A Real-Time Identification Method of a Slow Process Parameters Using Adaptive IIR-OSLMS Filters

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Abstract: - This paper present a real time identification of the parameters value of a slow process using adaptive IIR-OSLMS filters. This kind of process can be assimilating to a time constant and a delayed time. To ensure the convergence of the adaptive algorithm the initial values of the parameters can be compute using an on-line identification method. The measured temperature is affected by noise, so it was used a ALMS filter to reject the noise.

Key-Words: - Adaptive algorithm, slow process, identification method, noise cancellation, numeric filter

1 Introduction

The heating process of an electrical resistance furnace is a slow process and is very difficult to control it because the parameters values of the system of the electrical resistance furnace cannot be compute with accuracy. These values are adequate for designing the heating process regulator. In [8] and [9] is been considered that this process can be very well approximated taking into consideration that the heating process model has a time constant and a delayed time.

Because the parameters of the system can be modifying in the heating process, it is required to compute them in real time. In order to solve this problem, for the identification of the system it can be used an adaptive filter. The coefficients of the adaptive filter are modifying at every each iteration, having as consequence that the parameters of the system can be also compute at every each iterations. The temperature control system is conditioned by the convergence of the adaptive algorithm. One of the convergence criterions for an adaptive filter is the initial value of the parameters of the filter and from this reason, the initial values were computed using an on-line method.

An experimentally determination leads to the conclusion: if the values of the samples are distorted by the additive noises, it has to be used a smoother filter.

2 Problem Formulation

One of the problems that must be solved consists in regulation of the slow process, which is a very difficult activity because the parameters of the process are variable in time in many situations.

In some applications, such as heating process of electrical resistance furnace, the output signal is delayed comparative to the input signal by a time constant, as in relation

$$y(t) = x(t-\tau) \quad , \tau > 0 \quad , \tag{1}$$

where τ is a delayed time constant or time propagation constant.

The transfer function of such a process is

$$H_\tau(s) = e^{-\tau s} \quad . \tag{2}$$

In [9] it is shown that the model of the electrical resistance furnace is a model with a time constant and a delayed time defined by the relation:

$$H(s) = \frac{K \cdot e^{-\tau s}}{1+Ts} \text{ , where T, } \tau > 0. \tag{3}$$

In (3) K is the amplification coefficient, τ is the delayed time and T is the time constant.

2.1. The approximation of the parameters system function model

One of the problems that must be solved consists in approximation of $e^{-\tau s}$ with a rational function.

The transfer function which approximate $H_\tau(s)$ is $H_{\tau a}(s)$, where

$$H_{\tau a}(s)=\frac{1+c_1\cdot s+c_2\cdot s^2+\cdots+c_n\cdot s^n}{1+d_1\cdot s+d_2\cdot s^2+\cdots+d_n\cdot s^n},\ b_n\neq 0. \quad (4)$$

The coefficients of $H_{\tau a}(s)$ transfer function can be compute by developing the function $H_\tau(s)$ in Taylor series in origin. Such an approximation knows as Pade approximation of n+k order, where n is the order of denominator and k is the order of nominator.

In [8] are presented the most used Pade approximations by (2+0), (2+1), (1+1) and (2+2) order.

$$\begin{aligned}
H_{\tau a1}(s)&=\frac{1}{1+\tau s+\frac{\tau^2}{2}\cdot s^2}\ ,\\
H_{\tau a2}(s)&=\frac{1-\frac{1}{3}\tau s}{1+\frac{2}{3}\tau s+\frac{\tau^2}{2}s^2}\ ,\\
H_{\tau a3}(s)&=\frac{1-\frac{\tau}{2}s}{1+\frac{\tau}{2}s}\ ,\\
H_{\tau a4}(s)&=\frac{1-\frac{\tau}{2}s+\frac{\tau^2}{12}\cdot s^2}{1+\frac{\tau}{2}s+\frac{\tau^2}{12}\cdot s^2}.
\end{aligned} \quad (5)$$

2.2. Determining the system transfer function of numerical system

To obtain the system transfer function of numerical system we use one of the Pade approximation forms of $e^{-\tau s}$, resulting the relation:

$$H_a(s)=\frac{K}{1+s\cdot T}\cdot H_{\tau a}(s)\ . \quad (6)$$

The numerical transfer function system results by using the transform methods of the analogical filter in a numerical filter. The two methods that we are studied are:

1. The approximation of differential equation by finite difference method in which the system function is obtain from relation:

$$H(z)=H_a(s)\Big|_{s=\frac{1}{T_e}\cdot\left(1-z^{-1}\right)}; \quad (7)$$

2. The bilinear transform method in which the system function is obtained from relation:

$$H(z)=H_a(s)\Big|_{s=\frac{2}{T_e}\cdot\frac{1-z^{-1}}{1+z^{-1}}}\ . \quad (8)$$

Irrespective of the used Pade approximation, the general expression on the system function can be written as:

$$H(z)=\frac{b_0+b_1\cdot z+b_2\cdot z^2+b_3\cdot z^3}{1+a_1\cdot z+a_2\cdot z^2+a_3\cdot z^3}. \quad (9)$$

The system function coefficients was determined in both method and it can be observed that only Pade approximation (1+1) gives two poles of the system function. Also, we can notice that the values of the system function coefficients depend on sampling period, which means that the sampling period influences the poles position and the stability of the system.

The authors simulated the behavior of the obtained filters for the four Pade approximations to different values of the parameters of the system. The conclusion is that to ensure the convergence for the coefficients of the adaptive filter at coefficients values of the filter that would result for the chosen values of the parameters of the system, it is required to grow the sampling period in proportion to the number of the poles of the system function.

2.3. The determination of the coefficients of the process model

We determined the coefficients of the system function in the case of using both methods of equivalence and all the 4 Padé approximations, but the only approximation that gave the system function only 2 poles is the Padé approximation (1+1). In this case the coefficients values are:

$$\begin{aligned}
b_0&=-\frac{kT_e\left(\tau-2T_e\right)}{\left(T+T_e\right)\left(\tau+2T_e\right)}\\
b_1&=\frac{k\tau T_e}{\left(T_e+T\right)\left(2T_e+\tau\right)}\\
a_1&=-\frac{2\tau T+2T_eT+T_e\tau}{\left(T_e+T\right)\left(2T_e+\tau\right)}\\
a_2&=\frac{\tau T}{\left(T_e+T\right)\left(\tau+2T_e\right)}\\
b_2&=a_3=0
\end{aligned} \quad (10)$$

Making use of the coefficients of the system function, we can compute the parameters of the model of the heating process according to relations:

$$
\tau = \frac{2T_e}{\frac{b_0}{b_1} + 1}
$$
$$
T = \frac{T_e}{-\frac{a_1}{a_2} - 2 - \frac{2T_e}{\tau}} \tag{11}
$$
$$
K = \frac{b_1}{a_2} \cdot \frac{T}{T_e}
$$

Since the values of the parameters of the system model can be finding by knowing the values of the adaptive filter, we had to choose the optimal identification algorithm with respect to the convergence rate, as well as to stability. We also had to choose the form of implementation, direct of lattice, as well as the method of equivalence for the analog filter with a numeric one.

2.4. Defining the IIR-OSLMS filters

One of the applications of adaptive filters is identification. In this case, the purpose of the adaptive filter is to supply a model that will represent the best approximation of the unknown system. There are some situations when the model of the unknown system is defined through a rational function and its coefficients must be determinate using the adaptive filter. In this situation, the adaptive filter will be an IIR filter, described by relation (12).

$$
\sum_{k=0}^{N} a_k(n)\, y(n-k) = \sum_{k=0}^{N} b_k(n) \cdot x(n-k), \tag{12}
$$

where $a_0=1$.

