Real-Time Modeling and Prediction of Physiological Hand Tremor

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ABSTRACT

This paper provides results of our investigation of adaptive algorithms for real-time modeling and prediction of physiological tremor signals. The goal of the investigation is to find effective methods which are suitable for small embedded systems used in real-time signal processing of physiological hand tremor. Our investigation shows that physiological hand tremor can be represented with an AR(3) process. Based on this fact it is possible to identify the model of the physiological hand tremor with simple adaptive algorithms. On the other hand an adaptive linear predictor can also be realized based on the same adaptive algorithms, which is significant for the suppression of physiological hand tremor in hand-held tools.

1. INTRODUCTION

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

Tremor investigations mainly focus on the modeling of the tremors in order to distinguish different causes of tremor patients [1][2][3]. There are also a number of researches for the suppression of the physiological tremors by measuring the tremor movement and compensating the movement in a hand-held tool [4]. For the practical applications such a system needs a small but effective signal processing electronics for the data processing and the control the actuators in real-time.

Physiological tremor is approximately a linear and Gaussian random process [1]. 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 provides effective methods for the identification, on-site monitoring and suppressing of physiological tremor.

The goal of our investigation is to find effective methods which are suitable for small embedded systems used in real-time signal processing of physiological hand tremor. This paper provides some results of the investigation.

2. DSP Test System of physiological Hand tremor

The test system is based on the DSP controller TMS320F2812 of Texas Instruments. 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 signal acquisition, processing and control in a single chip realization. The block diagram of the test system is shown in Fig. 1.

The physiological tremor is generated with the outstretched hand. During a test the hand is loaded with a weight (5 to 10 pounds) so that physiological tremor can be generated effectively during a test. During one test, the hand is kept outstretched for 60 seconds.

The hand tremor is measured with two dual-axis MEMS accelerometers ADXL202EB from Analog Devices, Inc. The sensors and 50-Hz low-pass filters are mounted in a small box which is fixed on 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 in the rate 200 samples/sec. Total 12000 samples are sampled for 60 seconds for one complete test.

By considering the frequency of physiological tremors distributed in the range of 2.5 Hz to 13 Hz, a 10-order Butterworth digital band-pass filters are applied for the preprocessing the detected tremor signals in three-dimensions.

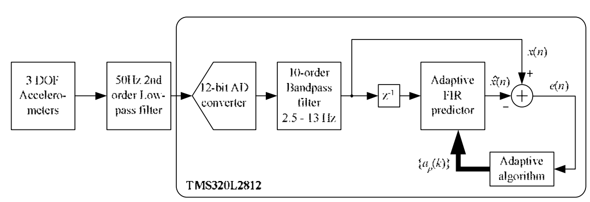

Fig. 1 Block diagram of the test system for physiological hand tremor

Figure 2 shows a sampled time series of physiological hand tremor in a complete test.

3. MODELING OF PHYSIOLOGICAL TREMOR OF OUTSTRETCHED HAND

The physiological tremor can be modeled as an AR(p) process with order p. The advantages of AR model are 1) convenient in model identification, 2) an AR spectrum can have much better frequency resolution, 3) convenient for realization, especially in the small embedded system where memory and computation complexity are strictly limited.

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

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

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 we can find the optimal order number by investigating the performance of mean square error (MSE) related to order number p which is calculated in Levinson-Durbin recursive algorithm [5].

Levinson-Durbin algorithm is an order excursive algorithm to design the optimal one-step forward linear (FIR) predictor as shown in Fig. 3. For each order p, the algorithm provides the coefficients $\{a_p(k),\ k = 1, 2, \ldots, p\}$ for the optimal linear predictor and the minimal mean square error (MMSE), or residual error. By analyzing the function of MMSE related to order number we can get the optimal order number for a random process. Fig. 4 shows the MMSE property related to order number p for the sampled time series shown in Fig. 2. The residual error (MMSE) becomes stable at about 0.0005 when the order p is larger than 2. In fact all test results with different subjects in our investigation verified that the physiological hand tremor of outstretched hand can be modeled as AR(3) process with order 3.

