

A New Algorithm for the Estimation of Variable Time Delay of Discrete Systems

(이산형 시스템의 시변지연시간 추정 알고리즘)

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要約

미지시변지연 시간을 실시간 추정하는 새로운 알고리즘을 제시하였다. 예측오차를 최소화하는 개념에 근거를 둔 이 방식은 극점과 영점에 관계된 최소 갯수의 파라미터만 식별하므로 파라미터수령에 필요한 persistently exciting 조건이 완화된다. 적응제어에 쓰이는 일반적인 가정하에서 이 알고리즘이 프로세스의 시변지연 시간을 정확히 추정함을 보였다. 기존의 다른 방식들에 비하여 계산량도 적으며, 이 방식은 지연시간이 클 수록 기존방식에 비해 효과적이다.

매우 좋은 컴퓨터 시뮬레이션 결과를 얻었다. 이 방식은 지연시간이 큰 프로세스의 적응제어에 효과적으로 사용될 수 있다.

Abstract

A new on-line estimation algorithm for a time varying time delay is proposed. This algorithm is based on the concept of minimization of prediction error. As only the parameters directly related to the poles and zeros of the process are estimated in the algorithm, persistently exciting condition for the convergence of parameters can be less restrictive. Under some assumptions which is necessary in adaptive control, it is shown that this algorithm estimates time varying time delay accurately.

In view of computational burden, this algorithm needs far less amount of calculations than other methods. The larger the time delay is, the more effective this algorithm is. Computer simulation shows good properties of the algorithm. This algorithm can be used effectively in adaptive control of large dead time processes.

I. Introduction

In recent years, self-tuning control has received considerable attention, mainly as a

result of advances in computer technology. Current interest in self-tuning scheme was largely stimulated by the development of the self-tuning regulators (STR) by Astrom and Wittenmark [1] and the self-tuning controller (STC) of the Clarke and Gawthrop [2].

In both approaches, the time delay of the process is assumed to be known a priori as condition for the global convergence. However, in most industrial applications, the time delay of the process is often either unknown

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or time varying. Indeed, a mismatch in the time delay may result in poor, or even unstable performances [4,5]. In this cases, a dead time compensation technique is required so that the STC algorithm can be utilized to handle processes with variable time delay. Some methods developed up to recent years can be classified in two approaches: (1) an explicit one which is an on-line dead time estimation, represented in Kurz et al. [4] and Wong et al. [6]; (2) an implicit one which makes the order of input parameters be extended to the maximum dead time, developed by Wellstead et al. [5] Ydstie [7] and Chien et al [8].

All the above methods for the dead time compensation have a major drawback that the number of parameters to be estimated increases with the maximum time delay. This is undesirable for two main reasons when the system time delay is large: (1) the persistent excitation [9] of input sequences which is a condition for parameter convergence is difficult to be satisfied, (2) the adaptive capability of the controller is aggravated, since it takes a long time for parameters to be retuned according to a change in the system dynamics.

We have proposed a new algorithm for the time delay estimation of the process in which the dead time changes discretely. Basic concept of the approach is the minimization of prediction errors. In this procedure, an indirect predictor set and prediction error set are constructed and the time delay corresponding to the minimum prediction error is expected to be the true time delay of the process. The main advantage of this algorithm is that the number of parameters to be estimated is independent of the number of the time delay.

The purpose of this paper is to analyze some properties of the time delay estimation algorithm suggested in [10,11]. Some simulations show the good performance of the algorithm.

II. Time Delay Estimation

1. Problem Statements

The process to be considered is a single-input single-output linear discrete time system which can be described by the difference equation

where

$$A(q^{-1})y(t) = q^{-d^0} B(q^{-1})u(t) + w(t) \quad (1)$$

$$A(q^{-1}) = 1 + a_1 q^{-1} + \dots + a_n q^{-n} \quad (2)$$

$$B(q^{-1}) = b_0 + b_1 q^{-1} + \dots + b_m q^{-m}, \quad (3)$$

q^{-1} is a backward shift operator, and d^0 is the time delay of the process which is assumed to be an unknown time varying positive integer. $y(t)$ is an output signal, $u(t)$ is a control input signal, and $w(t)$ is a white noise process with distribution $\sim N(0, \sigma^2)$.

