DSP Controller Based Signal Processing of Physiological Hand Tremor

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Abstract—**This paper presents our research in real-time adaptive signal processing of physiological hand tremor with a DSP controller. A DSP controller can be applied in this application because of its high-performance in the signal processing and its capability in the realization of a single-chip embedded system for both real-time signal processing and control applications. The potential applications of the system include the long-term on-site monitoring of physiological tremor and the suppression of physiological tremor in a hand-held tool. Because of the limited memory and the operation speed provided by a DSP controller, recursive least-squares (RLS) adaptive algorithm is investigated in the modeling and on-line prediction of physiological hand tremor. The effectiveness of the algorithm is illustrated with the simulation and experimental results.**

I. INTRODUCTION

TREMOR is a rhythmic involuntary oscillatory movement of body parts with a relative fixed frequency and amplitude. Physiological tremor is the tremor that healthy subjects often suffer from due to stress, nervous, or some other reasons. Tremor, especially the hand tremor may seriously interfere with the personal activities.

In the tremor investigation the acceleration of tremor movement is often measured with accelerometers and processed as random time series. For the analysis of the time series various algorithms of statistical signal processing can be applied. Many tremor investigations focus on the modeling various tremors in order to find the statistical characteristics of tremors and distinguish causes of tremor patients [1, 3 - 6].

The model of physiological tremor is analyzed in [1] based on the physics of the tremor process that arises from random motor-unit mechanical impulses being applied to the resonant system. It is suggested to apply low order AR or ARMA model for the modeling of physiological hand tremor. [5] provides the comparison of the analysis of the tremor data based on nonparametric and parametric estimation of Power Spectra Density (PSD). Applications of high-order statistics in the analysis of tremor signals are described in [3]. Three major types of tremors: physiological, essential, and parkinsonian tremors are investigated by applying high-order statistics. It shows that the time series of physiological tremor could be modeled as a linear, Gaussian random process, while the time series of parkinsonian tremor and essential tremor tend to be nonlinear chaotic processes.

A number of researches target the suppression of physiological tremors by measuring the tremor movement and compensating the movement in a hand-held tool [2][7]. The adaptive compensation of physiological tremor is introduced in [2], where the algorithm of WFLC (weighted-frequency Fourier linear combiner) is developed and applied in the test system.

This paper presents our research in real-time adaptive signal processing of physiological hand tremor with a DSP controller. The DSP controller is applied in this application because of its high-performance in the signal processing and its capability of realizing a single-chip embedded system for both real-time signal processing and control applications. Because of the small-size realization of sensor and signal processing circuits, the potential applications of the system will be the long-term on-site monitoring of physiological tremor and the suppression of physiological tremor in a hand-held tool.

A small-sized embedded system with a DSP controller often suffers from the limited memory and the operation speed compared to a host computer. For this reason the algorithms requiring large random access memory (RAM) and high computation complexity such as DFT, (discrete Fourier Transformation) should be avoided. This paper suggests the application of the recursive least-squares (RLS) adaptive algorithm in modeling physiological hand tremor and on-line forward prediction. The effectiveness of the algorithm is illustrated with the simulation and experimental results.

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II. DSP Test System of Physiological Hand Tremor

The test system is based on a DSP controller TMS320F2812 of Texas Instruments, Inc. The DSP controller has a 32-bit DSP core. Its on-chip memory includes 18KWord RAM and 128KWord flash memory. The chip also contains a 12-bit AD converter with 16 channel inputs and several other peripherals for control and communication applications. Therefore this DSP controller can be used for the realization of signal acquisition, processing and control in a single chip. The block diagram of the test system is shown in Fig. 1.

The physiological tremor is generated with an outstretched hand. A weight (5 to 10 pounds) may be held in the hand during a test.

The hand tremor is measured with two dual-axis MEMS accelerometers ADXL202EB from Analog Devices, Inc. The sensors and 50-Hz 2nd-order low-pass filters are installed in a sensor box which is held in the hand during a test. The measured results are the time-series of acceleration in three dimensions, x-y-z.

