Modified Finite Impulse Response 모델들을 이용한 시스템 모델 식별

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System Identification with Modified Finite Impulse Response Models

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INTRODUCTION

The design of modern digital controllers for multivariable dynamic processes requires models that give an accurate description of the dynamics of the process. The true dynamic relationship between the output and the input variables is often difficult to model from physical fundamental principles. Thus, for control of chemical dynamic systems, identification must frequently be done using the input-output data and linear or nonlinear stochastic model. There are several system identification methods using black-box models, which are Output Error (OE), Box-Jenkins (B-J), Steiglitz-McBride (S-M), (High Order) Autoregressive and eXternal input (ARX), Instrumental Variable (IV) and Finite Impulse Response (FIR) methods [1-6].

Kang [7] did extensive Monte-Carlo simulation for single-input and single-output (SISO) system to compare the performance of several principal model identification methods for several different model structures and several noise levels. The most successful overall, and nearly in every case, was identification with FIR function representation. The FIR model consists of a set of numerical coefficients corresponding to the z-transform of the impulse response of the process. The FIR method has the drawback that it requires a large number of parameters, leading to a high variance of estimate and a high dimensional regression problem, particularly in multivariable systems.

Kang's results from the extensive comparison of different system identification methods by using Monte-Carlo simulation provided the motivation to develop the modified FIR method, reducing the number of regression parameters drastically, with holding advantages of FIR method.

THEORETICAL DEVELOPMENT

The transfer function for multiple-input and single-output (MISO) system can be written as the following FIR model equation :

$$y(t) = \sum_{i=1}^{m}\sum_{k=1}^{K_i} u_i(t-k)b_{i,k} + \varepsilon(t), \qquad t = K+1,\cdots,N \tag{1}$$

where m is a number of inputs,

$u_i(t-k)$ is i-th input at time $t-k$,

$y(t)$ is the output at time t,

$b_{i,k}$ is an impulse response coefficient at time $t-k$ for i-th input,

$\varepsilon(t)$ is a noise at time t,

N is total number of data point to be used in regression,

K_i is a number of impulse response coefficients for i-th input u_i,

$K = \max\{K_i : i=1,\cdots,m\}$, the maximum number of coefficients required in the individual FIR's.

In this work, modified representation of the FIR (MFIR) was considered only for values of the response function which was monotonic decreasing for increasing values of time, i.e. past the last extremum of the impulse response function. The assumption of such a monotonic decreasing region of the FIR is true for overdamped response systems including inverse response systems. Most complex chemical processes such as large multicomponent distillation columns in petrochemical industry correspond to these cases.

In this work, all of the region before the last extremum, i.e., before the monotone region, is modeled as the ordinary FIR. The multi-step method was applied to all or part of the remaining monotone function.

The inner summation of equation (1) is grouped into l_i major blocks and j-th major block is subdivided into $q_{i,j}$ subblocks with $r_{i,j}$ elements in each subblock. Then this equation can be written as following :

$$y(t)=\sum_{i=1}^{m}\Big(\sum_{k=1}^{q_{i,1}r_{i,1}}u_i(t-k)b_{i,k}+\sum_{k=1+q_{i,1}r_{i,1}}^{q_{i,1}r_{i,1}+q_{i,2}r_{i,2}}u_i(t-k)b_{i,k}+\cdots+\sum_{k=1+\sum_{j=1}^{l_i-1}q_{i,j}r_{i,j}}^{\sum_{j=1}^{l_i}q_{i,j}r_{i,j}}u_i(t-k)b_{i,k}\Big)=\sum_{i=1}^{m}\Big(\sum_{k=1}^{q_{i,1}r_{i,1}}u_i(t-k)b_{i,k}+\sum_{L=2}^{l_i}\sum_{k=1+\sum_{j=1}^{L-1}q_{i,j}r_{i,j}}^{\sum_{j=1}^{L}q_{i,j}r_{i,j}}u_i(t-k)b_{i,k}\Big) \quad (2)$$

Assume that the first major block corresponds to the ordinary FIR model so that the value at each sample point represents a parameter. Thus the number of parameters in each subblock within the first major block for i-th input, $r_{i,1}$, is 1. Also assume that $q_{i,1}$ is the location of the last extremum for i-th input.

In this case the parameters within each subblock within over 2nd major block have a near linear relationship. This assumption for a near linear relationship can be also extended to the first parameter in next subblock. Using these assumptions the above equation can be rearranged into a equation with fewer parameters than the original one.

We propose three algorithms to calculate the parameters located in the interior positions within each subblock.

The first one (MFIR1 model) uses the assumption of a continuous and piecewise linear approximation within each subblock.

The second algorithm (MFIR2 model) uses the assumption of a piecewise constant approximation within each subblock.

The third one (MFIR3 model) uses the assumption of a piecewise continuous and piecewise linear approximation within each subblock.

SIMULATION STUDY and RESULTS

Proposed MFIR models were tested with several examples and the comparison with standard FIR model was done. The result of one of them is provided in this paper. This is a three-input simulation example of overdamped fifth order, inverse response third order and overdamped fourth order systems. The simulation model was

$$y(t) = \sum_{i=1}^{3} G_i(q)u_i(t) + v(t) \quad (3)$$

where $G_i(q)$ is a rational form of transfer function for i-th input and $v(t)$ is a simulated colored noise. Simulated noise to signal ratio (NSR) was 0.5.