A version of the LMS algorithm, the OSLMS filtering, is obtained by updating the filter's coefficients, starting from relation (13), and is given in [1]

$$
\mathbf{w}_N(n+1) = \mathbf{w}_N(n) + \alpha \cdot \mathbf{M}_N(n)\mathbf{a} \tag{13}
$$

where α is the adaptive parameter and $\mathbf{M}_N(n)$ is a matrix having the dimensions (NxL) given by relation

$$
\mathbf{M}_N(n) = T\{e(n)\mathbf{x}_N(n)\}. \tag{14}
$$

By T{·} we understand an algebric transformation of increasing ordering applied to each sequence line

$$
\begin{aligned} &\{e(n)\mathbf{x}_N(n)\ \ e(n-1)\mathbf{x}_N(n-1)\ \cdots \\ &e(n-L+1)\mathbf{x}_N(n-L+1)\} \end{aligned} \tag{15}
$$

and the vector **a** is given by relation

$$
\mathbf{a}^t = [a(1)\ \ a(2)\ \cdots\ a(L)]\ , \tag{16}
$$

a representing the weight coefficient vector of the elements of matrix $\mathbf{M}_N(n)$. Parameter L usually takes odd values, being named as length of the ordering window. Line i of matrix $\mathbf{M}_N(n)$ is a line that can be written as

$$
\begin{aligned} &T\{e(n)\cdot x(n-i+1)\ e(n-1)\cdot x(n-i)\ \cdots \\ &e(n-L+1)\cdot x(n-i-L+2)\} \end{aligned} \tag{17}
$$

where $i = 1,\cdots,N$. To be noticed that each prediction coefficient is calculated by applying relation (1). If all the coefficients of vector **a** are equal to 1, the OS filters thus obtained are called rectifier OS filters.

The output of the OSLMS filters is obtained according to the same relations as in the general case

$$
y(n) = \mathbf{w}_N^T(n) \cdot \mathbf{x}_N(n) \tag{18}
$$

and the prediction error is given by relation

$$
e(n) = d(n) - y(n). \tag{19}
$$

According to matrix **a**, we can obtain different types of particular OSLMS filters [12]. Thus, if matrix **a** is defined according to relation (20), we obtain the median filter LMS (MLMS).

$$
\begin{cases} a\left(\dfrac{L+1}{2}\right) = 1 \\ a(i) = 0, \quad if \quad i \neq \dfrac{L+1}{2} \end{cases}. \tag{20}
$$

An equivalent notation for the MLMS filter is

$$
\mathbf{w}_N(n+1) = \mathbf{w}_N(n) + \alpha \cdot med\{e(n)\mathbf{x}_N(n)\}_L, \tag{21}
$$

where $med\{e(n)\mathbf{x}_N(n)\}_L$ is a column vector with N lines, containing mean elements of

$$
\begin{aligned} &\{e(n)\mathbf{x}_N(n)\ \ e(n-1)\mathbf{x}_N(n-1)\ \cdots \\ &e(n-L+1)\mathbf{x}_N(n-L+1) \end{aligned} . \tag{22}
$$

If the matrix **a** has been defined according to relation (23), we obtain the mean filter LMS (ALMS)

$$
a(i) = \frac{1}{L}, i = 1,\cdots,L\ , \tag{23}
$$

whose equivalent notation is given by

$$
\mathbf{w}_N(n+1) = \mathbf{w}_N(n) + \alpha \cdot mean\{e(n)\mathbf{x}_N(n)\}_L. \tag{24}
$$

IIR adaptive filters can be implemented as in direct form and also in lattice form.

The authors are presenting 3 algorithms that can be used for the recalculation of the coefficients of the adaptive filter: using gradient algorithm, Steiglitz-McBride algorithm and Sharf algorithm.

These algorithms can be used if a Gaussian noise overlaps on the output signal of the unknown system. If on the output signal of the unknown system overlaps impulses with high amplitude and short duration, the values of the coefficients of the adaptive filters can be variable.

In [5] it is demonstrate that a method to decrease the influence of the impulses with high amplitude and short duration consist in using an OSLMS filter.

Based on these, the authors defined an IIR-adaptive filter that recalculates the coefficients with one of three identification algorithms, combined with an ordering operation.

IIR filter can be implemented directly and also using lattice structures (using any of three algorithms), and there are 6 possibilities to recalculate the coefficients of the adaptive filter. With the earlier mentioned notations, the relations for computing the filter coefficients, proposed by authors are:

a1) Gradient algorithm, direct form

$$\begin{pmatrix} \mathbf{a}(n+1) \\ \mathbf{b}(n+1) \end{pmatrix} = \begin{pmatrix} \mathbf{a}(n) \\ \mathbf{b}(n) \end{pmatrix} + \mu \cdot T \begin{Bmatrix} -e(n)\mathbf{Y}_{\mathbf{A}}(n) \\ e(n)\mathbf{X}_{\mathbf{A}}(n) \end{Bmatrix} \cdot \mathbf{a} \quad (25)$$

a2) Gradient algorithm, lattice form

$$\begin{pmatrix} \mathbf{k}(n+1) \\ \mathbf{b}(n+1) \end{pmatrix} = \begin{pmatrix} \mathbf{k}(n) \\ \mathbf{b}(n) \end{pmatrix} + \mu \cdot T \begin{Bmatrix} -e(n)\hat{\mathbf{U}}_{\mathbf{A}}(n) \\ e(n)\mathbf{X}_{\mathbf{A}}(n) \end{Bmatrix} \cdot \mathbf{a} \quad (26)$$

b1) SHARF algorithm, direct form

$$\begin{pmatrix} \mathbf{a}(n+1) \\ \mathbf{b}(n+1) \end{pmatrix} = \begin{pmatrix} \mathbf{a}(n) \\ \mathbf{b}(n) \end{pmatrix} + \mu \cdot T \begin{Bmatrix} -c(n)\mathbf{y}(n) \\ c(n)\mathbf{x}(n) \end{Bmatrix} \cdot \mathbf{a} \quad (27)$$

where

$c(n) = e(n) - 0.6 \cdot e(n-1)$

b2) SHARF algorithm, lattice form

$$\begin{pmatrix} \mathbf{k}(n+1) \\ \mathbf{b}(n+1) \end{pmatrix} = \begin{pmatrix} \mathbf{k}(n) \\ \mathbf{b}(n) \end{pmatrix} + \mu \cdot T \begin{Bmatrix} -c(n)\mathbf{u}(n) \\ c(n)\mathbf{x}(n) \end{Bmatrix} \cdot \mathbf{a} \quad (28)$$

c1) Steiglitz Mc-Bride algorithm, direct form

$$\begin{pmatrix} \mathbf{a}(n+1) \\ \mathbf{b}(n+1) \end{pmatrix} = \begin{pmatrix} \mathbf{a}(n) \\ \mathbf{b}(n) \end{pmatrix} + \mu \cdot T \begin{Bmatrix} -e(n)\mathbf{D}_{\mathbf{A}}(n) \\ e(n)\mathbf{X}_{\mathbf{A}}(n) \end{Bmatrix} \cdot \mathbf{a} \quad (29)$$

c2) Steiglitz Mc-Bride algorithm, lattice form

$$\begin{pmatrix} \mathbf{k}(n+1) \\ \mathbf{b}(n+1) \end{pmatrix} = \begin{pmatrix} \mathbf{k}(n) \\ \mathbf{b}(n) \end{pmatrix} + \mu \cdot T \begin{Bmatrix} -e(n)\mathbf{U}_{\mathbf{A}}(n) \\ e(n)\mathbf{X}_{\mathbf{A}}(n) \end{Bmatrix} \cdot \mathbf{a} \quad (30)$$

With this aim, we tested 3 identification algorithms: the gradient algorithm, the Steiglitz Mc-Bride algorithm and the SHARF one, each of them being implemented both in direct and lattice form, by using one of the two methods of equivalence for the analog filter with a numeric one.