The physiological tremor is sampled at the rate 200 samples/sec. Total 12000 samples are sampled for 60 seconds for one complete test.

The main functions in DSP program are digital band-pass filters, adaptive algorithms for modeling and linear prediction of physiological hand tremor, and serial communication.

The conventional frequency distribution of physiological hand tremor is from 2.5 Hz to 13 Hz. A 10th-order Butterworth digital band-pass filter with the pass-band 2.5 Hz to 13 Hz is used for preprocessing the detected tremor signals in each axis, as depicted in Fig. 1. The digital band-pass filter is programmed mainly in assembly languages for the high speed operation. The total execution time of the three digital filters for three axes is about 3 microseconds.

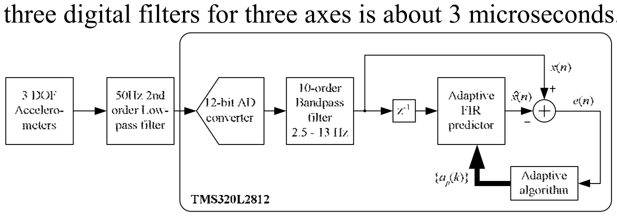

Fig. 1 Block diagram of the test system for physiological hand tremor

The adaptive algorithm, Recursive Least Square (RLS) is applied to the realization of the adaptive modeling and linear prediction of physiological tremor. The model of the physiological tremor is assumed as AR(3) random process. The adaptive linear predictor in Fig. 1 consists of two parts: an FIR (Finite Impulse Response) predictor of 3rd-order and an RLS adaptive algorithm. The function is programmed in C language. The execution time is about 150 microseconds for one axis. To process the three axes it takes total execution time of 450 microseconds.

A serial communication function is designed to realize the communication with a host computer for the transmission of commands and data in the experiments. During a test the sampled data after the band-pass filters and the identified coefficients of AR(3) models of three axes are transmitted to a host computer for further analysis and comparison.

III. Modeling of Physiological Tremor of Outstretched Hand

Physiological tremor is approximately a linear, Gaussian random process. The frequency is from 2.5 Hz to 13 Hz. For the modeling and prediction of a physiological tremor signal autoregressive (AR) processes and associated algorithms can be used. This makes it convenient to realize effective methods for identifying, on-site monitoring, and suppressing of physiological tremor.

The physiological tremor can be modeled as an AR(p) process with order p. The advantages of the AR model are convenient calculation of statistical signal processing algorithms for model identification and realization, especially in the small embedded system where memory and computation complexity are strictly limited.

To identify a tremor signal for medical diagnosis it generally requires the estimation of the power spectra density (PSD). The nonparametric methods, such as Welch algorithm is often used to estimate the PSD from the sampled time series. Such estimation needs a relatively large computation of FFT and therefore, is suitable for the calculation with a host computer. In the real-time signal processing of tremor signal based on an AR model we can identify the model coefficients instead of PSD, based on the algorithms such as Levinson-Durbin or adaptive filters. As long as the coefficients of an AR model are identified, we can use it for different applications, such as linear

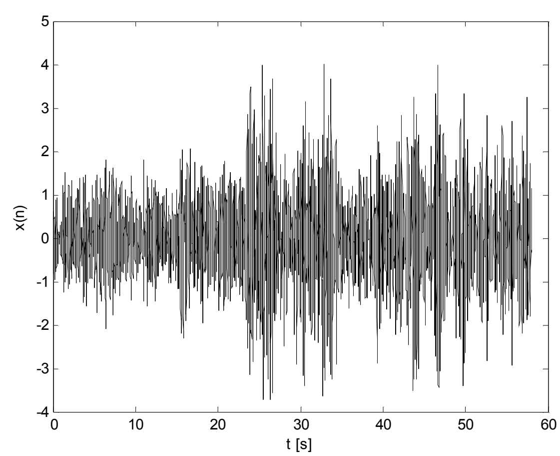

Fig. 2 A sampled time series of physiological hand tremor

prediction which may be used in the suppression of hand tremor in hand-held tools, or monitoring the hand tremor by further analysis of the coefficients. In data communication about the tremor characteristics it is also more convenient to transmit the coefficients of an AR model instead of PSD. When it is required, PSD can be estimated based on the AR coefficients in a parametric method in a host computer.