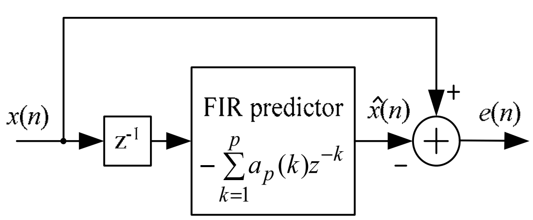

Fig. 3 Block diagram of linear forward predictor

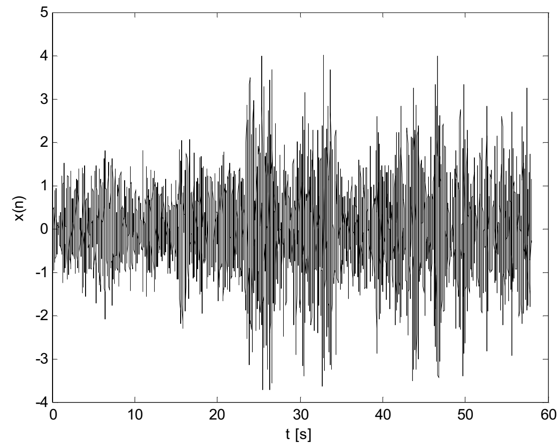

Fig. 2 A sampled time series of physiological hand tremor

After the estimation of AR(3) process for the sampled time series, the power spectra density (PSD) can be calculated based on the AR(3) model. The comparison between the PSD calculated with AR(3) model and PSD estimated in Welch algorithm shown in Fig. 5. The PSD from AR(3) possesses the main features of PSD of the raw data of the sampled time series.

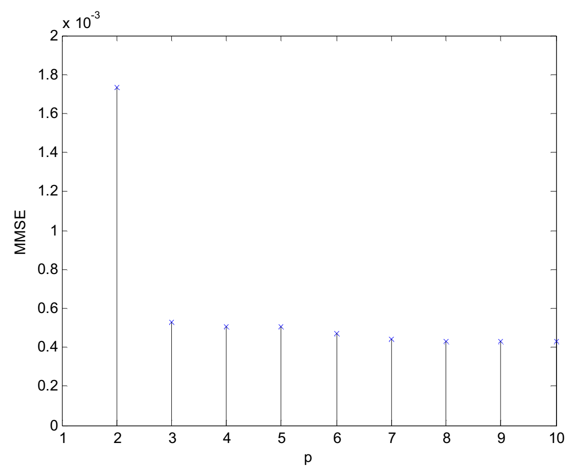

Fig. 4 MMSE related to order p of an AR process

4. 4. ADAPTIVE MODELING AND PREDICTION

Adaptive algorithm can be used to identify the coefficients of optimal linear predictor in Fig. 3. From the properties of optimal linear predictors [5] we know that if the sampled random process is an AR(p) process (1) with the same order of the linear predictor, then the coefficients of the optimal linear predictor are equal to the coefficients of AR(p) process, i.e.

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

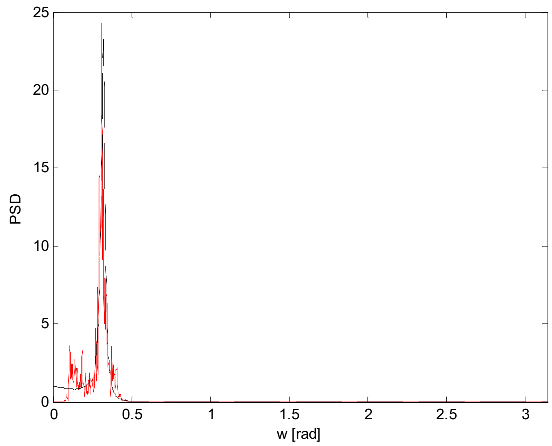

Fig. 5 PSD comparison, dashed-line: PSD calculated from AR(3) model and solid-line: PSD estimated in Welch method

Based on this principle the adaptive algorithms for the linear predictors can be used to identify the model of AR(p) random process.