For this goal, there were identified the parameters of the unknown system with the transfer function:

$$H(z) = \frac{-0{,}1 - 1{,}3z^{-1} + 1{,}6z^{-2}}{1 - 1{,}19z^{-1} + 0{,}7z^{-2}} \quad . \quad (31)$$

This system has the values of the reflection coefficients $k_1 = -0{,}7$ şi $k_2 = 0{,}7$. At the input of the unknown system was applied a noise with gaussian distribution. All simulations were realised using the same value of the adaptation parameter $\mu = 0{,}05$ and with the same window length (9 samples).

It was determined experimentally for these value of the adaptation parameter, respective the values of the window length, that a number of 5000 samples are enough in order to all the coefficients of the adaptive filter to converge to the values of the unknown system.

To study the behaviour of the IIR-OSLMS filters, [10], [11], in situation when appear impulse perturbations with high amplitude and short duration, at the unknown system output it considers that appear 3 impulses of different amplitude, 2, 3 respective 4 units, that are situated on samples positions with numbers 2000, 3000 respective 4000.

For the first two algorithms it was represented the variation form of the IIR adaptive filter coefficients, the ALMS adaptive filter coefficients, respective the MLMS adaptive filter coefficients implemented in direct and lattice form. The results are presented in figures 1 -14.

It was determined the followings:

1. In direct form of implementation the IIR and ALMS filters have similar properties (the convergence speed and also the influence of impulses with high amplitude and short duration). The MLMS filter has a reduced speed convergence, but the influence of impulses with high amplitude and short duration is reduced.

2. In lattice form of implementation the IIR and ALMS filters have similar properties (the convergence speed), but the influence of impulses with high amplitude and short duration on variation of coefficients is higher in MLMS filter case. In this case too, MLMS filter has a reduced convergence speed, and the influence of impulses with high amplitude and short duration on variation of coefficients is reduced.

3. Comparing the characteristics of the two algorithms, it is obvious that convergence speed is the same, no matter of implementation form and the kind of filter. In the same time, the influence of impulses with high amplitude and short duration on variation of coefficients is reduced at SHARF algorithm.

4. In case of Steiglitz-McBride algorithm, the author concluded experimentally that the IIR-OSLMS filters are not convergent for the chosen values of adaptation parameter and window length. In figures 13 and 14 was presented the variation of coefficients for IIR adaptive filter using this algorithm in the both implementation forms. The variation forms of the coefficients were made after iterated tests, because this algorithm wasn't convergent in many cases.

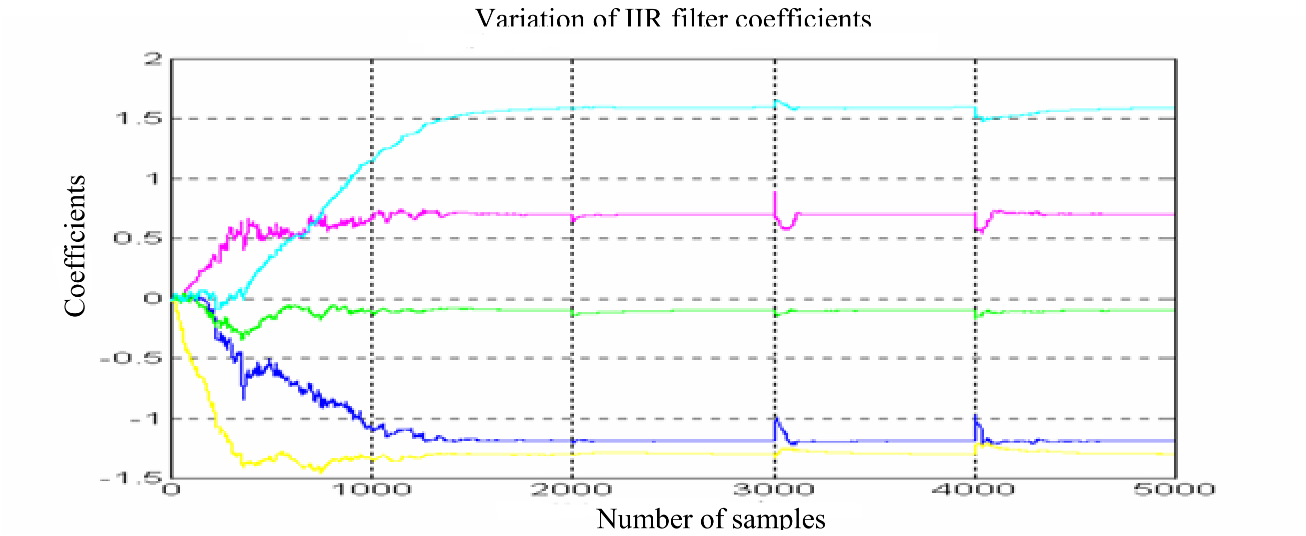

Figure 1. Variation of IIR filter coefficients, gradient algorithm, direct form.

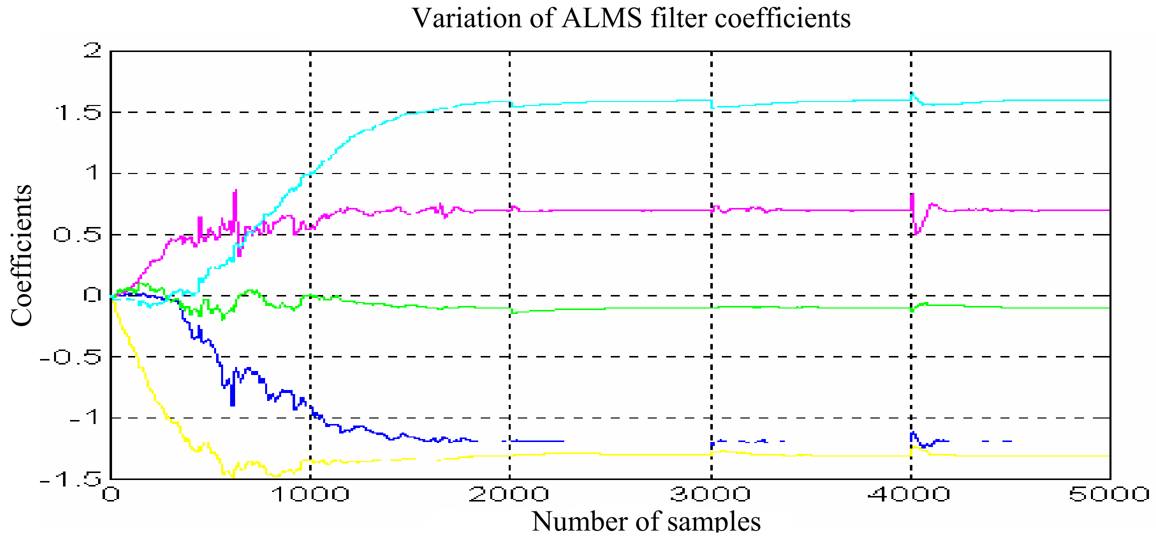

Figure 2. Variation of ALMS filter coefficients, gradient algorithm, direct form.