Another important property of the AR model for the tremor analysis is that a low order AR model is good enough for the physiological hand tremor. Based on our tests the order of the AR process for hand tremor with outstretched hand is about 3 to 4. In the following we will show the effectiveness of an AR process in modeling hand tremor process with respect to PSD and in linear prediction based on sampled time series of physiological hand tremor.

An AR process of order p is represented as AR(p). An AR(p) process $\{x(n)\}$ is given by

$$x(n)+\sum_{k=1}^{p} a_k x(n-k)=w(n) \quad (1)$$

where $\{a_k, k = 1, 2, \ldots p\}$ are the coefficients and $\{w(n)\}$ is a white noise process with Gaussian distribution and variance σ^2.

For a sampled data set of physiological tremor of outstretched hand the AR model can be identified by designing an optimal FIR predictor as depicted in Fig. 3. $\hat{x}(n)$ is the one-step forward predicted value of $x(n)$ based on the p sampled values $x(n\text{-}1)$, $x(n\text{-}2)$, … $x(n\text{-}p)$,

$$\hat{x}(n)=-\sum_{k=1}^{p} a_p(k)x(n-k) \quad (2)$$

The prediction error $e(n)$ is

$$e(n)=x(n)-\hat{x}(n)=x(n)+\sum_{k=1}^{p} a_p(k)x(n-k) \quad (3)$$

The coefficients $\{a_p(k), k\text{=}1, 2, \ldots, p\}$ of the pth-order FIR predictor are optimized so that the mean-square error of the FIR predictor is minimized at the order p. The minimum mean square error (MMSE) of the pth-order FIR predictor is denoted as E_p^e,

$$E_p^e=\min\left\{E\left[\left|e(n)\right|^2\right]\right\} \quad (4)$$

If the physiological hand tremor in the test is an AR(p) stationary random process given in (1), the optimal FIR predictor of the same order in (2) will provide the same coefficients as in (1), i.e.

$$a_p(k)=a_k \qquad for\ k=1,2,\cdots,p$$

and the process of the prediction error will be a white noise.

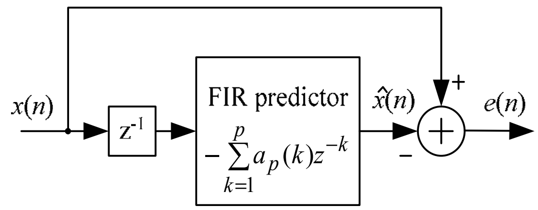

Fig. 3 Block diagram of linear forward prodictor

To find the proper order p of an AR model for the physiological hand tremor we need to find the relationship between the MMSE of the prediction error and the order p. The MMSE reduces with the increase of order p. However the MMSE prediction error E_p^e will not change much when the prediction error $e(n)$ approaches to a white noise sequence. E_p^e is also referred to as the residual error of a p-order linear predictor.

For a given time series of a hand tremor signal, the optimal order number and coefficients of the FIR predictor can be estimated by applying Levinson-Durbin recursive algorithm. Levinson-Durbin algorithm is an order excursive algorithm to design an optimal FIR one-step forward linear predictor as shown in Fig. 3. For each order beginning from p=1, the algorithm provides the optimal coefficients and the residual error. By analyzing the function of MMSE with respect to an order number we can get the optimal order number for a random process. Fig. 4 shows the MMSE property related to the order number p calculated in Levinson-Durbin algorithm. The residual error (MMSE) becomes stable at about 0.0005 when the order p is larger than 2.