In this paper we don't take the unmodeled dynamics into consideration. So the process to be considered and its model have the same dimensions, (n, m) , and the model is given as follows.

where

$$A(q^{-1})y(t) = q^{-d} B(q^{-1})u(t) + w(t) \quad (4)$$

$$A(q^{-1}) = 1 + a_1 q^{-1} + \dots + a_n q^{-n} \quad (5)$$

$$B(q^{-1}) = b_0 + b_1 q^{-1} + \dots + b_m q^{-m} \quad (6)$$

and d denotes the time delay of the model which has the meaning of the delay-variable to be estimated.

2. Algorithm

The following assumptions are necessary to establish the new algorithms.

Assumptions:

1. Initial value of d^0 is known.
2. Control input signal $u(t)$ satisfies the persistently exciting condition and SNR is sufficiently large.
3. d^0 is positive integer and changes slowly within the range of $d^0 - s, d^0 + s$.

Assumption 1 can be satisfied by off-line identification, and assumption 2 is commonly used in adaptive control. The fractional delay is not considered. "s" indicates the range of

delay variation during one sampling interval.

Under above assumptions, once the model parameters are estimated by a recursive least square estimation (RLSE), then $(2s+1)$ indirect adaptive predictors are generated by N (averaging horizon) step past parameters. The prediction errors are calculated from the predictions $y(t|t-d)$, where d is numbers from d^0-s to d^0+s , and the measured output $y(t)$.

When a dead time change occurs, it is expected that the variance of the prediction error corresponding to the true dead time is a minimum.

The original version of the algorithm is presented at [10,11].

Here, we present a summary of the method as follows:

Algorithm 1

Step 1: Let $d^0 = \hat{d}^0$, where \hat{d}^0 is the initial or estimated value of d^0 , and identify the model parameter $\hat{\theta}$, where $\hat{\theta}(t-d^0) = [\hat{a}_1, \dots, \hat{a}_n, \hat{b}_0, \dots, \hat{b}_m]^T$.

Step 2: Construct an indirect predictor set

$$\hat{y}(t|t-d) = G(q^{-1})y(t-d) + F(q^{-1})\hat{B}(q^{-1})U(t-d)$$

$$1 = F(q^{-1})\hat{A}(q^{-1}) + q^{-d}G(q^{-1})$$

for $d = d^0-s, \dots, d^0+s$

where $s \geq 1$ and $\hat{A}(q^{-1})$ and $\hat{B}(q^{-1})$ are polynomials at time $t-N$.

Step 3: Construct a prediction error set.

$$\eta_d(t) = [y(t) - y(t|t-d)], \text{ for } d = d^0-s, \dots, d^0+s$$

Step 4: Determine new estimate of d^0 , \hat{d}^0 , by the following criterion.

$$\begin{aligned} \hat{d}^0 &= \min_d E[\eta_d^2(t)] \\ &= \min_d \left[\frac{1}{N} \sum_{t=N+1}^t \eta_d^2(t) \right] \end{aligned}$$

Step 5: Go to step 1.

Remark 1:

Variation of the process time delay makes

the estimated model parameter deviate rapidly from the process parameter. To check the variation of the time delay, it is recommended that the parameters used in prediction be the past one, which has been identified before the change of time delay. As the expectation of the prediction error variance was replaced by a time average, it is necessary to choose the averaging horizon N properly. By our experiences, $N = n+m+d^0$ is a good one. Algorithm 1 can be applied, if the frequency of time delay changes is not faster than N .

