Real-time Implementation of an Identifier for Nonstationary Time-varying Signals and Systems

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Abstract

A real-time identifier for the nonstationary time-varying signals and systems was implemented using a low cost DSP(digital signal processing) chip. The identifier is comprised of I/O units, a central processing unit, a control unit and its supporting software. In order to estimate the system accurately and to reduce quantization error during arithmetic operation, the firmware was programmed with 64-bit extended precision arithmetic. The performance of the identifier was verified by comparing with the simulation results. The implemented real-time identifier has negligible quantization errors and its real-time processing capability crresponds to 0.6 kHz for the nonstationary AR (autoregressive) model with n = 4 and m = 1

Ⅰ. Introduction

In the field of time series analysis for system or signal identification, time series are often encountered in which the statistics of the data exhibit a nonstationary situation. In fact, the time series of the most physical system has nonstationary statistics. However, nonstationary time series analysis is very complex to compute in contrast to the analysis of stationary time series data. In addition, heavy amounts of data processing are burden in general purpose digital computer. Therefore, the nonstationary data processing has been tried by assuming that the data under consideration is piece-wise stationary [1-3].

Recently, due to advance in digital signal processing and VLSI technology, low cost DSP chips have been produced, which alleviate the heavy computational problems. Several algorithms for the analysis of signal processing have been suggested. Kitagawa and Gersch used the nonstationary time series analysis method in seismic data analysis [2], and Moser showed that this algorithm could be useful in real-time processing [3].

When used for real-time processing, however, Moser's algorithm was accompanied by the difficulty of requiring heavy amounts of computation. This difficulty may outweigh the algorithm's usefulness.

In this paper, the real-time identifier was realized using the nonstationary identification algorithm and a TMS320 (Texas Instruments) DSP chip.

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Ⅱ. Formulation for the Identification of Nonstationary Time-varying Signal

Nonstationary time series are used to represent any class of data whose statistical properties change with time. The vast majority of physical data actually fall into this category. It is only for reasons of approximation and simplicity that many data are arbitrarily assumed to be stationary. Nonstationary data are obtained, for example, under transient operating conditions when an environment changes suddenly, or during long range operating periods when system properties change so that a given input will produce a variable output [4].

Nonstationary time sequence, $y(k)$, is as follows:

$$y(k)=\sum_{i=1}^{n} a_i(k)\,y(k-i)+w(k),\ k=0,1,2,\ldots, \tag{1}$$

where a_i is the smoothness prior nonstationary AR parameter, and

$$a_i(k)=\sum_{j=1}^{m} b_{ij}(k)\cdot a_i(k-j)+v_i(k) \tag{2}$$

Here $w(k)$ in Eq.(1) and $v_i(k)$ in Eq.(2) are orthogonal to each and the second order moment of the ergodic white gaussian process with zero mean is

$$Var[w(k)]=W(k),\ Var[v_i(k)]=V_i(k),$$

where k represents discrete time and a_i and b_{ij} are nonstationary AR parameters. In the sense of bayesian, the most moderate choice of the smoothness prior is to model the m'th order difference equation as follows[2-3]:

$$\nabla^m a_i(k) = v_i(k), \tag{3}$$

where ∇ is the difference operator. For example,

$$\nabla a(k) \equiv a(k) - a(k-1). \tag{4}$$

In the nonstationary sequence representation of Eq.(1) and (2), the AR parameter can be changed into the following state space equation.

$$x(k+1) = A(k)x(k) + u(k) \tag{5}$$

$$y(k) = C(k)x(k) + w(k) \tag{6}$$

where the estimated AR parameter is $x(k)$:

$$x(k) = \begin{bmatrix} a_i(k) \\ \vdots \\ a_n(k) \\ a_i(k-1) \\ \vdots \\ a_n(k-1) \\ a_i(k-m+1) \\ \vdots \\ a_n(k-m+1) \end{bmatrix} \tag{7}$$

$$A(k) = \begin{bmatrix} b_{11} & & b_{12} & & & b_{1m} & \\ b_{21} & 0 & b_{22} & 0 & \cdots & b_{2m} & 0 \\ \cdot & & \cdot & & & \cdot & \\ & \cdot & & \cdot & & \cdot & \\ & \cdot & & \cdot & & \cdot & \\ 0 & b_{n1} & 0 & b_{n2} & 0 & & b_{nm} \\ I_{n(m-1)*(m-1)} & & & & 0_{n(m-1)*n} & & \end{bmatrix} \tag{8}$$