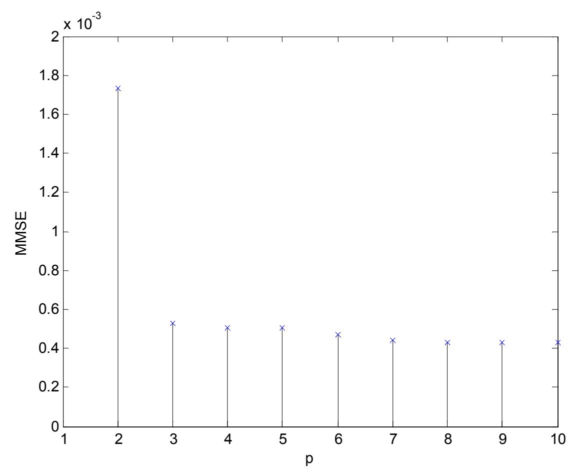

Fig. 4 MMSE related to order p of an AR process

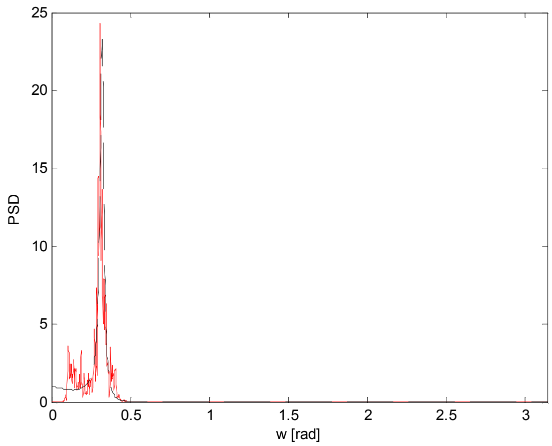

Fig. 5 PSD comparison, dashed-line: PSD calculated from AR(3) model and solid-line: PSD estimated in Welch method

The PSD calculated based on the AR(3) model is compared with PSD estimated in Welch algorithm shown in Fig. 5. The PSD calculated from the estimated AR(3) model is a good approximation of the PSD calculated by Welch algorithm.

The test results show that the physiological hand tremor can be modeled as an AR(3) process. This fact can be explained in physics. As [1] explained the tremor arises from random motor-unit mechanical impulses being applied to the same resonant system that is excited by external impulses to the outstretched hand. A second-order difference equation can always account for at least 90% of the explainable part of the tremor variance.

IV. Adaptive Modeling and Prediction

Physiological hand tremor is not a stationary random process. The statistical characteristics change with the time and states of tested subjects. For the long-term on-line monitoring and suppression applications an adaptive algorithm is necessary.

The block diagram of an adaptive FIR predictor is

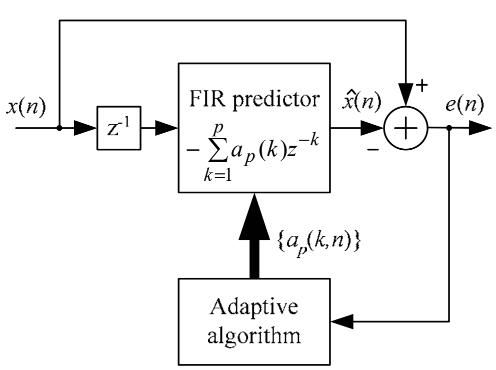

Fig. 6 Block diagram of an adaptive FIR predictor

depicted in Fig. 6, in which an adaptive algorithm is added to the FIR predictor. The adaptive algorithm provides the estimation of the FIR coefficients of the predictor by tracking the statistical characteristics of a random process based on the prediction error and the sampled tremor values. With the adaptive predictor two main goals, adaptive prediction of the physiological tremor and on-line identification of the model coefficients, can be achieved.

Two algorithms are investigated in this research: LMS (Least Mean Square) algorithm and RLS (Recursive Least-Squares) algorithm. The former is very simple but has a problem with convergence. The coefficients converge very slowly with quite large errors. The test shows that LMS based adaptive predictor can not effectively track the change of statistical characteristics of the physiological hand tremor. RLS algorithm needs more computation compared to LMS algorithm; however, it provides a good result for tracking the physiological hand tremor. In the following a brief description of RLS algorithm for 3rd-order predictor is provided [8].