Remark 2:

Differences between algorithm 1 and Kurz's method; Algorithm 1 identifies the $(n+m)$ parameters corresponding to only the system poles and zeros and finds the delay resulting in the minimum prediction error variance. In Kurz's method, however, the number of parameters to be estimated is increased to the number of poles plus zeros plus maximum time delay without regard to true time delay. Estimation of the actual time delay is done in every step by fitting the impulse response. Moreover, as the fitting procedure is based on the deterministic model without the consideration of noise dynamics, estimation of time delay is sensitive to noises. But in algorithm 1, as the average of prediction error variance is the criterion of estimation, estimation is less sensitive compared with the Kurz's method.

III. Analysis of the Algorithm

The following lemmas are necessary to show that the above algorithm estimates the true delay accurately.

Lemma 1.

Let $e_1(t)$ and $e_2(t)$ be stochastic sequences with zero mean, and let $e_3(t)$ be a deterministic term. In addition, $e_1(t)$ and $e_2(t)$ are assumed to be uncorrelated with each other.

Define $\epsilon(t) = e_1(t) + e_2(t) + e_3(t)$, then $E[\epsilon^2(t)]$ is minimized when each of $E[e_1^2(t)]$, $E[e_2^2(t)]$, and $E[e_3^2(t)]$ is a minimum.

Proof:

$$\begin{aligned} E[\epsilon^2(t)] &= E[e_1^2(t)] + E[e_2^2(t)] + E[e_3^2(t)] \\ &\quad + 2E[e_1(t)e_2(t) + e_1(t)e_3(t) \\ &\quad + e_2(t)e_3(t)] \\ &= E[e_1^2(t)] + E[e_2^2(t)] + E[e_3^2(t)] \end{aligned}$$

From this, the lemma is self-evident.

From step 3 in algorithm 1, prediction error $\eta_d(t)$ is reformulated as follows

$$\begin{aligned} \eta_d(t) &= y(t) - \hat{y}(t|t-d) \\ &= y(t) - \hat{y}(t|t-d^0) + \hat{y}(t|t-d^0) \\ &\quad - \hat{y}(t|t-d) \end{aligned} \quad (7)$$

$$\begin{aligned} \hat{y}(t|t-d^0) &= \bar{G}(q^{-1}) y(t-d^0) \\ &\quad + \bar{F}(q^{-1}) \hat{B}(q^{-1}) u(t-d^0) \end{aligned} \quad (8a)$$

$$1 = \bar{F}(q^{-1}) \hat{A}(q^{-1}) + q^{-d^0} \bar{G}(q^{-1}) \quad (8b)$$

where

$$\bar{F}(q^{-1}) = 1 + \bar{f}_1 q^{-1} + \dots + \bar{f}_{d^0-1} q^{-d^0+1} \quad (8c)$$

$$\bar{G}(q^{-1}) = \bar{g}_0 + \bar{g}_1 q^{-1} + \dots + \bar{g}_{n-1} q^{-n+1} \quad (8d)$$

$$\begin{aligned} \hat{y}(t|t-d) &= G(q^{-1}) y(t-d) \\ &\quad + F(q^{-1}) \hat{B}(q^{-1}) u(t-d) \end{aligned} \quad (9a)$$

$$1 = F(q^{-1}) \hat{A}(q^{-1}) + q^{-d^0} G(q^{-1}) \quad (9b)$$

where

$$F(q^{-1}) = 1 + f_1 q^{-1} + \dots + f_{d-1} q^{-d+1} \quad (9c)$$

$$G(q^{-1}) = g_0 + g_1 q^{-1} + \dots + g_{n-1} q^{-n+1} \quad (9d)$$

$\hat{y}(t|t-d^0)$ is an optimal predictor, and $\hat{y}(t|t-d)$ is a predictor set constructed to check a delay change. \bar{F} and \bar{G} are obtained by solving eq. (8b), while F and G are found by solving eq. (9b)

Eq.(9b) is different from eq.(8b) in that d^0 is replaced by d . $\hat{A}(a^{-1})$, estimate of the polynomial $A(q^{-1})$, is common in two equations.