Let

$$u(k)^T = [v_1(k+1)\ v_2(k+1) \cdots v_n(k+1)\ 0 \cdots 0]_{1\times nm} \tag{9}$$

$$C(k) = [y(k-1)\, y(k-2) \cdots y(k-n) 0 \cdots 0]_{1\times nm} \tag{10}$$

The covariance matrix $v(k)$ of $u(k)$ is represented by (11)
$cov[u(k)] = V(k) =$

$$\begin{bmatrix} V_1(k+1) & 0 & & & 0 \\ 0 & V_2(k+1) & & & \\ & & \ddots & & \\ & & & V_n(k+1) & \\ & & & 0 & \ddots \\ 0 & & & & 0 \end{bmatrix} \tag{11}$$

The nonstationary time-varying system model, which converted into the state equation, can be solved into an useful solution, and the Kalman filter algorithm (as nonstationary identfier algorithm) can be applied to estimate the nonstationary AR parameters at each time interval k. The procedure to estimate parameters is as follow[5-7]:

$$\hat{x}(k+1/k) = [A(k) - K(k)C(k)]\hat{x}(k/k-1) + K(k)y(k) \tag{12}$$

$$K(k) = A(k)P(k/k-1)C(k)^T \cdot [C(k)P(k/k-1)C(k)^T + W(k)]^{-1} \tag{13}$$

$$\begin{aligned} P(k+1/k) &= A(k) \\ &\cdot [P(k/k-1) - P(k/k-1)C(k)^T \\ &\cdot (C(k)P(k/k-1)C(k)^T + W(k))^{-1} \\ &\cdot C(k)P(k/k-1)]A(k)^T + V(k) \\ &= E\{[x(k+1) - \hat{x}(k+1/k)] \\ &\cdot [x(k+1) - \hat{x}(k+1/k)]^T \\ &\{y(0), \cdots, y(k)\} \end{aligned} \tag{14}$$

Here, $\hat{x}(k+1/k)$ is the estimate of $x(k+1)$ from given data a kth sample time, and $P(k+1/k)$ is pridiction error covariance at that time. The stability of this algorithm is proved in [3].

Ⅲ. Design of the Real-time Identifier

In order to implement the real-time identifier, as described in the previous sections, it is necessary to select a DSP chip with appropriate parameters, such as memory size, speed, numberical accuracy and easy use of the assembly language. In this paper, Texas Instruments TMS320C25 digital signal processor[8] has been employed for the real-time identifier implementation.

The TMS320C25 provides on-chip memory that includes a 4096-by-16bit ROM and a 544-by-16bit RAM. To achieve maximum throughput, memory access time must be fast. In general, the real-time minimal through must satisfy the Nyquist rate. The internal memory banks of the TMS320C25 satisfy this condition.

Finite word-length registers of the DSP chip affect the accuracy of the algorithm [9]. These effects are found in quantization error and limit cycle. Quantization errors such as those due to analog-to-digital data conversion are influenced by the numbering system used to encode data (e.g., 2's complement, floating point, etc.). With recursive algorithms, the round-off or truncation errors can build up and affect the performance of the algorithm. Large-scale overflow limit cycles are caused when a system state (or variable) exceeds a prespecified bynamic range. This error can be disastrous if it is not corrected.

There are several ways to minimize the effects of finite word length. One approach is to properly scale the filter variables and parameters for each sample point. Another approach is to use the floating-point processor with large dynamic range. For example, the dynamic range of TMS320C25 (fixed point processor) and DSP32(floating point processor) is $2^{-15} \sim 1$ and, $10^{-38} \sim 10^{38}$, respectively. Although the floating point proccessor has a wide dynamic range, it is very expensive and hardware implementation is complex.

In this study, therefore, the TMS320C25 DSP chip was chosen, and 64 bit extended precision arithmetic was developed to reduce the effects of finite word length. Also, hardware size was reduced very compactly(about 10cm • 10cm).

The real-time identifier for the nonstationary time-varying signal constructed in this study is shown in Fig.1.

