Monitoring Accumulative Fatigue of Finger by Autoregressive Modeling of Physiological Tremor

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Abstract. In this study, block data structured autoregressive (AR) method is used to evaluate fatigue, based on physiological tremor during and after loading a weight mass on the index finger. The temporal changes in the prediction coefficients and the reflection coefficients are determined. AR spectral estimation with the ninth-order is obtained and presented in graphical form. The results indicate that the first prediction coefficient a_1 can be used to characterize the state of fatigue of finger muscle and the other prediction coefficients do not show any tendency for the finger load. The coefficient a_1 can be applied to monitor the accumulative fatigue induced by the weight loading for a duration of time. (*Appl Human Sci*, 14(1) : 29-36, 1995)

Keywords: physiological tremor, finger tremor, fatigue, AR model, weight load.

Introduction

Physiological tremor at rest was first recognized by Horsley and Schäffer in 1886. The weak mechanical vibration can be detected on the vibration of body part in a totally relaxed state. Over the years, a number of studies have been addressed to the question of whether physiological tremor is primarily dependent on central neural mechanism generating rhythmic motor activity or on peripheral factors (Allum 1984; Marsden 1978; Stein and Ögüztörel 1976). The physiological tremor, which is characterized by a typical oscillation having a stable sharp peak in the range of 8-12Hz, was investigated through many experiments. Moreover, two frequency components for finger tremor, which are ranged over both 8-12Hz and 15-30Hz, have been distinguished and are highlighted in understanding the underlying mechanism of the physiological tremor (Sakamoto et al. 1992 and 1993). In spite of many controversies about the origin of the physiological tremor, a model for the cause of two frequency bands for physiological tremor of human finger, which is called as finger tremor hereafter, was constructed by considering the interactions between neuromuscular and skeletal mechanical system (Miao and Sakamoto 1993).

The active role played by a tremor in human performance was discussed by Goodman and Kelso (1983), who studied the systematic phase relationship which existed between the initiation of movements and the tremor oscillations. They explained that: "the emphasis on 'instability' and on ways to reduce tremor oscillations may have led us to overlook the possible uses of tremor. Our results, of course, suggest that tremor does indeed play an important function. More generally, they underscore the potential significance of oscillatory processes in the initiation and control of movement." They suggested an applicable perspective using the *active* property of tremor oscillator. On the other hand, the nature of variation of physiological tremor was studied in relation to the loads like typing, weight load, and elastic load (Joyce and Rack 1974). The *inactive* property of finger tremor have been applied to estimate human fatigue and to evaluate the performance functions of the human limbs (Lippold 1981, Sakamoto et al. 1992). Such studies have practical meanings in many fields including biological engineering, ergonomics, and medical clinics.

In this paper, the accumulative fatigue, produced by loading an extra mass on finger for a duration of time, is studied from the analysis of variations of the finger tremor. We designed an experiment, where the subject was required to maintain a steady posture when the tremor was recorded from the index finger. In order to trace temporal changes of finger tremor, and thereby to trace the development of fatigue, one is compelled to analysis the data in an array of short data blocks in the time series. Since spectral estimation using the classical FFT approach suffers from poor frequency resolution for the short data block (Marple 1977), a digital analysis using autoregressive (AR) method is presented. The AR model, due to its good resolution property and reductions of computational complexity, was widely accepted as a means to extract the meaningful information from the time series of the biological systems. The accumulative fatigue is monitored by both AR parameters and power spectral plot.

Methods

1 Experimental Procedure

Experiments were done on the human index finger of nine normal subjects, aged 22-36 years. The methods of limbs fixation and position measurements were described in the preceding article (Sakamoto et al. 1992). A simple schematic demonstration is shown in Fig.1. An extra mass of 200g was added to the tip of the index finger to be tested. The magnitude of mass was selected under the criterion where the subject did not feel the weight at the first time but gradually feel fatigue with the load. In the experiment, the subject was instructed to maintain the index finger horizontally and stretched. He did this for a period of 360s (6 min) while the acceleration component of the finger tremor was measured by a sensor (MT-3T, Nihon Kohden).

After amplification and low-pass filtering at 1 kHz, the finger tremor was memorized on a multichannel data recorder (PC-108M, Sony). An A/D conversion,

Fig.1 A schematic diagram of experimental system and data processing for records of index finger tremor during loading 200 gram for a duration of 360s.

which was sampled in a rate of 100 Hz (i.e., sampling interval 10 ms), was made by reading the data from the tape and recording it into a memory of computer for AR modelings.