The following is well-known.

$$\begin{aligned} e(t) &= y(t) - \hat{y}(t|t-d^0) \\ &= w(t) + f_1 w(t-1) + \dots + f_{d^0-1} \\ &\quad w(t-d^0+1) \end{aligned} \quad (11)$$

Substitute eq. (11) into eq. (7), then

$$\eta_d(t) = e(t) + \hat{y}(t|t-d^0) - \hat{y}(t|t-d) \quad (12)$$

With the use of eqs. (9a) to (12),

$$\begin{aligned} \eta_d(t) &= e(t) + q^{-d^0} \bar{G}(q^{-1}) y(t) \\ &\quad + q^{-d^0} \bar{F}(q^{-1}) \hat{B}(q^{-1}) u(t) \\ &\quad - q^{-d} G(q^{-1}) y(t) \\ &\quad - q^{-d} F(q^{-1}) \hat{B}(a^{-1}) u(t) \\ &= e(t) + (q^{-d^0} \bar{G}(q^{-1}) - q^{-d} G(q^{-1})) y(t) \\ &\quad + (q^{-d^0} \bar{F}(q^{-1}) \hat{B}(q^{-1}) - q^{-d} F(q^{-1}) \\ &\quad \quad \hat{B}(q^{-1})) u(t) \end{aligned} \quad (13)$$

Since a control input $u(t)$ is purely deterministic, $y(t)$, an output, can be decomposed as follows.

$$y(t) = y_{det}(t) + y_{sto}(t) \quad (14)$$

$$y_{det}(t) \triangleq [q^{-d^0} B(q^{-1}) / A(q^{-1})] u(t) \quad (15)$$

$$y_{sto}(t) \triangleq [1/A(q^{-1})] w(t) \quad (16)$$

where $y_{det}(t)$ is purely deterministic, while $y_{sto}(t)$ is purely stochastic and has an autoregressive form driven by a white noise.

$y_{sto}(t)$ can be represented as eq. (17);

$$y_{sto}(t) = w(t) + \alpha_1 w(t-1) + \alpha_2 w(t-2) + \dots \quad (17)$$

Substituting eq. (14) into eq. (13), the followings are obtained.

$$\begin{aligned} \text{Let } e_1(t) &\triangleq (q^{-d^0} \bar{G}(q^{-1}) - q^{-d} G(q^{-1})) \\ &\quad y_{sto}(t) \end{aligned} \quad (18)$$

$$e_2(t) \triangleq e(t) \quad (19)$$

$$e_3(t) \triangleq (q^{-d^0} \bar{G}(q^{-1}) - q^{-d} G(q^{-1})) \\ y_{\det}(t) + (q^{-d^0} \bar{F}(q^{-1}) \hat{B}(q^{-1}) \\ - q^{-d} F(q^{-1}) \hat{B}(q^{-1})) u(t) \quad (20)$$

$$\text{Then } \eta_d(t) = e_1(t) + e_2(t) + e_3(t) \quad (21)$$

where $e_3(t)$ is a purely deterministic term.

The relations of the each terms in eq.(17) needs more considerations as seen below.

Now we will show that the algorithm estimates a delay accurately. Here the cases where $d \geq d^0$ and $e \geq d^0$ are taken into consideration.

Lemma 2.