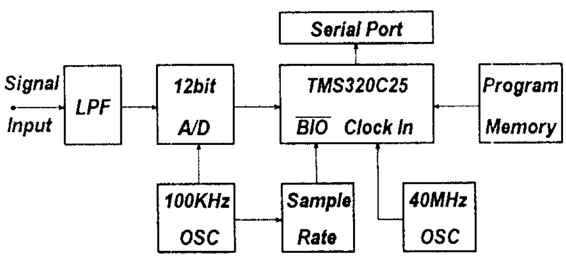

Figure 1. Schematic diagram of the real-tme identifier

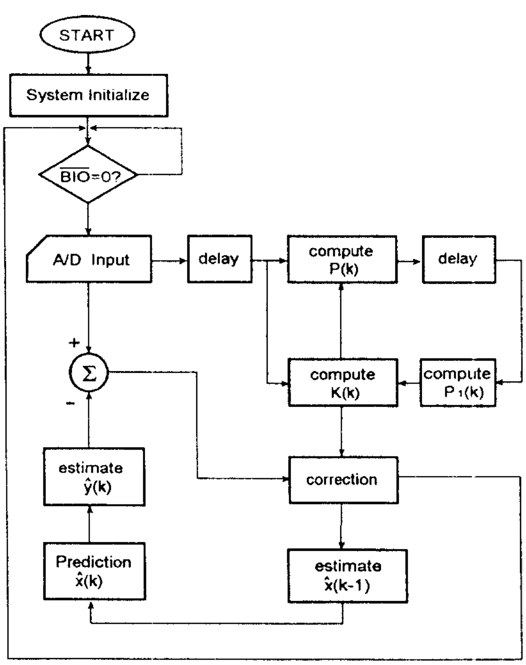

Figure 2. Flow chart of the identifier algorithm

To prevent aliasing error the low pass filter is employed, and program memory includes identifier algorithm, initial covariance value, and input noise variance value. TMS 320C25 DSP chip performs identifier algorithm, estimates AR parameters, and transmites parameters to PC.

A flow chart of the identifier algorithm is shown in Fig.2. Initial values are stored in the internal data memory of TMS320C25 during system initialization. Whenever $\overline{BIO}$ signal is low the nonstationary signal is sampled, and then covariance matrix and Kalman gain are computed. This convariance matrix is stored in the internal data memory and used to compute Kalman gain next As $\hat{x}(k-1)$ is estimated using this Kalman gain, so $\hat{x}(k)$ will be predicted. From this $\hat{x}(k)$, $\hat{y}(k)$ will be estimated and prediction error will be computed. By this prediction error and Kalman gain, AR parameters are corrected. Thre is executed repeatedly.

Ⅳ. The Performance Evaluation of the Real-time Identifier

The performance of the real-time identifier has been verified by two steps. First, the signal with different AR (autoregressive) parameters in the two interval was generated by filtering the white gaussian noise. Then the convergence behavior of the identifier was compared with that of GL(gradient lattice) algorithm [1]. Second, the performance of the realized identifier was evaluated by comparing the result obtained from direct biasing of the nonstationary signal to the identifier with the result of a floating point simulation. With the surface electrode (TECA, NCS 2000) attatching to the portion from which the EMG signal can be well obtained at the normal human biceps of the arm, the EMG signal is sampled while the operation of lifting up and down the 14kg load. Abrupt flexion of arm causes the EMG signal to be suddenly large and have unstable waveform in the initial stage of action because the muscle become burden.

The EMG signal is acquired during 1 second at the following condition; 1024Hz sampling frequency, gain of 2000 times and the bandpass filter of 0.5~500Hz passband. The RUN test is accomplished to verify the nonstationary of the sampled data [4].

Consider a sequence of N observed values of a random variable x where each observation is classified into one of two mutually exclusive categries, which may be identified simply by plus(+) or minus(−). A run is defined as a sequence of identical observations that is followed and preceded by a different bservation or no observation at all.

The number of runs which occur in a sequence of observations gives an indication as to whether or not results are independent random observations of the same radnom variables. Specifically, if a sequence of N observations are independent observations of the same random variable, that is, the probability of a (+) or (−) result does change from one observation to the next, then the sampling distribution of the number of runs in the sequence is a random variable r with a mean value and variance as follows;

$$\mu_r = \frac{2N_1 N_2}{N} + 1 \tag{15}$$

$$\sigma_r^2 = \frac{2N_1 N_2(2N_1 N_2 - N)}{N^2(N-1)} \tag{16}$$

Here, N_1 is the number of (+) observations and N_2 is the number of (−) observations.

In this experiment, the nonstationary identifier was constructed for the nonstationary model order n = 4, smoothness prior order m = 1 and used the suboptimal assumption of constant input noise variance $V(k) = I$ in the identifier and $V(k) = 0.00002I$ in the floating point simulation, where I is the identity matrix. In the identifier, the normalized value is 2048 since the input range of the identifier is ±1[V] and the A/D converter has 12bit resolution.