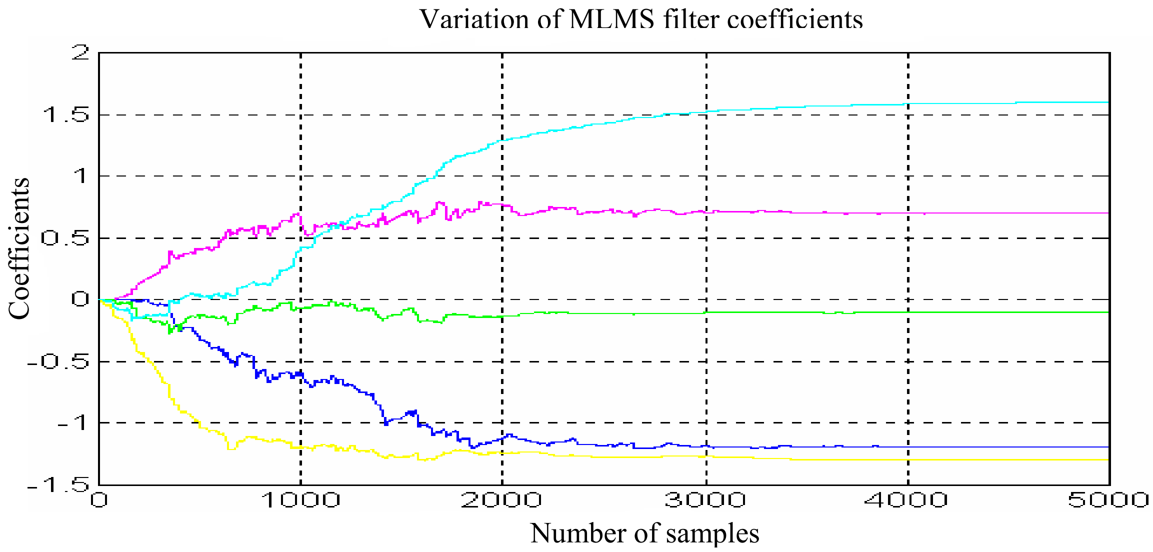

Figure 3. Variation of MLMS filter coefficients, gradient algorithm, direct form.

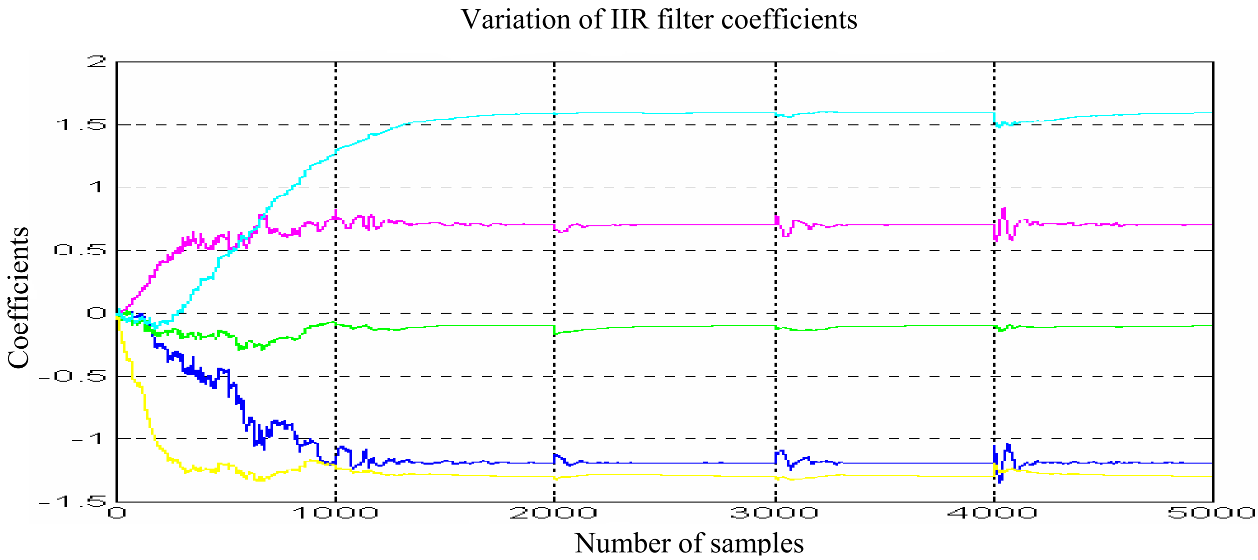

Figure 4. Variation of IIR filter coefficients, gradient algorithm, lattice form.

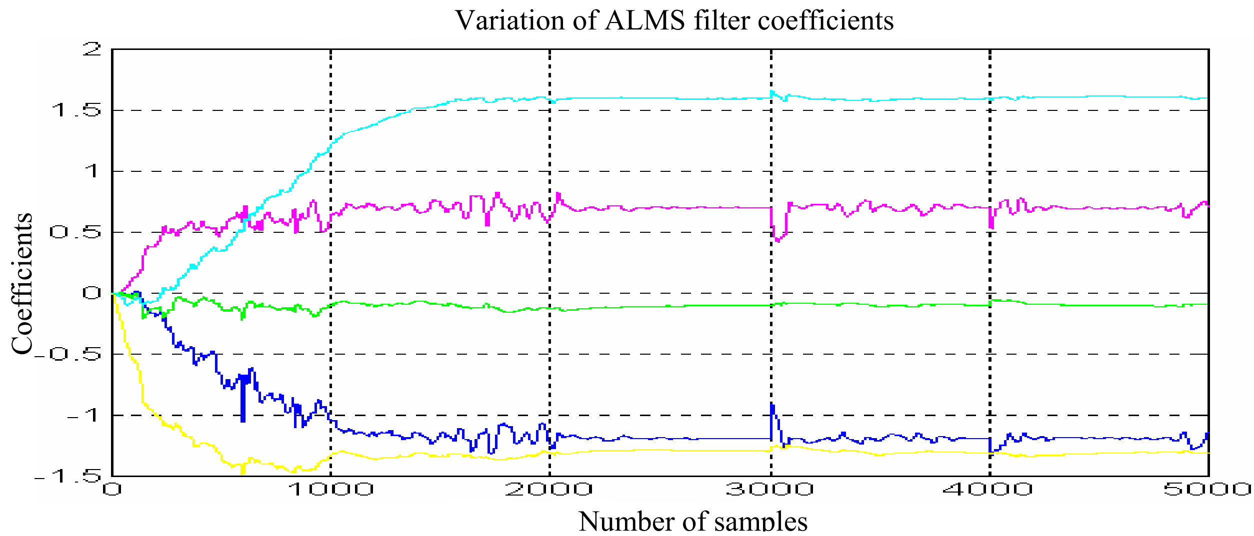

Figure 5. Variation of ALMS filter coefficients, gradient algorithm, lattice form.

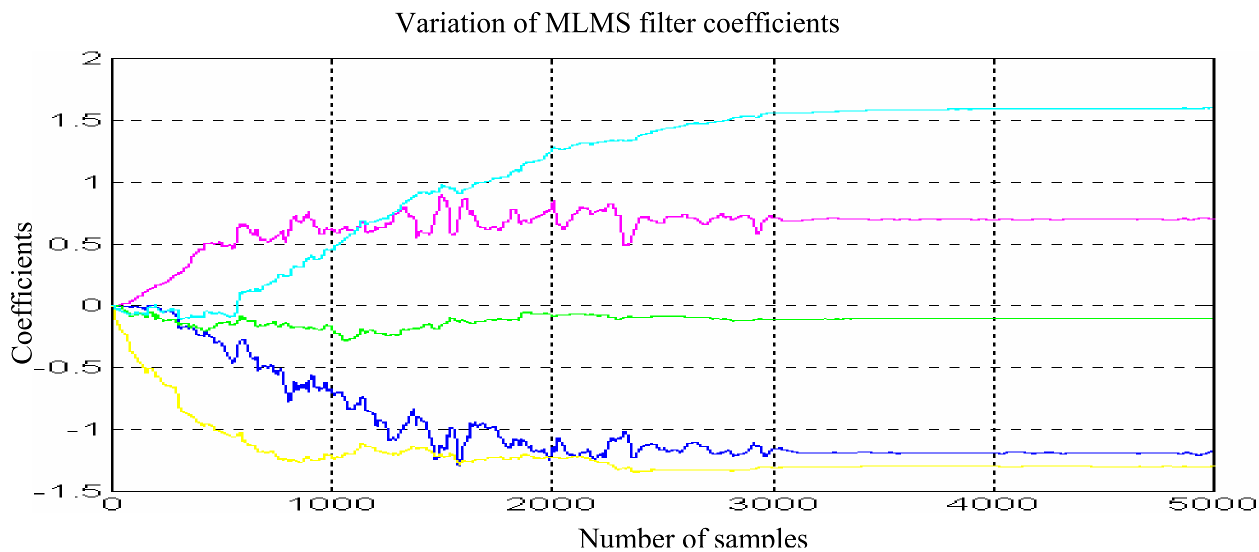

Figure 6. Variation of MLMS filter coefficients, gradient algorithm, lattice form.