If $d \geq d^0$, $E[\eta_d^2(t)]$ is minimized when $d = d^0$.

proof:

If $d = d^0 + 1$, with the use of eqs.(8c), (8d), (9c), and (9d), eqs. (18) to (19) are rewritten as

$$e_1(t) = q^{-d^0} [g_0 + (\bar{g}_1 - g_0) q^{-1} + \dots \\ + (\bar{g}_{n-1} - g_{n-2}) q^{-n+1} \\ + (g_{n-1}) q^{-n}] y_{\text{sto}}(t) \quad (22)$$

$$e_2(t) = e(t) \quad (19)$$

$$e_3(t) = q^{-d^0} [\bar{g}_0 + (\bar{g}_1 - g_0) q^{-1} + \dots \\ + (\bar{g}_{n-1} - g_{n-2}) q^{-n+1} + (g_{n-1}) q^{-n}] \\ y_{\det}(t) + \dots \quad (23)$$

If $d = d^0$, these are changed to

$$e_1(t) = q^{-d^0} [(g_0 - \bar{g}_0) + (\bar{g}_1 - g_1) q^{-1} + \dots \\ + (\bar{g}_{n-1} - g_{n-1}) q^{-n+1}] y_{\text{sto}}(t) \\ = 0 \quad (24)$$

$$e_2(t) = e(t) \quad (19)$$

$$e_3(t) = q^{-d^0} [(g_0 - \bar{g}_0) + (\bar{g}_1 - g_1) q^{-1} + \dots \\ + (\bar{g}_{n-1} - g_{n-1}) q^{-n+1}] y_{\det}(t) + \dots \\ = 0 \quad (25)$$

In cases of $d \geq d^0$, $e_1(t)$ is composed of $w(t-d^0)$, $w(t-d^0-1)$,, and $e_2(t)$ consists of $w(t)$,, $w(t-d^0+1)$. As $e_1(t)$ and $e_2(t)$ are uncorrelated, we can apply lemma 1. Thus minimum of $E[\eta_d^2(t)]$ is acquired when each term of $E[e_1^2(t)]$, $E[e_2^2(t)]$, and $E[e_3^2(t)]$ is a minimum. If $d = d^0$, $\bar{f}_1 = f_1$ and $\bar{g}_i = g_i$ since f_i and \bar{g}_i are calculated from N -step past parameters.

$$E[\eta_{d^0+1}^2(t)] = E[e_1^2(t)] + E[e_2^2(t)] + e_3^2(t) \quad (26)$$

$$E[\eta_{d^0}^2(t)] = E[e^2(t)] = \sum_{i=0}^{d^0-1} f_i^2 \sigma^2 \quad (27)$$

Since

$$E[e_1^2(t)] + e_3^2(t) > 0, \quad (28)$$

$$\therefore E[\eta_{d^0}^2(t)] < E[\eta_{d^0+1}^2(t)]. \quad (29)$$

For $d \geq d^0 + 2$, the same result is easily obtained.

In general, we can replace expectation by a time average in the small interval where the process can be regarded as a stationary ergodic process. So the true delay d^0 is found with a procedure in step 4 in algorithm 1. But, if $d < d^0$ (e.g. $d = d^0 - 1$), $e_1(t)$ and $e_2(t)$ have a term $w(t-d+1)$ in common, and as a result, $e_1(t)$ and $e_2(t)$ are correlated. Therefore we can't use lemma 1 in such a case.

Lemma 3:

Assuming that SNR is sufficiently large and $d \leq d^0$, $E[\eta_d^2(t)]$ is minimized when $d = d^0$.

Proof:

$$E[\eta_{d^0}^2(t)] = E[e_1^2(t)] + E[e_2^2(t)] \\ + E[e_3^2(t)] + 2E[e_1(t) e_2(t)] \quad (30)$$

$$E[\eta_d^2(t)] = E[e_2^2(t)] = E[e^2(t)]$$

To verify that $E[\eta_d^2(t)] > E[\eta_{d^0}^2(t)]$ for $d < d^0$, the following inequality should be satisfied.

$$E[e_1^2(t)] + E[e_3^2(t)] + 2E[e_1(t) e_2(t)] > 0 \\ \text{for } d \leq d^0 - 1 \quad (31)$$