The coefficient vector of the predictor at time n is defined as

$$\mathbf{a}_3(n) = \begin{bmatrix} a_3(1,n) \\ a_3(2,n) \\ a_3(3,n) \end{bmatrix}$$

where $a_3(k,n)$ for k=1,2,3 are the estimated coefficients for $a_3(k)$ of the linear predictor at time n.

The sampled tremor signal $x(n)$ is used as input signal and the input vector at time n is denoted as

$$\mathbf{X}_3(n) = \begin{bmatrix} x(n-1) \\ x(n-1) \\ x(n-3) \end{bmatrix}$$

The input data is prewindowed as $x(n) = 0$ for $n < 0$.

The prediction error of the adaptive linear predictor at time l with the estimated coefficients at time n is,

$$e_3(l,n) = x(l) + \mathbf{a}_3^T(n)\mathbf{X}_3(l) \qquad for\ l = 0,1,\ldots,n \quad (5)$$

In the RLS algorithm the coefficient vector $\mathbf{a}_3(n)$ is determined so that the weighted sum ξ_3 of magnitude-squared errors is minimized.

$$\xi_3 = \sum_{l=0}^{n} w^{n-l} \left| e_3(l,n) \right|^2 \quad (6)$$

where w is a weighting factor in the range $0 < w \le 1$.

The purpose of the factor w is to weight the most recent data points more heavily and thus to allow the prediction coefficients to adapt to time-varying statistical characteristics of the data. This is accomplished by using the exponential weighting factor with the past data.

The minimization of (6) with respect to the filter-coefficient vector yields the set of linear equations

$$\mathbf{R}_3(n)\mathbf{a}_3(n) = -\mathbf{D}_3(n) \quad (7)$$

where both $\mathbf{R}_3(n)$ and $\mathbf{D}_3(n)$ are correlation matrices,

$$\mathbf{R}_3(n) = \sum_{l=0}^{n} w^{n-l} \mathbf{X}_3^*(l) \mathbf{X}_3^T(l)$$

$$\mathbf{D}_3(n) = \sum_{l=0}^{n} w^{n-l} \mathbf{X}_3^*(l) x(l)$$

The solution of (7) is

$$\mathbf{a}_3(n) = -\mathbf{R}_3^{-1}(n) \mathbf{D}_3(n) \tag{8}$$

The solution requires the calculation of the matrix inverse $\mathbf{R}_3^{-1}(n)$. In the RLS algorithm the matrix inverse is denoted as

$$\mathbf{P}_3(n) = \mathbf{R}_3^{-1}(n)$$

Instead of direct calculation, the inverse is found recursively in RLS algorithm by calculating the Kalman gain vector $\mathbf{K}_3(n)$ and updating the inverse $\mathbf{P}_3(n)$ for each recursive step as the following.

$$\mathbf{K}_3(n) = \frac{\mathbf{P}_3(n-1)\mathbf{X}_3^*(n)}{w + \mathbf{X}_3^T(n)\mathbf{P}_3(n-1)\mathbf{X}_3^*(n)}$$
$$\mathbf{P}_3(n) = \frac{1}{w}\left[\mathbf{P}_3(n-1) - \mathbf{K}_3(n)\mathbf{X}_3^T(n)\mathbf{P}_3(n-1)\right] \tag{9}$$

Correspondingly the solution of the coefficient vector (8) is also found recursively in the algorithm as

$$\mathbf{a}_3(n) = \mathbf{a}_3(n-1) - \mathbf{K}_3(n) e_3(n) \tag{10}$$

where $e_3(n)$ is the estimated prediction error,

$$e_3(n) = e_3(n, n-1) = x(n) + \mathbf{a}_3^T(n-1)\mathbf{X}_3(n) \tag{11}$$

The coefficient vector and matrix inverse are initialized as

$$\mathbf{a}_3(-1) = \mathbf{0}$$

$$\mathbf{P}_3(-1) = \frac{1}{\delta}\mathbf{I}_3$$

where $\mathbf{I}_3$ is a 3x3 unit matrix and δ is a small positive number.