Another reason to use the adaptive algorithm is that the physiological hand tremor is generally not a statistical random process. With the adaptive algorithm the system identification can automatically tracking the change of the statistical characteristics of the hand tremor for the model identification and prediction of the physiological hand tremor.

The block diagram of adaptive linear predictor is depicted in Fig. 1. Two adaptive algorithms are researched in the test, 1) LMS (least mean square) adaptive algorithm and 2) RLS (recursive least-squares) algorithm. The advantages of LMS method are simple, easy to be realized and robust. The disadvantage is the slow converging speed.

5. RESULTS

For comparison the estimated coefficients of AR(3) for the sampled time series in Fig. 2 are calculated with the Levinson-Durbin algorithm (LD algorithm) as a reference given in Table I.

The figure 6 shows the test results of LMS adaptive algorithm, in which the coefficients can not converge fast enough to reach the reference during the sampled date set. The coefficients at the end of test are given in Table I.

The figure 7 shows the test results of RLS adaptive algorithm, in which the coefficients can converge to the results very fast. The coefficients at the end are very close to the calculated values from Levinson-Durbin algorithm.

The results show 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

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

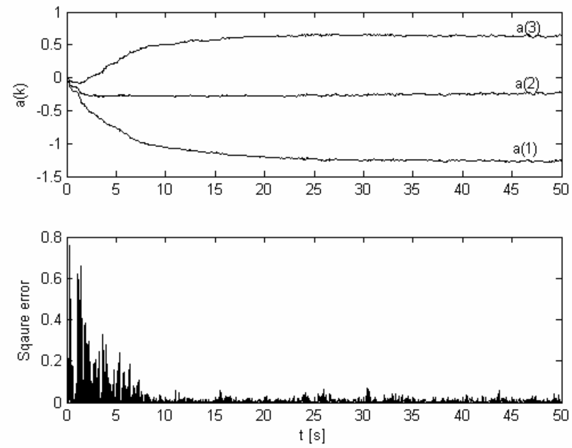

Fig. 6 Parameters and prediction error of adaptive linear predictor in LMS algorithm

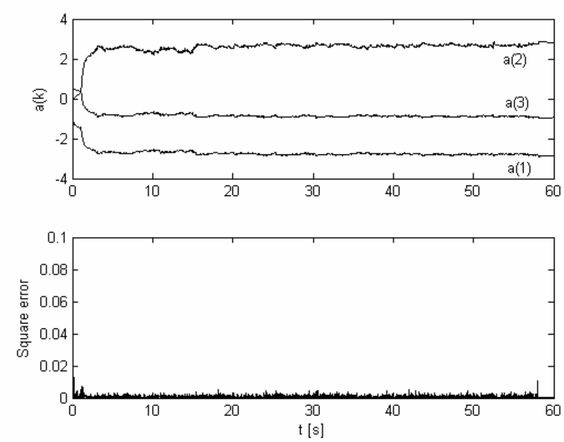

Fig. 7 Parameters and prediction error of adaptive linear predictor in RLS algorithm

6. CONCLUSIONS

The research show that physiological hand tremor measured with outstretched hand can be modeled as AR(3) process. The model is close to the practical sampled time series in both prediction and PSD analysis. Based on this fact it is possible to realize the RLS adaptive algorithm for the identification the coefficients of AR(3) process for the physiological hand tremor and the forward prediction of hand tremor in a small embedded system. It is significant for the development of handheld instruments for the monitoring the hand tremor and handheld tools with the suppression of physiological hand tremor.

7. REFERENCES

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