As only $w(t-d^0+1)$ is a common term in $e_1(t)$ and $e_2(t)$, it is satisfied that

$$-k \sigma^2 \leq 2E[e_1(t) e_2(t)] \leq k \sigma^2 \quad (32)$$

where $k=2 * |f_{d^0-1} \cdot g_0|$

In this case, $e_3(t)$ is deterministic and

$$\begin{aligned} e_3(t) = & q^{-d^0+1} [-g_0 + (\bar{g}_0 - g_1) q^{-1} + \dots \\ & + (\bar{g}_{n-2} - g_{n-1}) q^{-n+1} + \bar{g}_{n-1} q^{-n}] y_{det}(t) \\ & + q^{-d^0} [(1 + \bar{f}_1 q^{-1} + \dots + \bar{f}_{d^0-1} q^{-d^0+1}) \\ & - q(1 + f_1 q^{-1} + \dots + f_{d^0-2} q^{-d^0+2})] \\ & u(t) \end{aligned} \quad (33)$$

From eq. (31) and eq. (32),

$$E[e_1^2(t)] + e_3^2(t) > k \sigma^2 \quad (34)$$

As $e_3^2(t)$ in eq.(34) implies the power of inputs and outputs, the inequality (34) is satisfied provided that SNR is large.

Theorem:

Under the assumptions in chapter II, the variance of prediction error corresponding to the true delay is the minimum. That is $d^0 = \min_d E[\eta^2(t)]$ for $d^0 - s \leq d \leq d^0 + s, \forall t. \quad (35)$

Proof:

As results of lemma 2 and lemma 3, it is evident.

Remark 3:

Algorithm 1 is the same as the previous one^(10,11) in basic concept. But the previous one used $\hat{\theta}(t)$ in constructing adaptive predictor, while algorithm 1 uses $\hat{\theta}(t-d^0)$. Using $\hat{\theta}(t-d^0)$, Algorithm 1 is proved to estimate delay exactly.

IV. Simulation Results and Discussion

Digital computer simulation was done for the process given below.

$$\begin{aligned} A(q^{-1}) &= 1 - 0.4 q^{-1} - 0.32 q^{-2} \\ B(q^{-1}) &= 0.6 + 0.3 q^{-1} \end{aligned} \quad (36)$$

where d^0 is time varying positive integer and is changed sequentially to 2 -1 -2 -3 -4 at every to steps as in Fig. 1. Fig. 2 is the features of $E[\eta_d^2(t)]$ for $d=1, 2, 3, 4$.

In Fig. 3, real line is "true delay (d^0)" and a dotted line is "estimated delay (\hat{d}^0)". Input signal had sufficiently rich frequencies and SNR was 14.9 dB.

In Fig. 2 & Fig. 3, input signal is

$$\begin{aligned} u(k) = & (3.1 \sin(3.8k) + \sin(k) - 4.4 \sin(5.3k) \\ & + 3 \cos(8.4k)) / 10 + 1 \end{aligned} \quad (37)$$

Additive noise is $0.3w(k)$, where $w(k)$ is white Gaussian process with variance 1.

Fig. 3 also shows that parameters are well updated.

Fig. 4 represents the case of SNR=20.3 dB, where input signal is given as eq. (37) Additive noise is $0.1 w(k)$.

Fig. 5 is the graph of d^0 , and \hat{d}^0 when SNR=30.2 dB, where input signal is

$$\begin{aligned} U(k) = & (3.1 \sin(3.8k) + \sin(k) - 4.4 \sin(5.3k) \\ & + 3 \cos(8.4k)) / 30 + 1 \end{aligned} \quad (38)$$

Additive noise is $0.03w(k)$. In the simulations all the initial parameters are zero.