V. Simulation and Experiments

The experiments with the DSP test system include the simulation of two adaptive algorithms, and the tests of the adaptive predictor realized in DSP controller. The experimental system is illustrated in Fig. 7.

The adaptive predictors based on the RLS algorithm and the LMS algorithm are first simulated with the simulation models developed in Simulink. The sampled time series of physiological hand tremor is shown in Fig. 2, which is the normalized output of a 10th-order Butterworth band-pass filter. The sampled time series is fed to the simulation models of adaptive predictors. The simulated results are shown in Fig. 8 and Fig. 9. As a reference, the coefficients of the predictor are also estimated for the sampled time series based on Levinson-Durbin algorithm (LD algorithm). For comparison the coefficients of the predictor estimated

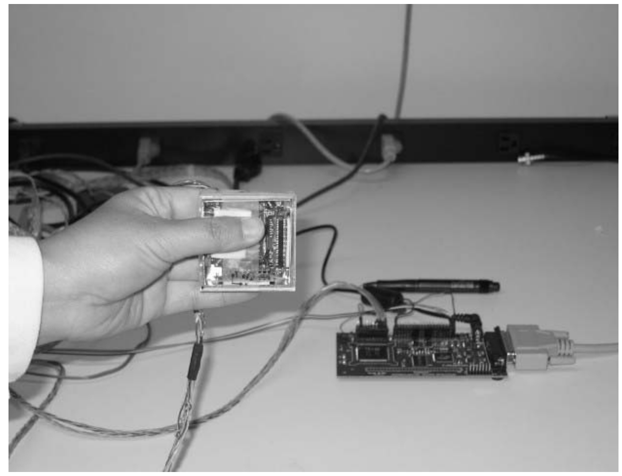

Fig. 7 Experimental system based on a DSP controller

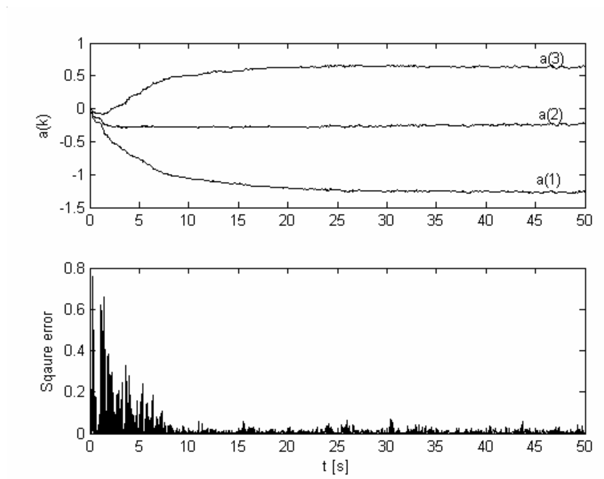

Fig. 8 Simulated results of coefficients and prediction error of adaptive predictor in LMS algorithm

in three algorithms are given in Table I.

The simulated results of the LMS adaptive predictor illustrate that the coefficients can not converge fast enough to reach the reference during the sampled data set.

The simulated results of the RLS adaptive predictor illustrate that the coefficients converge very quickly. The coefficients in stable state are very close to the calculated values from Levinson-Durbin algorithm. The prediction error is an order less than that of LMS adaptive predictor. The simulation results verify that the RLS algorithm is more suitable for the adaptive identification and prediction of physiological hand tremor.

Table I Estimated coefficients of AR(3) process

Algorithm	$a_3(1)$	$a_3(2)$	$a_3(3)$
LD Algorithm	-2.7288	2.5774	0.8342
LMS	-1.256	-0.2212	0.6365
RLS	-2.889	2.831	0.9421

The experimental results of the DSP controller based test system are depicted in Fig. 10 and 11.

Figure 10 shows the sampled tremor time series, the prediction error, and the identified coefficients. The magnitude of the prediction error is less than 2% of the magnitude of the tremor signal.