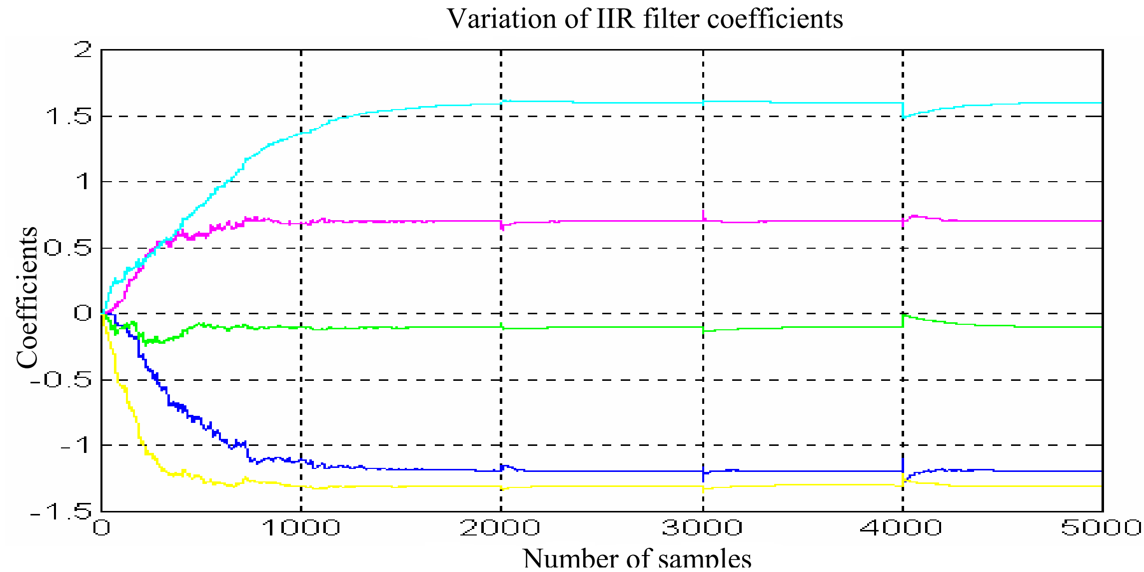

Figure 7. Variation of IIR filter coefficients, SHARF algorithm, direct form.

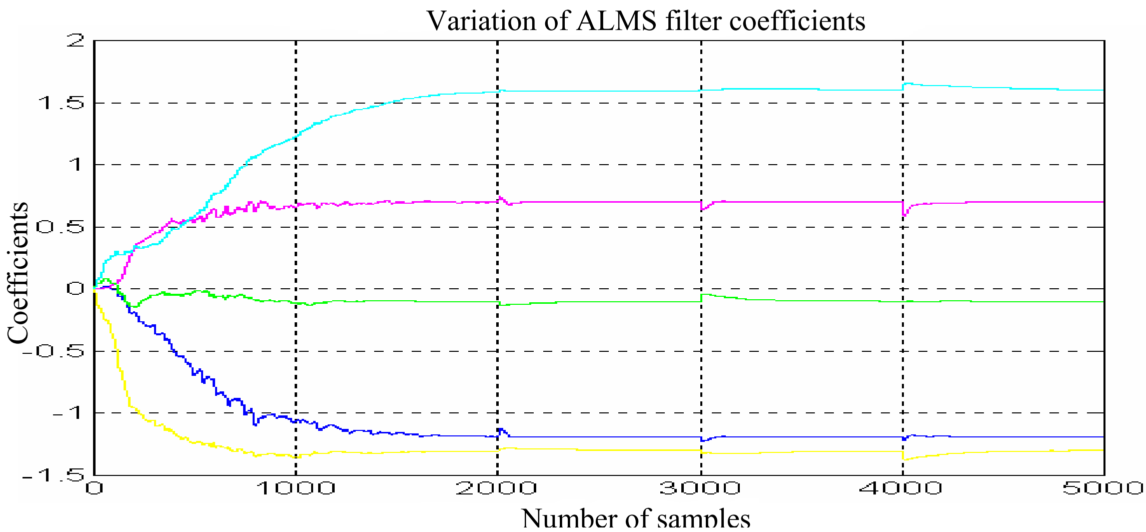

Figure 8. Variation of ALMS filter coefficients, SHARF algorithm, direct form.

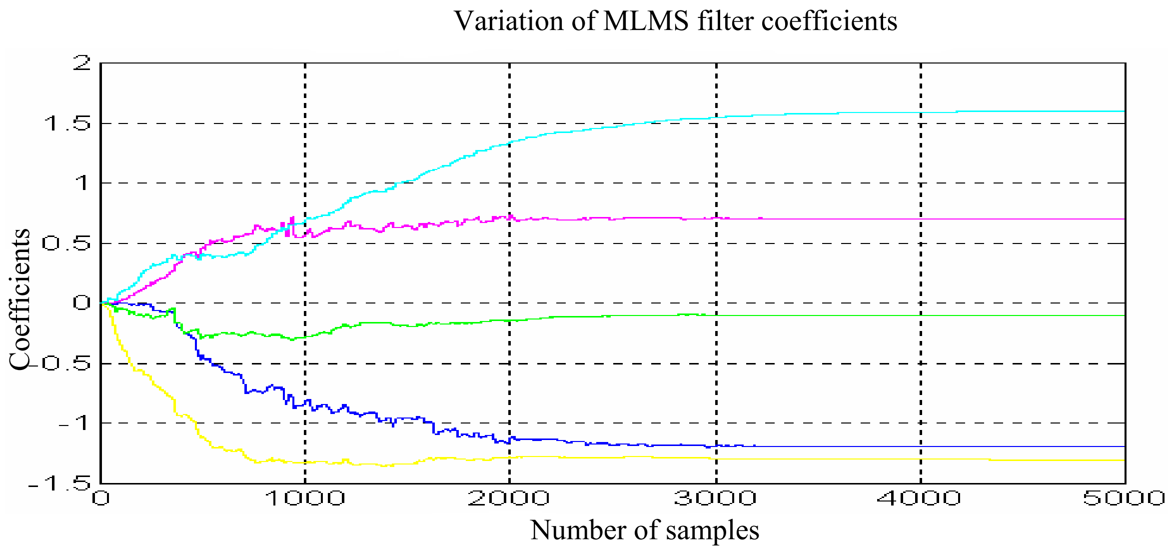

Figure 9. Variation of MLMS filter coefficients, SHARF algorithm, direct form.

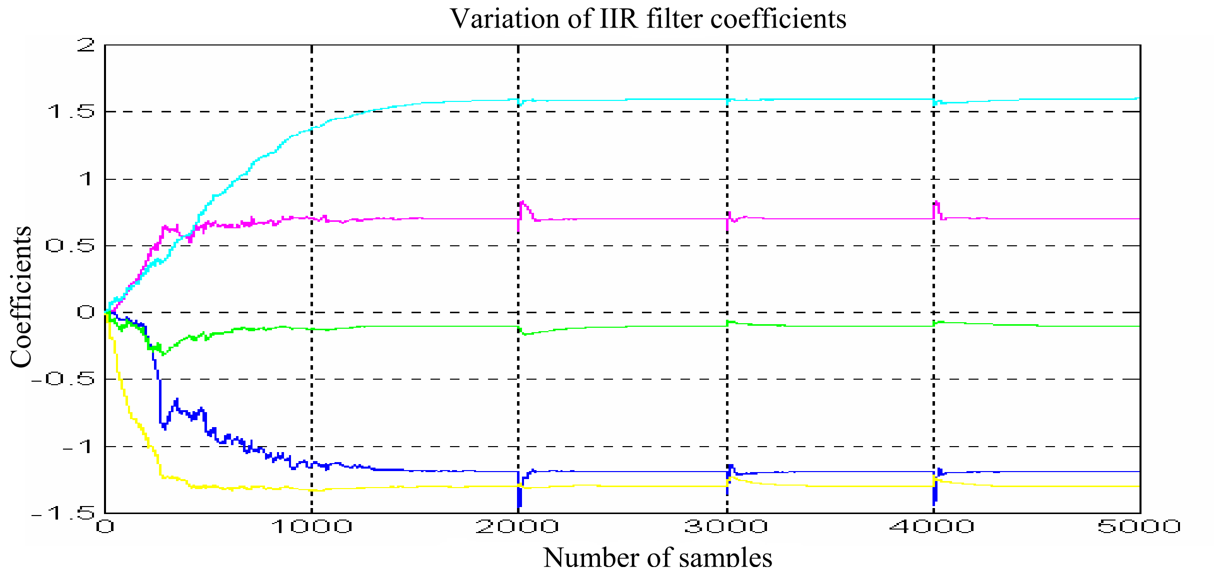

Figure 10. Variation of IIR filter coefficients, SHARF algorithm, lattice form.