Simulation results show that the algorithm estimates a time-varying time delay accurately. For good parameter estimation, not only large SNR but also persistently exciting condition are necessary. In discrete system, persistently exciting condition depends on the magnitude of input signal variation. If a input signal doesn't satisfy persistently exciting condition, the input signal may be almost constant and in this circumstance time delay mismatch ($d^0 \neq \hat{d}^0$) makes no problems. To estimate time

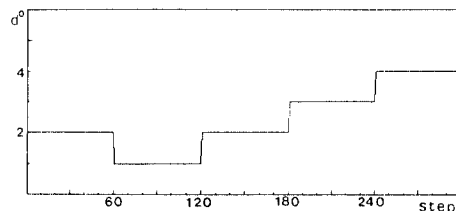


Fig. 1. Time delay of process.

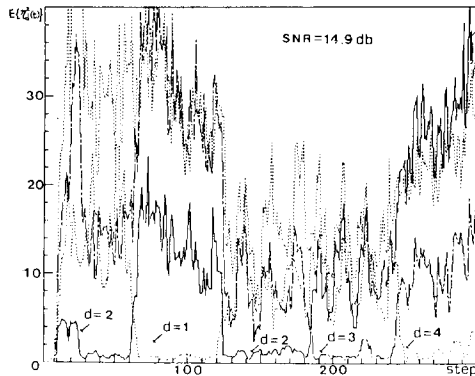


Fig. 2. Expectation of prediction error.

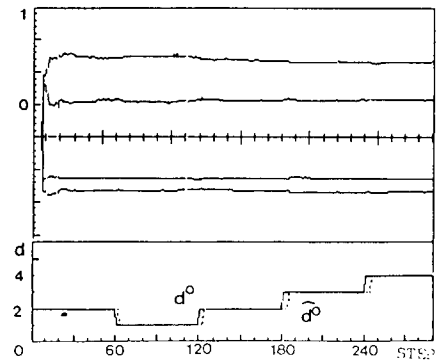


Fig. 5. Delay & parameter SNR=30.2dB.

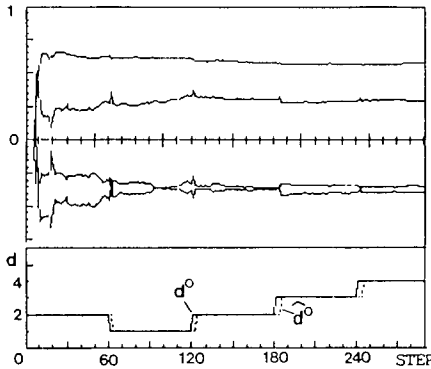


Fig. 3. Delay & parameter SSNR=14.9dB.

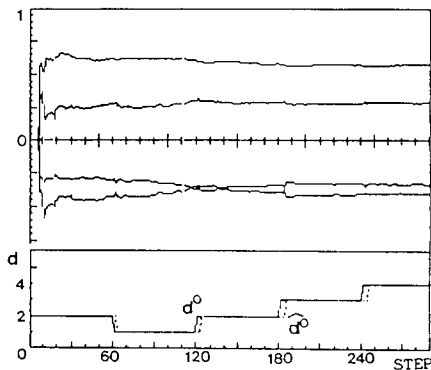


Fig. 4. Delay & parameter SNR=20.3dB.

delay accurately, more strict persistent exciting condition is desired than theoretical persistent exciting condition.

In this algorithm only numbers of parameters are estimated. And it needs far less

calculations than any other methods which use extended parameterization techniques. The amount of calculations needed for the construction of predictors is negligible compared with the amount of calculations needed for parameter estimation. Fractional time delay is not considered in this paper.

V. Conclusion

In this paper, a new on-line estimation algorithm for a time varying time delay is suggested, which is based on the concept of minimization of prediction error. Under some assumptions, it is shown that this algorithm estimates time varying time delay exactly.

In view of computational burdens, the algorithm needs far less calculations than other methods. The larger the time delay is, the more effective this algorithm is this algorithm can be used effectively in adaptive control of discrete systems with time varying time delay.

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