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Adaptive Recursive Least Squares Algorithm for Joint FIR Filtering and Pre-Delay Tracking and Its Application in the Chemical Industry Process Modeling

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***Abstract* — In this paper, the joint FIR filtering and pre-delay tracking system identification problem is considered. The input signal to the unknown system is first delayed then filtered. An adaptive recursive least squares algorithm based on fast transversal filters is developed and applied to the field data from the chemical industry process of some synthetic ammonia plant. In the simulation of 25 hours field running, it gives a relative prediction error no more than 3.6% and the modeling results are reasonable.**

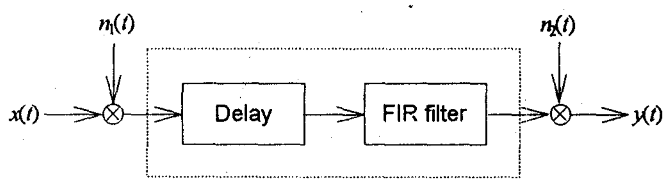

Fig. 1. Pre-delay system considered in this paper. $n_1(t)$ and $n_2(t)$ are additive input and output noises respectively.

I. INTRODUCTION

Industrial process modeling has always been regarded a tough task, especially in the chemical industry processes with long pure delays. The unknown system can be modeled as a pure time delay in series with a linear filter Identification of such systems is difficult by using conventional adaptive modeling techniques. Though it is reasonable to assume separate delay unit and filter unit, it is almost impossible to separate their influence in the model evaluation signal, thus the integrate adaptive system of separately designed delay estimation and adaptive filter may not achieve acceptable modeling results. Time-varying delay has not only made model prediction difficult but also laid constrains on the stability of the whole control systems. It is a key factor that should be considered into system models.

Though many efforts have been made on the time delay estimation(TDE)[1-5], to the best of our knowledge, there have been few published works dealing with the identification of joint filtering and delay tracking apart from [6-8]. [8] treats the case where the input signal to the unknown system is first delayed then filtered(fig. 1). They describe gradient-based algorithms for joint adaptive TDE and IIR filtering. [7] treats the other case where the input signal to the unknown system is first filtered then delayed. They describe a complex recursive least squares(RLS) algorithm for joint TDE and FIR filtering based on fast transversal filters(FTF)[9]. We call these two cases as pre-delay and post-delay ones respectively.

In this paper, we develop an adaptive RLS algorithm for joint FIR filtering and pre-delay tracking. The recursions are different from those in the post-delay case and thus the algorithm is far different from the one in [7]. The algorithm is implemented and tested on the field data from the chemical industry process of the Hebei Xuanhua synthetic ammonia plant. The identification results are reasonable and well demonstrate the algorithm's prediction ability.

II. MODEL DESCRIPTION AND SYMBOL DEFINITION

Suppose the input and output signals be $x(t)$ and $y(t)$ respectively(Fig. 2), where time t=1,2,3,.... Let the order of the adaptive FIR filter be p. Our task is to minimize an exponentially weighted sum of model prediction error energy,

$$\min\{\min\{e^T(t,p,l)\Lambda e(t,p,l): w(t,p,l)\}: l=0,1,2,...\} \quad (1)$$

Least squares criterion is adopted in minimizing the error energy over the filter weight vector $w(t,p,l)$, while local comparison of the expectation of the least squares error

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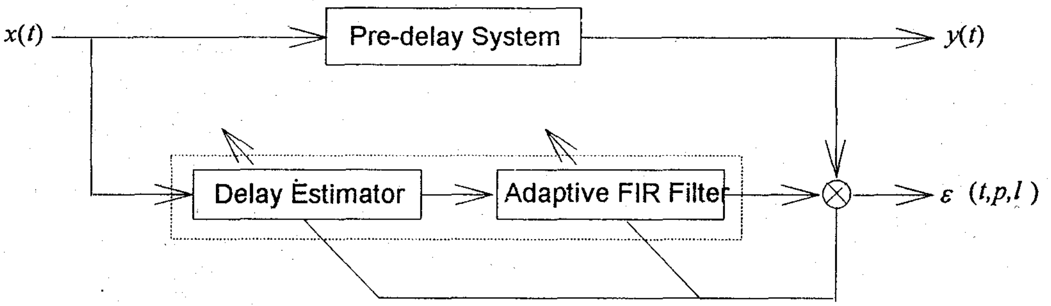