2 AR Model

An AR analysis is a process whereby the presented sample $x(n)$ is estimated from knowledge of its past samples:

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

where $x(n)$ is the n -th sample, p is the model order, $e(n)$ is the residue error, and the AR coefficients $\{a_k | k=1, 2, \dots, p\}$ are the characterization of the generating AR process. Burg's method extracts the reflection coefficients (ρ_i) and determines the prediction coefficients (a_i) using the Levinson recursion algorithm (Kay and Marple 1981). According to the method, a procedure of minimization of function J_{err} is applied under the constrained condition that the prediction coefficient satisfies the Levinson recursion for all orders from 1 to p :

$$a_k^{(p)} = a_k^{(p-1)} + d_p^{(p)} a_{p-k}^{(p-1)} \quad (2)$$

where $a^{(j)}$ represents j -th prediction coefficient at order α . The function J_{err} is defined as

$$J_{err} = \sum_{n=p}^{N-1} (f_p^2(n) + b_p^2(n)) \quad (3)$$

where N is the number of data and $f_p(n)$ corresponds to the forward prediction error, and $b_p(n)$ corresponds to the backward prediction error. They can be shown as follows.

$$f_p(n) = x(n) + \sum_{k=1}^p a_k x(n-k) \quad (4)$$

$$b_p(n) = x(n-p) + \sum_{k=1}^p a_k x(n-p+k) \quad (5)$$

$$f_p(n) = f_{p-1}(n) + d_p^{(p)} b_{p-1}(n-1) \quad (6)$$

$$b_p(n) = b_{p-1}(n) + d_p^{(p)} f_{p-1}(n-1) \quad (7)$$

The pair of relations, i.e. eqns. (6) and (7), give rise to the so called lattice filter structure (Ansourian et al. 1989). Setting the derivative of the J_{err} with respect to $d_p^{(p)}$ to zero, it is found that

$$\rho_p = d_p^{(p)} = \frac{-2 \sum_{k=p}^{N-1} f_{p-1}(k) b_{p-1}(k-1)}{\sum_{k=p}^{N-1} (f_{p-1}^2(k) + b_{p-1}^2(k-1))} \quad (8)$$

where reflection coefficient ρ_i is defined as $d_i^{(i)}$, i.e. $\rho_i \equiv d_i^{(i)}$. The reflection coefficient possesses the property of $|\rho_i| \leq 1$ for every i . From the reflection coefficients, eqn. (2) generates all prediction coefficients.

The AR estimation of the power spectral density function is given by

$$S_{xx}(f) = \frac{\sigma_p^2}{|1 + \sum_{k=1}^p a_k \exp(-j2\pi kf)|^2} \quad (9)$$

where σ_p^2 is the variance of error $e(n)$ which is assumed to be white noise, and f is the frequency.

The best choice of the order p is necessary in practical calculation. A guess of too low order p results in a highly smoothed spectral estimate. Too high order introduces spurious details into the spectrum. The prediction error $FPE(p)$ called as Akaike final prediction error criterion provides an objective base for selection of the AR model order (Akaike 1970). The $FPE(p)$ is defined as

$$FPE(p) = \sigma_p^2 \left(\frac{N+p+1}{N-p-1} \right) \quad (10)$$

The best order p selected is the one for which the $FPE(p)$ is minimum. Fig.2 displays a typical example of the $FPE(p)$, where N is 200 points in the finger tremor. The value of p depends on the data of the subject and the data interval taken. The value of p at minimum $FPE(p)$ exists in the range from 6 to 9 for the whole data. In order to take the value of p uniformly in the analyses, the value was taken to be 9, since the larger value shows smaller value of $FPE(p)$. It is shown that the generally acceptable order is about 9 which will produce a reasonably well-fitted model.

Results

The %MVC (percent of Maximum Voluntary Contraction) of finger muscle, during loading of 200g on finger to be tested, was measured and it ranged from 15% MVC to 21%MVC for all subjects. With force of the %

Fig.2 An example of Akaike's final prediction criterion, $FPE(p)$, as a function of model's order p for a segment of finger tremor signal. (The segment contains 200 samples).

MVC, the finger which prolonged a duration, say 6min, can lead to fatigue (Enoka and Stuart 1992). As the subject begins to feel fatigued the amplitude of finger tremor is enhanced. An increasing acceleration of the amplitude of finger tremor is observed in Fig.3.

The enhanced physiological tremor is known to be an indication of fatigue, as illustrated by Joyce and Rack (1974) and Hagbarth and Young (1979). In order to describe the enhanced finger tremor, and therefore to evaluate the accumulative fatigue, a block data structured AR method is employed to analyze the underlying process. Concretely, the AR modeling of the temporal changes in the finger tremor signal is done with a moving window containing $N=200$ samples (2 sec) from which AR parameters and the power density spectra are estimated. This data block (window) chosen is long enough to ensure the necessary information accurately determined from the short data, while still being short enough for the data block to be stationary. After the calculations, the window advances at a step of 100 samples for the computations of AR parameters or 200 samples for the spectral estimation.