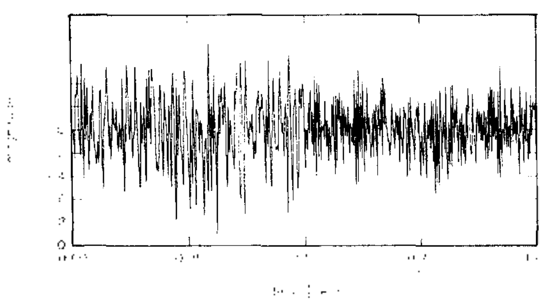

Figure 3. Signal generated by filtering white gaussian noise.

Table 1. AR parameter values for each time interval.

Para. value \ n	1-512	513-1024
$a_1(n)$	1.97	1.35
$a_2(n)$	−2.08	−1.52
$a_3(n)$	1.22	0.95
$a_4(n)$	−0.40	−0.30

The signal generated by filtering the white gaussian noise is shown in Fig.3. The parameters corresponding to each time interval are shown in table 1.

The convergence speed of the parameters by the GL algorithm and the identifier algorithm are shown in Fig.4 and the mean square error for 64 blocks (each block includes 16 data samples) is shown in Fig.5.

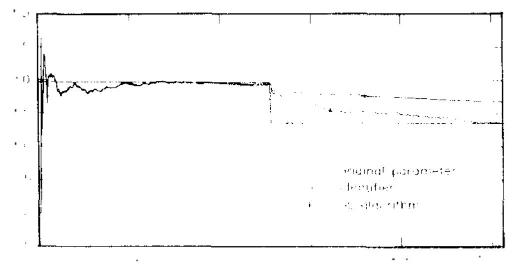

Figure 4. Convergence speed of parameter $a_1(n)$ for GL and identifier algorithm

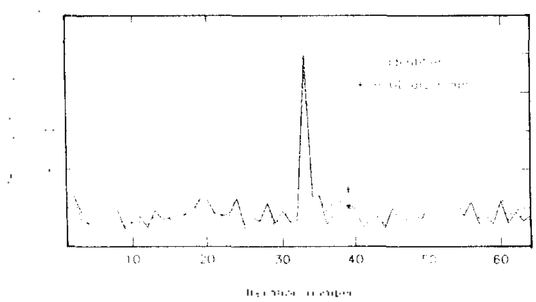

Figure 5. Mean square error curve for $a_1(n)$

In Fig.4, the real parameter value changes abruptly at the 513th sample number. The parameter value varies from 1.97 to 1.35. Comparing the real parameter value with the estimated parameter value, the parameter value estimated by the GL algorithm varies by 0.29 from the 513th to the 1024th sample number. This variation rate is 46.8% of the real parameter variation. In the case of the identifier algorithm, the estimated parameter value varies by 0.58 from the 513th to the 1024th sample number, and this variation is 93.5% of the real parameter variation. Therefore, we can see that the convergence speed of the identifier is 7.76 times faster that of the GL algorithm in the case of the abrupt change signal (or the nonstationary signal). In Fig.5, we can observe the variation of MSE (mean square error). One the parameter value varies abruptly, the MSE of the identifier over the GL algorithm is improved about 30∼50%.

The EMG signal obtained from the biceps muscle is shown in Fig.6. Even when there is no voluntary change of muscle state, myoelectric signals with long duration are probably nonstationary due to the physiology of the system [10]. If it was possible for the neural input and blood or oxygen supply to the muscle to remain constant, the output(EMG) might exhibit stationary. Since this is not the case, we must examine the myoelectric activity during a short time period when these inputs are relatively constant and the EMG is perhaps weakly stationary.

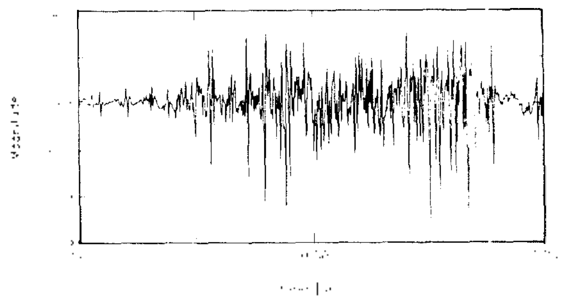

Figure 6. Nonstationary electromyographic signal

To evaluate the stationarity of the turbulence data, the sample data was divided into 32 segments of equal length (32 samples each), and a sample standard deviation deviation was computed for each segment. The median standard deviation of the acquired EMG signal is 0.231 Now let it be hypothesized that the data are nonstationary. From RUN distribution table [4], this hypothesis would be accepted at the $\alpha=0.05$ level of significance if the number of runs observed in the sequence of standard deviations relative to the median was less than 11 or more than 22. From table 2, it is seen that only 4 runs occur in the sequence. Hence, the hypothesis of nonstationarity is accepted at the 5 percent level of significance, meaning the data should be considered nonstationary.