Fig. 2. Pre-delay system identification model.

energy is used to optimize the objective function over delay estimation l, where l is a discrete variable of 0,1,2,.... Here are the symbol definitions.

$$e(t,p,l)=y(t)+X(t-l,p)w(t,p,l)\in R^{L\times 1}, \quad (2)$$

$$y(t)=(y(t),y(t-1),y(t-2),\cdots,y(1),0,\cdots,0)\in R^{L\times 1}, \quad (3)$$

$$X(t,p)=(x(t),x(t-1),x(t-2),\cdots,x(t-p+1))\in R^{L\times p}, \quad (4)$$

$$x(t)=(x(t),x(t-1),x(t-2),\cdots,x(1),0,\cdots,0)\in R^{L\times 1}, \quad (5)$$

$$\Lambda=\mathrm{diag}(1,\lambda,\lambda^2,\cdots,\lambda^{i-1},0,\cdots,0)\in R^{L\times L}, \quad (6)$$

where λ is the forgetting factor, L is a sufficiently large number. With a little abuse of the symbol definition, in the following, we assume $w(t,p,l)$ is the least squares weight vector, $\underline{e}(t,p,l)$ is the least squares weighted error vector and $\varepsilon(t,p,l)$ is the least squares weighted total error energy for the delay estimation l:

$$\underline{e}(t,p,l)=\underline{y}(t)+\underline{X}(t-l,p)w(t,p,l), \quad (7)$$

$$\varepsilon(t,p,l)=\langle\underline{e}(t,p,l),\underline{e}(t,p,l)\rangle, \quad (8)$$

where

$$\underline{y}(t)=\Lambda^{1/2}y(t), \quad (9)$$

$$\underline{X}(t,p)=\Lambda^{1/2}X(t,p). \quad (10)$$

The algorithm is based on the fast transversal filters of the input signals: the forward predictor, the backward predictor and the vector π predictor, where $\pi=(1,0,\cdots,0)\in R^{L\times 1}$. Their least squares weight vectors are $A(t,p)=(1, a^{\mathrm{T}}(t,p))^{\mathrm{T}}$, $B(t,p)=(b^{\mathrm{T}}(t,p), 1)^{\mathrm{T}}$ and $C(t,p)$ respectively. The forward prediction error, the backward prediction error and the vector π prediction error are

$$f(t,p)=\underline{X}(t,p+1)A(t,p) \quad (11)$$
$$=(f(t,p),f(t-1,p),f(t-2,p),\cdots,f(1,p),0,\cdots,0)\in R^{L\times 1},$$

$$g(t,p)=\underline{X}(t,p+1)B(t,p) \quad (12)$$
$$=(g(t,p),g(t-1,p),g(t-2,p),\cdots,g(1,p),0,\cdots,0)\in R^{L\times 1},$$

$$\gamma(t,p)=\pi+\underline{X}(t,p)C(t,p) \quad (13)$$
$$=(\gamma(t,p),\gamma(t-1,p),\gamma(t-2,p),\cdots,\gamma(1,p),0,\cdots,0)\in R^{L\times 1}.$$

Their least squares total weighted error energies are

$$\alpha(t,p)=\langle f(t,p),f(t,p)\rangle, \quad (14)$$

$$\beta(t,p)=\langle g(t,p),g(t,p)\rangle, \quad (15)$$

$$\gamma(t,p)=\langle\gamma(t,p),\gamma(t,p)\rangle \quad (16)$$

respectively.