The examples of continuous graphs of the prediction coefficients a_i and reflection coefficients ρ_i during maintaining the weight load of 200g on index finger are shown in Fig.4 for a subject S8. In a_i for $i=1$, there is a pronounced trend, and for $i \geq 2$, the coefficients remain approximately unchanged, as displayed in Fig.4. Further illustrations are displayed in Fig.5 for subject of S7 and S9, as shown in the examples. All the subjects show a similar tendency of trend for the coefficient a_1 . The averaged value of a_1 ($p=9$) drops from -0.868 to -1.251 with a slope of $-9.789 \times 10^{-4} [s^{-1}]$ (in Fig.5(a), S7) and from -0.920 to -1.124 with a slope of $-6.720 \times 10^{-4} [s^{-1}]$ (in Fig.5(b), S9).

It is noted that the greater the %MVC for a loading, the more rapidly the muscle fatigue (Bellemare and

Fig.3 A recording of variations of acceleration amplitude of finger tremor during holding the load of 200g for 360s.

Fig.4 A typical example of temporal variations of a_i and ρ_i just after loading of mass 200g for a duration of 360s. In (a), lower curve: first prediction coefficient a_1 ; upper curve: second one a_2 ; dotted line: third one a_3 ; thin line: fourth one a_4 . Similarly in (b), lower curve: first reflection coefficient ρ_1 ; upper curve: second one ρ_2 ; dotted line: third one ρ_3 ; thin line: fourth one ρ_4 .

Grassino 1982). For the subjects S7 and S9, the percent of MVC is measured to be 20.9%MVC and 17.3%MVC respectively, and as displayed in Fig.5, a more rapidly drop of prediction coefficient a_1 is found for S7 which exerted a greater force (or %MVC) than S9 does. Therefore, a_1 is the most important variable in our AR model. The decreased trend can be used as a characterized index for fatiguing influence on neuromuscular system.

Fig.6 depicts a waterfall representation of the AR spectral estimation for a subject, where 180 blocks are computed. The time traverses along the vertical axis with a total of 180×200 samples (=360s). The frequency traverses along the horizontal axis.

Fig.6 reveals two interesting features of the time

Fig.5 The variation of first prediction coefficient as a function of elapsed time for subjects of S7 in (a) and S9 in (b), during holding a load of 200g. The dotted line represents the means of the a_1 with small oscillations indicated as a solid line. For S7 and S9, the %MVC is 20.9%MVC and 17.3%MVC respectively, and more than (b), a rapidly decreasing rate of the mean value of a_1 is seen in (a).

series. (1) Some kinds of fluctuations appear in the time-varying amplitude. A possible relationship existed between the fluctuation and the periodicity in EEG (electroencephalogram), ECG (electrocardiogram), and MV (microvibration), was studied by Keidel et al. (1986). They conjectured that the modulation of the amplitude might depend on central oscillations of the nervous system. (2) There are two reproducible peaks in the spectrum. Also, although two peak bands were found in the early period of time (Randall and Stiles 1964; Stiles and Randall 1967), the two peaks as a characterization of physiological tremor have been missed by some tremor investigators (Rietz and Stiles 1974); either for the reason of their questionable measurement method in

Fig.6 Waterfall plot of AR spectrum during loading of mass 200g for subject S7. A window of 2s block is advanced in a step of 2s. Two peaks are shown at around 8Hz and 14Hz.

which the high peak can not be detected, or for their disregarding the meaning of high frequency component. Based on the experimental result in Fig.6, we insist that the two peaks are important and intrinsic to the finger tremor (Miao and Sakamoto 1993).

Discussion

The activation of the neuromuscular system at any intensity of force exerted will eventually elicit fatigue, as reviewed by Enoka and Stuart 1992. The mechanisms underlying muscle fatigue varies with the level of the force that is exerted. The greater the force during a task or loading, the more rapidly the muscle fatigue (Bellemare and Grassino 1982). Of the variety of methods to examine muscle fatigue, a simple approach using physiological tremor have been studied by Hagbarth and Young 1979, Lippold 1981, and Stiles 1976. They discussed the relationship between fatigue influence and amplitude enhancement in physiological tremor. In our study, in order to understand physiological process underlying fatiguing effect, we examined fatigue development under persisting finger muscle contraction induced by adding 200g weight load on the finger. An AR model fitted to finger tremor signals was used and the AR parameters, especially a_i , were proposed to characterize the finger fatigue during a mass loading. The slopes estimated from the variation of a_i with respect to time, which are explained in Fig.5, correspond to different speeds of fatigue development. Some problems associated with AR model and AR parameters are shown in the following.