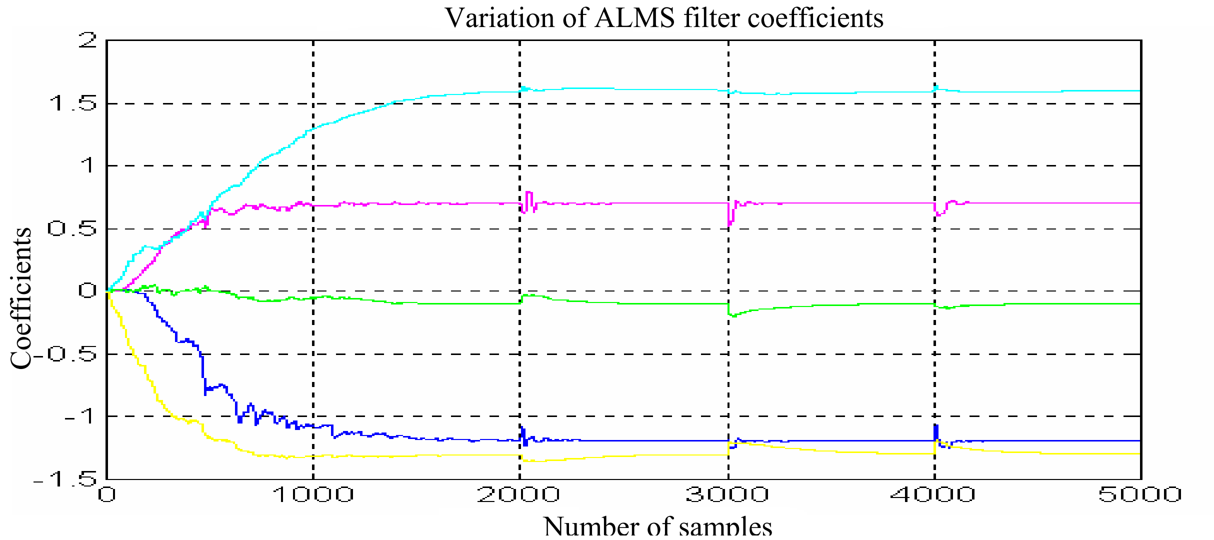

Figure 11. Variation of ALMS filter coefficients, SHARF algorithm, lattice form.

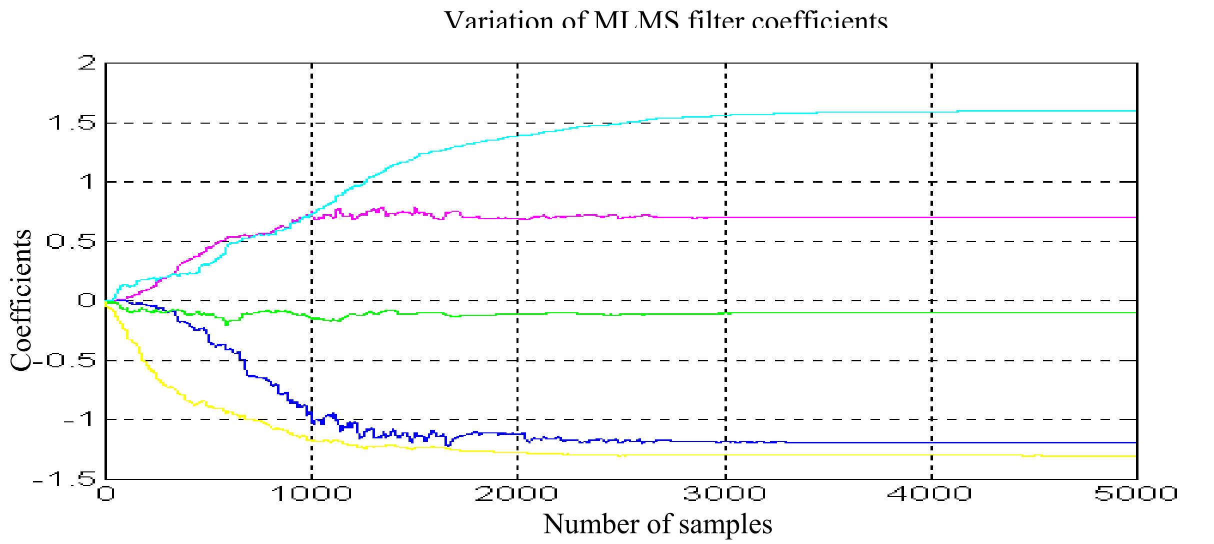

Figure 12. Variation of MLMS filter coefficients, SHARF algorithm, lattice form.

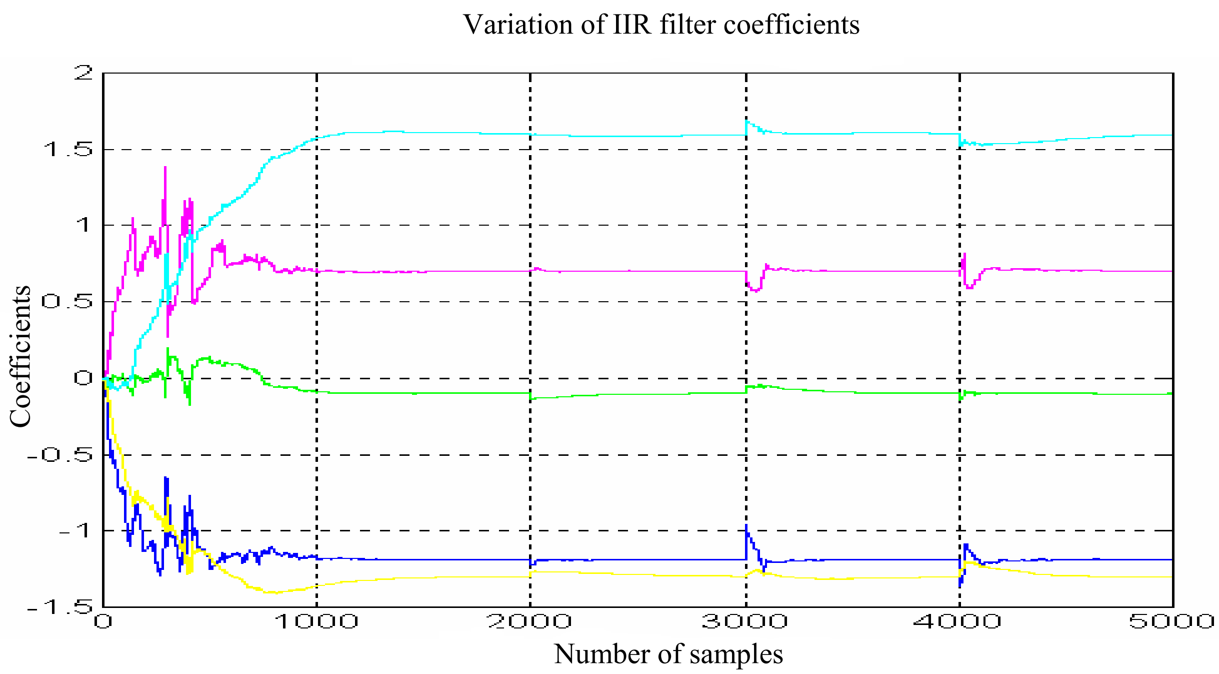

Figure 13. Variation of IIR filter coefficients, Steiglitz-McBride algorithm, direct form..