Besides the above conventional definitions, we introduce forward and backward cross correlations.

$$u(t,p,l)=\langle f(t-l,p),\underline{y}(t)\rangle=\langle f(t-l,p),\underline{e}(t,p,l+1)\rangle, \quad (17)$$

$$v(t,p,l)=\langle g(t-l,p),\underline{y}(t)\rangle=\langle g(t-l,p),\underline{e}(t,p,l)\rangle. \quad (18)$$

Let

$$\underline{u}(t,p,l)=\alpha^{-1}(t-l,p)u(t,p,l), \quad (19)$$

$$\underline{v}(t,p,l)=\beta^{-1}(t-l,p)v(t,p,l), \quad (20)$$

$$e^{\mathrm{P}}(t,p,l)=\gamma^{-1}(t-l,p)e(t,p,l). \quad (21)$$

III. THE LAG-RECURSIVE EQUATIONS AND THE JOINT ALGORITHM

Lag recursive equations are key points in integrating the delay tracking and the filter identification in an adaptive algorithm. In the following, we list out the main and basic recursive equations. The lag forward and backward recursions of the optimal filter's weight vector and the sum of squared errors can be easily derived from these equations.

$$w(t-1,p,l)=w(t,p,l)-C(t-l,p)\gamma^{-1}(t-l,p)e(t,p,l) \quad (22)$$

$$w(t,p+1,l)=\begin{bmatrix}0\\ w(t,p,l+1)\end{bmatrix}-A(t-l,p)\alpha^{-1}(t-l,p)u(t,p,l) \quad (23)$$

$$w(t,p+1,l)=\begin{bmatrix}w(t,p,l)\\ 0\end{bmatrix}-B(t-l,p)\beta^{-1}(t-l,p)v(t,p,l) \quad (24)$$

$$\varepsilon(t,p,l)=\lambda\varepsilon(t-1,p,l)+e^2(t,p,l)\gamma^{-1}(t-l,p) \quad (25)$$

$$\varepsilon(t,p+1,l)=\varepsilon(t,p,l+1)-u^2(t,p,l)\alpha^{-1}(t-l,p) \quad (26)$$

$$\varepsilon(t,p+1,l)=\varepsilon(t,p,l)-v^2(t,p,l)\beta^1(t-l,p) \quad (27)$$

Note, the delay estimation l appears inside the parameters' time index. Thus the algorithm should be carefully designed so as to avoid repetitive computation of the input signal's FTF parameters. The following algorithm is of least time complexity. Its recursion scheme is thus: at time t, with current delay estimation l, first update FTF for time $t-l$; then apply lag backward recursions to $\varepsilon(t-1,p,l)$ to get $\varepsilon(t-1,p,l-1)$; collect average error energy for these least squares error energy; compare the average error energy and adapt l; by using derivative information from quantities for lag $l+1$, set up a new set of joint estimation parameters so that next time's call of FTF update procedures will always have one sample more in $t-l$. Here is the main part of joint identification algorithm.

computation of $\varepsilon(t-1,p,l-1)$:

$u(t-1,p,l-1)=\lambda u(t-2,p,l-1)+f^P(t-l,p)e(t-1,p,l)$

$\underline{u}(t-1,p,l-1)=u(t-1,p,l-1)\alpha^{-1}(t-l,p)$

$\underline{v}(t-1,p,l-1)=\underline{u}(t-1,p,l-1)a_p(t-l,p)-w_p(t-1,p,l)$

$v(t-1,p,l-1)=\underline{v}(t-1,p,l-1)\beta(t-l,p)$

$\varepsilon(t-1,p,l-1)=\varepsilon(t-1,p,l)$

$\quad -u(t-1,p,l-1)\underline{u}(t-1,p,l-1)+v(t-1,p,l-1)\underline{v}(t-1,p,l-1)$

preparation for update smoothness:

$u(t-2,p,l-2)=\lambda u(t-3,p,l-2)+f^P(t-l,p)e(t-2,p,l-1)$

$e(t-1,p,l-1)=e(t-1,p,l)-f(t-l,p)\underline{u}(t-1,p,l-1)+g(t-l,p)\underline{v}(t-1,p,l-1)$

average error energy collection and comparison:

$\underline{\varepsilon}(t-1,p,l-1)=\underline{\varepsilon}(t-2,p,l-1)+[\varepsilon(t-1,p,l-1)-\underline{\varepsilon}(t-2,p,l-1)]/cmp$

$\underline{\varepsilon}(t-1,p,l)=\underline{\varepsilon}(t-2,p,l)+[\varepsilon(t-1,p,l)-\underline{\varepsilon}(t-2,p,l)]/cmp$

$\underline{\varepsilon}(t-1,p,l+1)=\underline{\varepsilon}(t-2,p,l+1)+[\varepsilon(t-1,p,l+1)-\underline{\varepsilon}(t-2,p,l+1)]/cmp$

If $cmp=T$, Then

$\quad lnew=\arg\min[\underline{\varepsilon}(t-1,p,l-1),\underline{\varepsilon}(t-1,p,l),\underline{\varepsilon}(t-1,p,l+1)]$

$\quad cmp=0,\ \underline{\varepsilon}(t-1,p,lnew-1)=0,\underline{\varepsilon}(t-1,p,lnew)=0$

$\quad \underline{\varepsilon}(t-1,p,lnew+1)=0$

End If

Updates:

If $lnew=l-1$ Then

$\quad \varepsilon(t-1,p,lnew+1)=\varepsilon(t-1,p,l)$

$\quad v(t-1,p,lnew+1)=v(t-1,p,l)$

$\quad \varepsilon(t-1,p,lnew)=\varepsilon(t-1,p,l-1)$

$\quad e(t-1,p,lnew)=e(t-1,p,l-1)$

$\quad v(t-1,p,lnew)=v(t-1,p,l-1)$

$$\begin{bmatrix} w(t-1,p,lnew) \\ 0 \end{bmatrix}=\begin{bmatrix} 0 \\ w(t-1,p,l) \end{bmatrix}-A(t-l,p)\underline{u}(t-1,p,l-1)$$

$\quad +B(t-l,p)\underline{v}(t-1,p,l-1)$

$\quad u(t-2,p,lnew-1)=u(t-2,p,l-2)$

$\quad \underline{u}(t-2,p,lnew-1)=u(t-2,p,lnew-1)\alpha^{-1}(t-l,p)$

$\quad \underline{v}(t-2,p,lnew-1)=\underline{u}(t-2,p,lnew-1)a_p(t-l,p)$

$\quad -w_p(t-1,p,lnew)+\underline{C}_p(t-l,p)e(t-1,p,lnew)$

$\quad e(t-2,p,lnew-1)=e(t-2,p,l-1)-f(t-l,p)\underline{u}(t-2,p,lnew-1)$

$\quad +g(t-l,p)\underline{v}(t-2,p,lnew-1)$

$\quad u(t-3,p,lnew-2)=f(t-l,p)y(t-3)$

Else(* $lnew\geq l-1$ *)

$\quad [\varepsilon(t,p,l),e(t,p,l),w(t,p,l)]=$

$\quad\quad \mathrm{IncTime}[l,\varepsilon(t-1,p,l),w(t-1,p,l)]$

$\quad [\varepsilon(t,p,l+1),v(t,p,l),\underline{u}(t,p,l),\underline{v}(t,p,l)]=$

$\quad\quad \varepsilon\_\mathrm{IncLag}[\varepsilon(t,p,l),e(t,p,l),v(t-1,p,l),w_1(t,p,l)]$