From Table 1 it is seen that MFIR1, MFIR2 and MFIR3 models make the total number of regression parameters drastically fewer than for the standard FIR model. The CPU times for both three modified models are much shorter than for the standard FIR model. True and estimated impulse response coefficients and step response for input #2 are shown in Figure 1. Figure 2 shows the model validation plot. Sum of squared error (SOS) for estimated impulse response coefficients and the predicted output are shown in Table 2. From Tables and Figures mentioned above we can conclude that the performance of all modified FIR models is better than the standard FIR model. Among them the performance of MFIR1 and MFIR2 models is better than MFIR3 model. Model validation plots and the corresponding SOS for MFIR1 and MFIR2 show that the performance of MFIR1 is better than that of MFIR2. Model assumption for MFIR1 (continuous and piecewise linear approximation) is also physically more reasonable than MFIR2 (piecewise constant approximation).

Table 1 Several parameter values used in each model (i = 1,2,3)

	l_i	$q_{i1};r_{i1}$	$q_{i2};r_{i2}$	$q_{i3};r_{i3}$	$q_{i4};r_{i4}$	*TNP	K_i	**CPU
FIR model	1	200;1				600	200	2344.8
MFIR1	4	15;1	10;7	8;9	5;13	114	222	417.5
MFIR2	4	15;1	10;7	8;9	5;13	114	222	280.8
MFIR3	4	15;1	10;7	8;9	5;13	183	222	486.7

*TNP : total number of parameter in regression ;

** CPU time : CPU time for calculation of parameter (sec)

MFIR1:Modified FIR model 1;MFIR2:Modified FIR model 2;MFIR3:Modified FIR model 3

Table 2 Sum of squared errors in the impulse response and model validation plot

(A) Sum of squared errors (SOS) in Impulse Response : SOS of $(b_{est} - b_{true})$

	Input #1	Input #2	Input #3
Standard FIR model	0.9195	0.9159	0.7877
Modified FIR model 1	0.1093	0.0713	0.1167
Modified FIR model 2	0.1463	0.0752	0.1450
Modified FIR model 3	0.2109	0.1546	0.1918

** b_{est} = the estimated parameter ; b_{true} = the true parameter

(B) Sum of squared errors (SOS) in model validation plot

	SOS of $y_{est} - y_{true}$	SOS of $y_{est} - y_{obs}$
Standard FIR model	865.44	3518
Modified FIR model 1	90.89	2766
Modified FIR model 2	116.62	2828
Modified FIR model 3	179.60	2881

* y_{est} = the estimated parameter; y_{true} = the true parameter; y_{obs} = the observed parameter

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Figure 1 Comparison of impulse response coefficients and step response based on FIR model and modified FIR model 1, 2 & 3 for Test Problem (Input # 2). "solid" : True , "dotted" : Estimated
(a) : Standard FIR model ; (b) : Modified FIR model 1 (Continuous and Piecewise Linear)
(c) : Modified FIR model 2 (Piecewise Constant); (d) : Modified FIR model 3 (Piecewise Continuous and Piecewise Linear)

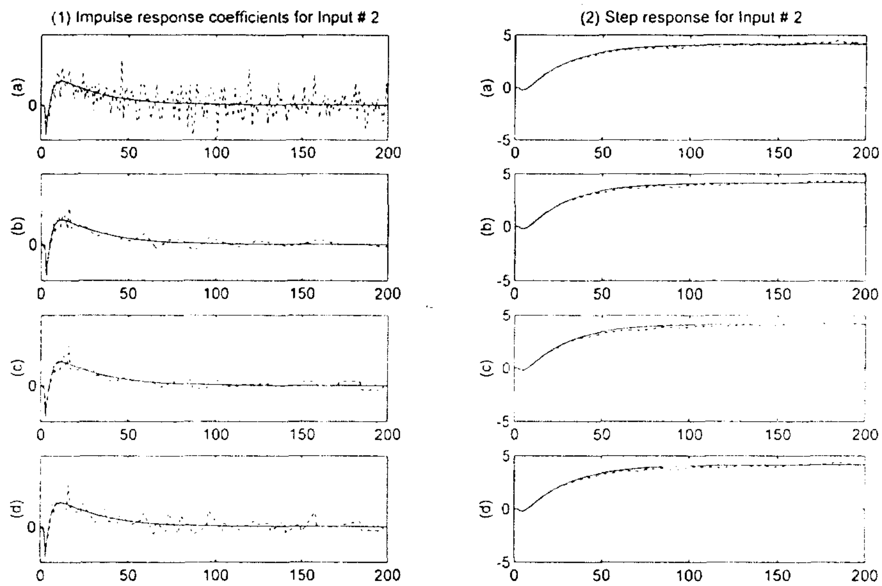

Figure 2 Comparison of observed, predicted and true output values for model validation of Test problem
"small circle" : observed, "dotted" : predicted, "solid" : true
(1) : Standard FIR model ; (2) : Modified FIR model 1 (Continuous and Piecewise Linear)
(3) Modified FIR model 2 (Piecewise Constant); (4) : Modified FIR model 3 (Piecewise Continuous and Piecewise Linear)