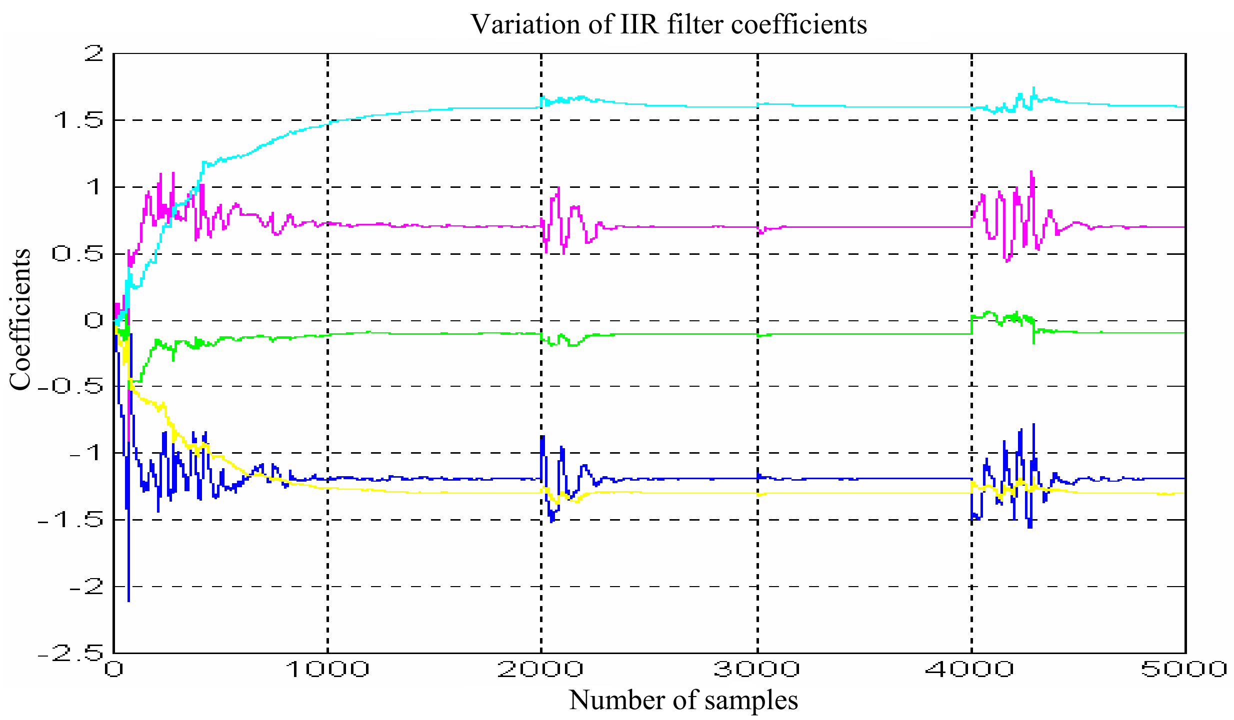

Figure 14. Variation of IIR filter coefficients, Steiglitz-McBride algorithm, lattice form.

5. The implementation of the IIR-adaptive filter doesn't need a lot of computations, but in case of implementation of MLMS adaptive filter the computation is more complicated, because of comparing operations.

6. MLMS filter has the best performances in field of influence of impulses with high amplitude and short duration on variation of coefficients, and it doesn't depend of the algorithm and the implementation form. It was concluded that in spite of a lot of computations for implementation, this filter has more advantages in eliminating the influence of impulses with high amplitude and short duration. Also, this kind of filter can be used

in on-line identifications of the parameters of slow processes.

The results of the tests meant to identify the heating process of the furnace, lead us to the conclusion that the Pade (1+1) approximation allows the easiest determination once the coefficients of the numeric adaptive filter are known.

We also determined experimentally that the most efficient algorithm of identification is the SHARF algorithm, implemented in its lattice form, the equivalence of the analogous filter with a numeric one being done by the method of the approximation of the differential equation with finite differences.

3. Problem Solution

In this part of this paper, the authors present a method that determines the adaptive filter coefficients. In the first step, using an on-line identification method, are estimate the initial values of the coefficients. In the second step, starting from these values and using an adaptive algorithm are computing the instantaneous values of adaptive filter.

3.1. The on-line identification method for the parameters of slow process with delayed time

The on-line identification method, that is presented in [8], consists in applying of an input signal to a system whom balanced state is described by the (X_0, Y_0) point. The relation (32) describes this input signal.

$$x(t)=\begin{cases} X_1 & 0\le t\le T_0 \\ X_0 & t>T_0 \end{cases} \quad . \tag{32}$$

The input signals form is presented in figure 15.

Applying this kind of input signal instead of the stage signal presents two advantages. The first advantage: it can be observed if the Y output can be stabilized in the same stationary Y_0 point, or not. If the Y_0 value can't be reached, we conclude that or the process is no stationary, which can conduct to a better approach of the model, or a perturbation appeared during the experiment, so the experiment must be resumed. The second advantage consists in the fact that differences $x(t)-X_0$ and $y(t)-Y_0$ are null after a time interval that is larger then process stabilization time interval, so the integrals

$$I_{XK}=\int_0^{\infty}(-t)^K\left[x(t)-X_0\right]\cdot dt \tag{33}$$

and

$$I_{YK}=\int_0^{\infty}(-t)^K\left[y(t)-Y_0\right]\cdot dt \quad , \tag{34}$$

where $K=0,\ 1,\ \ldots$, will be finite.

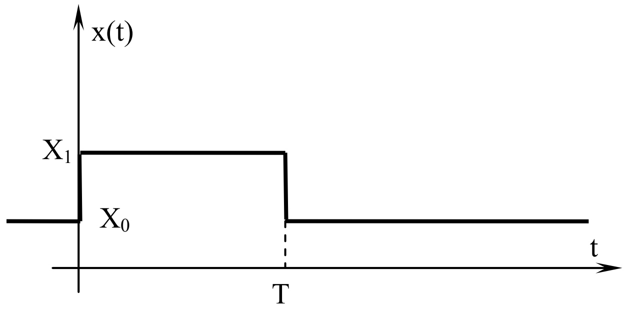

Figure 15. The input signal shape.

Taking into consideration that the chosen model depends by N parameters, the identification process consists in evaluation of H(s) function and the first N-1 derivatives in origin. The result is a N equation system with N variables. The solution of this equation system is the N system parameters.

The N-1 derivatives can be determined in recursive way, by the relation:

$$Y(s)=H(s)\cdot X(s)\ , \tag{35}$$

from which result

$$Y(0)=H(0)\cdot X(0) \tag{36}$$

and by successive derivations it can be obtained the general relation for the k-th order derivative in origin

$$H^{(K)}(0)=\frac{Y^{(K)}(0)-\sum_{i=1}^{K}C_K^i H^{(K-i)}(0)\cdot X^{(i)}(0)}{X(0)} \tag{37}$$

where

$$Y^{(K)}(0)=\int_0^{\infty}(-t)^K\left[y(t)-Y_0\right]\cdot dt\ , \tag{38}$$

$$X^{(K)}(0)=\int_0^{\infty}(-t)^K\left[x(t)-X_0\right]\cdot dt\ , \tag{39}$$

K= 0, 1, . . ., N-1.