$\quad e(t,p,l+1)=e(t,p,l)-g(t-l,p)\underline{v}(t,p,l)+f(t-l,p)\underline{u}(t,p,l)$

preparation for update smoothness:

$\quad v(t,p,l+1)=\lambda v(t-1,p,l+1)+g^P(t-l-1,p)e(t,p,l+1)$

If $lnew=l$ Then

$\quad t:=t+1$

Else(* $lnew=l+1$ *)

$\quad u(t-1,p,lnew-2)=u(t-1,p,l-1)$

$\quad \varepsilon(t,p,lnew-1)=\varepsilon(t,p,l)$

$\quad e(t,p,lnew-1)=e(t,p,l)$

$\quad u(t,p,lnew-1)=\underline{u}(t,p,l)\alpha(t-l,p)$

$\quad \varepsilon(t,p,lnew)=\varepsilon(t,p,l+1)$

$\quad e(t,p,lnew)=e(t,p,l+1)$

$$\begin{bmatrix} 0 \\ w(t,p,lnew) \end{bmatrix}=\begin{bmatrix} w(t,p,l) \\ 0 \end{bmatrix}-B(t-l,p)\underline{v}(t,p,l)$$

$\quad +A(t-l,p)\underline{u}(t,p,l)$

$\quad v(t,p,lnew)=v(t,p,l+1)$

$\quad \underline{v}(t,p,lnew)=v(t,p,lnew)\beta^1(t-l-1,p)$

$\underline{u}(t,p,lnew)=\underline{v}(t,p,lnew)b_p(t-l-1,p)-w_1(t,p,lnew)$
$u(t,p,lnew)=\underline{u}(t,p,lnew)\,\alpha(t-l-1,p)$
$\varepsilon(t,p,lnew+1)=\varepsilon(t,p,lnew)-$
$\quad v(t,p,lnew)\underline{v}(t,p,lnew)+u(t,p,lnew)\underline{u}(t,p,lnew)$

$cmp=1$
$\underline{\varepsilon}(t,p,lnew-1)=\varepsilon(t,p,lnew-1)$
$\underline{\varepsilon}(t,p,lnew)=\varepsilon(t,p,lnew)$
$\underline{\varepsilon}(t,p,lnew+1)=\varepsilon(t,p,lnew+1)$

$[\varepsilon(t+1,p,lnew),e(t+1,p,lnew),w(t+1,p,lnew)]=$
$\quad \text{IncTime}[lnew,\varepsilon(t,p,lnew),w(t,p,lnew)]$
$[\varepsilon(t+1,p,lnew+1),v(t+1,p,lnew),\underline{u}(t+1,p,lnew),$
$\quad \underline{v}(t+1,p,lnew)]=\varepsilon\_\text{IncLag}[\varepsilon(t+1,p,lnew),$
$\quad e(t,p,lnew),v(t,p,lnew),w_1(t,p,lnew)]$
$e(t+1,p,lnew+1)=e(t+1,p,lnew)$
$\quad -g(t-l,p)\underline{v}(t+1,p,lnew)+f(t-l,p)\underline{u}(t+1,p,lnew)$
$v(t+1,p,lnew+1)=g^P(t-l-1,p)e(t+1,p,lnew+1)$
$t:=t+2$

End If($lnew=l$)/Else
End If($lnew=l-1$)/Else
$l=lnew$

The procedure IncTime does the time forward recursions for both weight vector and the error energy, while the procedure ε_IncLag does the lag backward recursions for the error energy. Both procedures are straightforward from the basic recursive equations.

IV. EXPERIMENTAL RESULTS

The above joint algorithm is implemented and applied to the field data from the chemical industry process of the Hebei Xuanhua synthetic ammonia plant. The input signal $x(t)$ and the output signal are labeled as T-H2(transformed hydrogen) and F-H2(freshened hydrogen) respectively. The initial delay is obtained from their cross correlation analysis. The usual problems associated with conventional RLS algorithms are present. The rescue scheme is done from two respects: rescue for FTF and rescue for joint estimator. Fig. 3, 4 and 5 show the algorithm's modeling results.

