k - h^k\|^2 \geq \frac{p}{2} \left\{ -\frac{\eta_i^2}{2} + \frac{\eta_i^2}{2} \sqrt{1 + \frac{\sigma_i^2}{\eta_i^2}} \right\}$$

for any linear estimate \hat{h}^k of h^k .

Proof: Define

$$\theta(x) \triangleq \frac{(x + \eta_i^2)\sigma_i^2}{x + \eta_i^2 + \sigma_i^2}$$

and note that for equation (30), $\theta(\alpha_{(k-1)i}^2) = \alpha_{ki}^2$. Application of Lemma 1 yields

$$\lim_{k \rightarrow \infty} \alpha_{ki}^2 = -\frac{\eta_i^2}{2} + \frac{\eta_i^2}{2} \sqrt{1 + 4\frac{\sigma_i^2}{\eta_i^2}}, \quad i = 1, \dots, p.$$

Since

$$\inf_k \text{Tr} P_k = \lim_{k \rightarrow \infty} \text{Tr} P_k = \lim_{k \rightarrow \infty} \sum_{i=1}^p \alpha_{ki}^2 = \sum_{i=1}^p \left\{ -\frac{\eta_i^2}{2} + \frac{\eta_i^2}{2} \sqrt{1 + 4\frac{\sigma_i^2}{\eta_i^2}} \right\},$$

the result follows directly from Proposition 2. ||| Figure 1 provides a plot of the i^{th} component of the upper and lower bounds on the mean-square error when $X = I$ and R is diagonal.

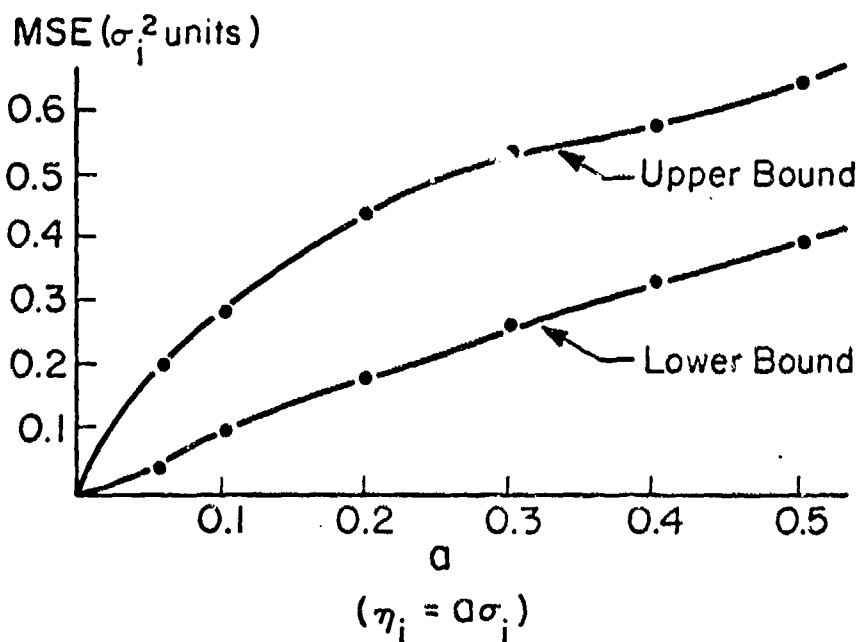


Figure 1. Bounds on Errors

COMMENTS

- (1) The results derived for estimating the parameters when they vary only between blocks of measurements can be extended to include the case where the parameters vary between each pair of measurements (see [3]).
- (2) The upper and lower bound expressions given by Propositions 1 and 2 provide criteria for determining whether or not a system can be considered as being slowly varying (see [3]).
- (3) The restriction to the case where X is the identity is in fact less restrictive than it would appear to be at first glance. The "standard

ϵ -representation" developed in [1] does provide such a model for a very large class of systems. Of course, the parametrization provided by this model may not be what is desired in a practical situation. However, our point of view as regards to the concept of slowly varying is that if there is any parametrization for which sufficiently good estimates can be made, then the system is slowly varying.

- (4) The estimate used at each state of the recursive estimation procedure is essentially the modified LUMV estimate described in [2].

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