The coefficients of the adaptive predictor are given in the dynamical waveforms in Fig. 11. For the comparison the simulated results are also shown in Fig. 11 in the red waveforms. The difference in the coefficients between the results generated by the test system and the simulation model is mainly due to the different data precision formats used in the algorithms. The simulation is executed in double precision (64 bits) while the realization in DSP control is in single precision (32 bits).

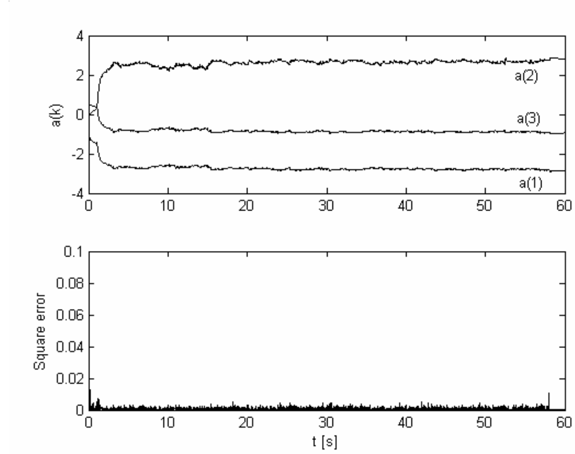

Fig. 9 Simulated results of coefficients and prediction error of adaptive predictor in RLS algorithm

VI. CONCLUSIONS

The paper presents the real-time adaptive signal processing of physiological hand tremor with a DSP controller. For the signal processing of physiological hand tremor, the tremor time series is modeled as an AR(3) process. The RLS adaptive algorithm is applied to the modeling and on-line predicting physiological hand tremor. The effectiveness of the algorithm is demonstrated by the simulation and experimental results.

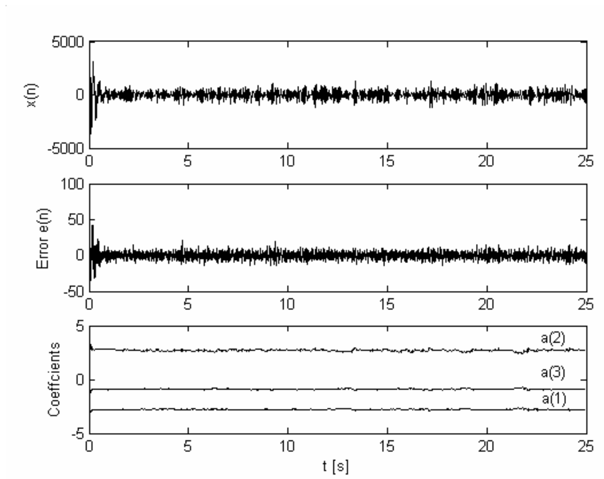

Fig. 10 Experimental results of sampled time series (top), prediction error (middle), and identified coefficients (bottom)

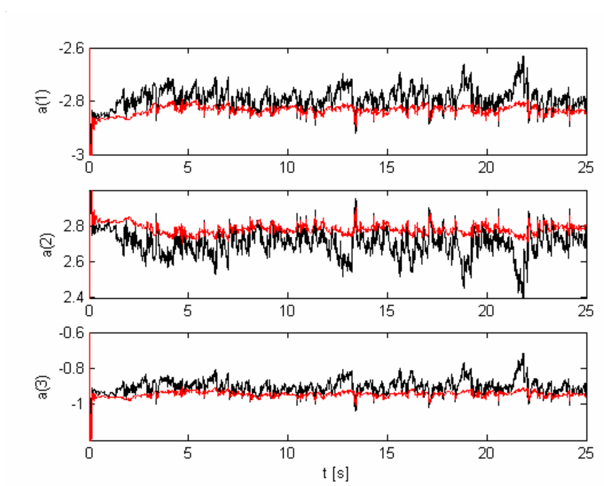

Fig. 11 Identified Coefficients of experimental system (black) and simulation model (red)

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