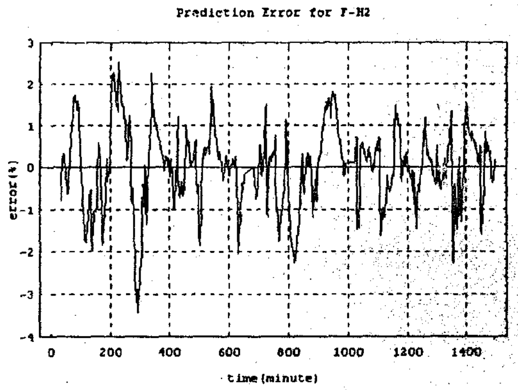

Fig. 3. Relative prediction error(RPE) curve of F-H2. $p=1$, $\lambda=0.944$, $T=10$. The prediction error is no more than 3.6% with its average value close to zero. Statistical results follows: 99% RPE are less than 3%, 93% RPE are less than 2% and 66% RPE are less than 1%.

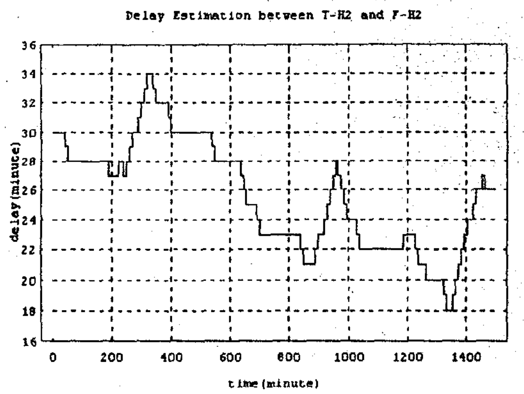

Fig. 4. Delay tracking curve between T-H2 and F-H2. $p=1$, $\lambda=0.944$, $T=10$.

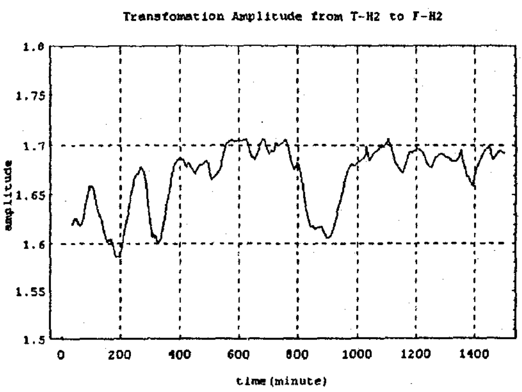

Fig. 5. The weight curve of joint estimator from T-H2 to F-H2. $p=1$, $\lambda=0.944$, $T=10$. The transformation amplitude has a mean of 1.65 and a fluctuation no more than 0.13.

From the above figures, we conclude that the model between T-H2 and F-H2 is a system with relative stable transformation amplitude but fairly long time-varying delay. This explanation is consistent with the actual transmission and purification processing from T-H2 to F-H2. See Fig. 6.

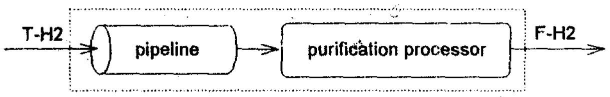

Fig. 6. The illustration of processing from T-H2 to F-H2.

V. CONCLUSION

An adaptive RLS algorithm for joint FIR filtering and pre-delay tracking based on FTF is developed and applied to the chemical industry process of synthetic ammonia plants. In the simulation of 25 hours field running, it gives relative prediction error no more than 3.6% and the modeling results are reasonable. This result is better than the various previous work we have tried on the process modeling where constant delay is assumed and obtained by cross correlation techniques of time delay estimation.

VI. ACKNOWLEDGMENT

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