The paramenters that were estimated by the identifier and floating point arithmetic algorithm are shown in Fig.7. The similarity of each result manifests the stability of identifier operation. Fig. 8 is the plotting of the EMG signal reconstructed from estimated model parameters. Fig. 9 is the autocorrelation function of the EMG signal acquired from the biceps muscle and the crosscorrelation function between the raw EMG signal and the reconstructed EMG signal. In Fig. 9, the crosscorrelation function manifests clearly that the reconstructed EMG signal by identifier and the raw EMG signal are highly correlated, and data shows that the identifier does identify the nonstationary signal very accurately.

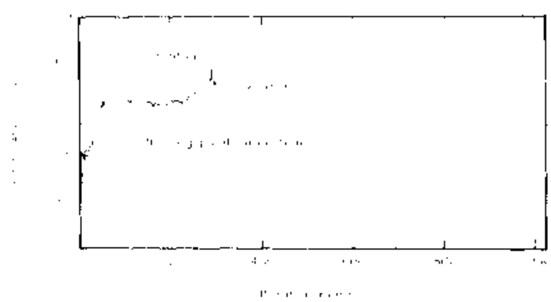

Figure 7. Estimated AR parameter ($a_1(n)$)

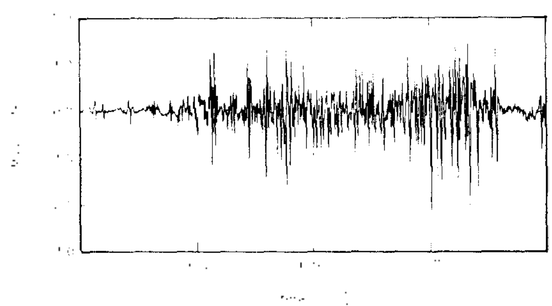

Figure 8. Reconstructed signal with estimated parameter by implemented identifier

Table 2. Stochastic value of each interval

(S.D.: Standard Deviation)

Block	mean	S.D.	Block	mean	S.D.	Block	mean	S.D.	Block	mean	S.D.
1	0.085	0.006	9	0.159	0.124	17	−0.232	0.241	25	−0.123	1.031
2	0.010	0.010	10	0.070	0.224	18	−0.065	0.191	26	0.047	0.620
3	0.063	0.002	11	0.041	0.083	19	0.007	0.163	27	0.141	0.844
4	0.040	0.012	12	0.065	0.252	20	0.230	0.202	28	0.130	0.246
5	0.085	0.004	13	0.046	0.424	21	−0.100	0.241	29	0.012	0.324
6	0.019	0.016	14	0.081	0.245	22	0.071	0.109	30	0.098	0.005
7	−0.005	0.023	15	0.048	0.619	23	0.189	0.431	31	−0.058	0.017
8	0.074	0.054	16	0.293	0.162	24	0.150	0.396	32	−0.051	0.072

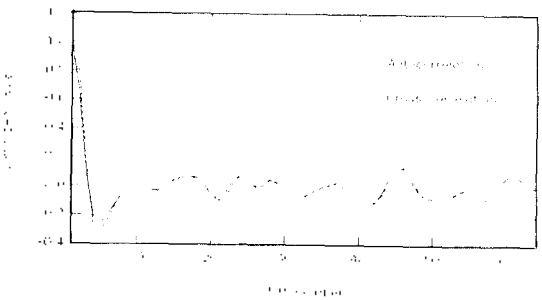

Figure 9. Autocorrelation function and crosscorrelation functon

The implemented real-time identifier has negligible quantization error because the identifier used 64 bit extended-precision arithmetic, and its real-time processing capability corresponds to 0.6kHz for the AR model with n = 4 and m = 1.

Ⅴ. Conculusion

This paper demonstrated that a real-time identifier for the nonstationary time-varying signal can be implemented using a fixed point DSP chip.

We summarize the results of this experimental study as follows:

1. Assuming that nonstationary signal regard to time-varying AR model, nonstationary identification algorithm could identify the parameter accurately.

2. It is possible that the nonstationary parameter identifier can be implemented such that it has real-time processing capability, and if is applicable to physically real nonstationary systems.

3. High numerical fidelity was obtained using 64 bit extended-precision arithmetic.

4. The identifier can be constructed in pocket size(10cm • 10cm) because the system was designed for low power consumption driven by a battery.

The designed real-time identfier is able to use FES (functional electrical stimulation) system for paraplegics, spectrum estimation, and adaptive signal processing for system identification.

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