The integrals that are obtained from (38) and (39) can be computed on a finite domain, $0\le t\le T_i$, where T_i represents the limits of integration. Using (37) it was computed successive for the model given by the relation (3):

$$\begin{aligned} &H(0)=K \\ &H'(0)=-K\cdot(T+\tau) \\ &H''(0)=K\cdot\left[(T+\tau)^2+T^2\right], \end{aligned} \tag{40}$$

These relations permitted the evaluation of the model parameters.

$$K = H(0)$$
$$T = \sqrt{\frac{H''(0)}{H(0)} - \left(\frac{H'(0)}{H(0)}\right)^2} \quad (41)$$
$$\tau = -\frac{H'(0)}{H(0)} - T \ .$$

3.2. Noise cancellation and evaluation of the model parameters

To study the possibility of noise cancellation it was applied a test impulse and the temperature values was measured. The impulse duration was 20 minute and sampling period was 0.2 seconds. The form of impulse is presented in figure 15.

In figure 16 it can be see the noise that affect the measured results. To cancel the noise it was used a MALMS filter, with a window of 75 samples. The results are presented in figure 17.

In scope of determining the values of the model parameters, the authors made 10 measurements with initial conditions starting from zero, the measurements results being presented in table 1.

Based on the results presented in table 1 the initial values of the models parameters were chosen $K = 440$, $T = 275$ seconds and $\tau = 66$ seconds.

Table 1.

No. crt.	K_m	T_m (sec)	τ_m (sec)
1	442,60	274,22	66,21
2	438,56	272,21	64,87
3	450,88	280,34	65,38
4	443,24	275,33	66,86
5	436,22	271,00	67,12
6	445,78	278,22	66,43
7	436,50	270,29	63,26
8	447,87	279,24	65,96
9	440,26	275,34	67,28
10	438,22	273,37	66,32

Using Pade approximation (1+1), it was applied at the input of the system, with has the system function given by relation (3), a rectangular signal. The filter coefficients variation is presented in figures 18 and 19, for the values 0,001 and 0,0015 of adaptation coefficient. It was observe that a greater value of the adaptation coefficient conduct to a better convergence of the filter coefficients, but the value of the adaptation coefficient cannot be chosen too great because the adaptive filter became unstable.

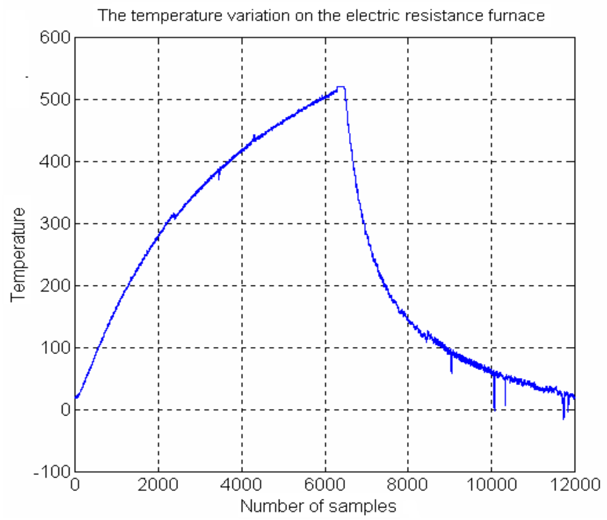

Fig. 16. The measured temperature.

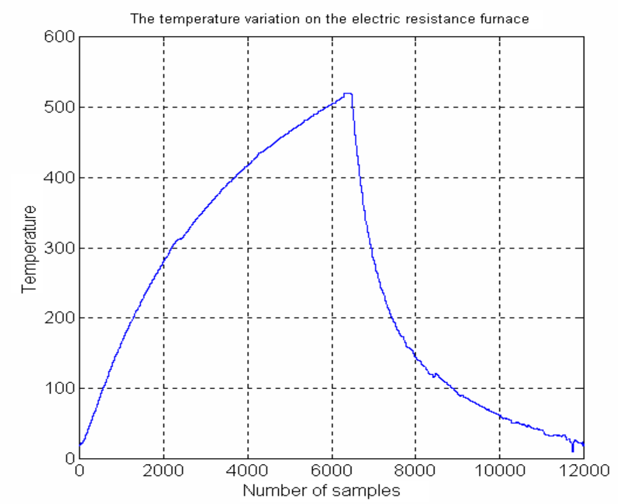

Fig. 17. The filtered measured temperature variation.

4. Conclusions

The on-line identification method has two disadvantages. First of them consists in the fact that if the duration of the test impulse and of the integration time are not chosen according to the real values of the process parameters, the measurement values of the parameters have great errors. The second disadvantages consist in fact that for measure the values of the parameters process the system must be take out of the stable state and the measured values are considered constants until a new measurement.

The system transfer function can be obtain using a Pade approximation of the transfer function which is associate on delayed time process and the discrete system function is obtained by equivalence of the analogical filter with a numerical filter.

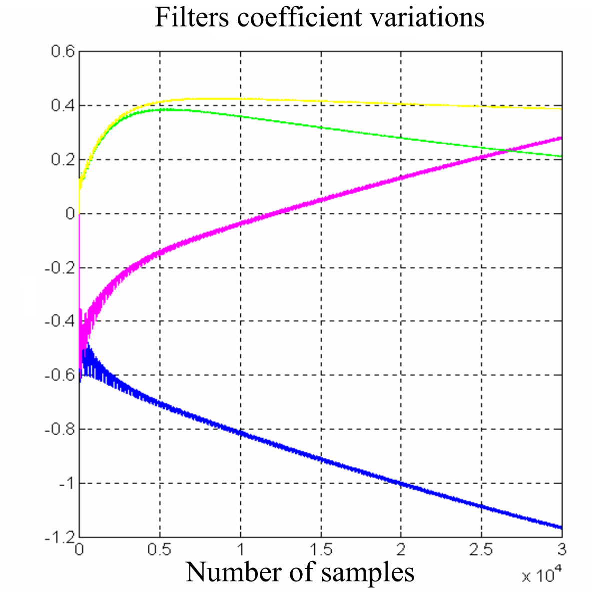

Fig. 18. Filters coefficients variations for $\mu = 0{,}001$.

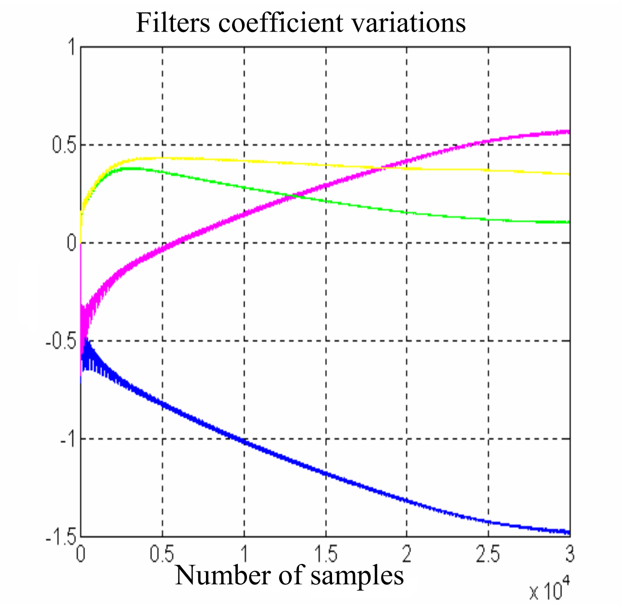

Fig. 19. Filters coefficients variations for $\mu = 0{,}0015$.

The authors determined the computing relations of the filter coefficients knowing the values of the parameters process, and also the inverse relations.

It was studied 3 identifications algorithms each implemented in direct form and lattice form, resulting that the lattice form has a better convergence speed than direct form and also that SHARF algorithm present the smallest oscillation.

Finally it was experimentally demonstrated that the using of the adaptive filter on identification of the parameters process is necessary a previous measure with another method in scope to obtain the initial values of the adaptive filter coefficients.

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