1 Parameter Variance

Firstly, it is noticed that the small oscillations seen in the graphs of a_i and ρ_i in Figs.4 and 5 come from a random nature in the sampled finger tremor signals. This randomness causes a variance (i.e. small oscillation) in the estimation of the parameters. A lower bound for the variances of a_i can be evaluated by the Cramer-Rao Lower Bound (CRLB)(Friedlander 1984):

$$\text{Var}\{\hat{a}_i\} \geq \frac{1}{N} [(1 + a_1^2 + a_2^2 + \dots + a_{i-1}^2) - (a_p^2 + a_{p-1}^2 + \dots + a_{p-(i-1)}^2)] \quad i=1,2,\dots,p \quad (11)$$

where it is assumed that $\hat{a}_i$ is a random process. The average of $\hat{a}_i$ is the true value of a_i and the variance of the process gives the small oscillation seen in graph of a_i . Especially, for $i=1$, we simply have

$$\text{Var}\{\hat{a}_1\} \geq \frac{1}{N} [1 - (a_p^2)] \quad (12)$$

If it is assumed that the observed variance is not far from the Lower Bound (i.e., the right hand side) of eqn. (12), then this CRLB estimates the small oscillations in parameter a_1 . The CRLB values are listed in Table 1 for nine subjects before the windows are moved. The group means of a_1 and $\sqrt{\text{CRLB}}$ for the nine subjects are evaluated to be -1.067 and 0.0703 respectively. The

estimation for the standard deviation of $\hat{a}_i$ (i.e., 0.0703), which corresponds to $\sqrt{CRLB}$, is found to be very small as shown in Table 1, when compared with the group mean (i.e., -1.067).

2 Adequacy and Stationary

An important assumption of the AR modeling is that residue error $e(n)$ is a white noise. The whiteness should be checked to determine the suitability of the model. One of the examples for the residue $e(n)$ produced by AR modeling of sample $x(n)$ is shown in Fig.7(a). Correspondingly, the AR spectra and autocorrelation function for $e(n)$ and $x(n)$ are displayed in Figs.7(b) and 7(c). As seen in Fig.7(c), the autocorrelation function of the $e(n)$ is distributed to be approximately zero, therefore, the whiteness for residues $e(n)$ can be guaranteed. Also, the whiteness of the residue $e(n)$ means that the AR modeling of the time series is optimal fitting which ensures the stationary of the signal in the short time block (e.g., 2s). Additionally, if the window block is taken as less than 2s, say the window is 1s in width and is moved with a step of 0.5s, the prediction coefficient a_1 is calculated and compared with Fig.5(b) which is replotted in Fig. 8(b). The curve shown in Fig.8(a) possesses approximately the same tendency and character as the curve of Fig. 8(b). Then the stationary within the block (2s) selected can be proved primarily.

3 On the AR Parameters

Finally, we will pay some attention to the possible implications and usefulness of AR parameters.

(1) The time series of tremor can be characterized by a set of prediction coefficients due to the good fitting using the AR model. According to the coefficients, therefore, various patterns of functional behavior and underlying processes of the time series can be identified and discriminated (Hefftner et al. 1988).

(2) As seen in eqn.(9), the parameters of $\{a_k|k=1,2,\dots,p\}$ and the variance of error σ_p^2 establish the power spectra. It is due to the fact that power spectra contains knowledge about energy distribution and oscillator presents.

(3) The AR process is a linear filter system in which the output corresponds to sampled data and input is a white noise. From this fact, the tremulous movement may be viewed as resulting from a mechanical system in which tremor signal is produced by a damped oscillator driven by a fluctuation force (Gantert et al. 1992). Concretely, the variance of error σ_p^2 reflects the fluctuation force which originated from the random firings of motor-neuron (Christakos 1982); a_k , especially a_1 in our records, captures the main properties of the mechanical system consisting of nervous and skeletal muscular processes. However, some detailed relation between parameter a_1 and fundamental variables is to be inquired.

(4) $\{a_k|k=1,2,\dots,p\}$ and σ_p^2 constitute the parameters for the optimum pth-order linear predictor (Kay and Marple 1981). The residue $e(n)$ is explained as one-step-ahead

Fig.7 Model checks for AR modeling of finger tremor data $x(n)$. (a) shows the raw data of residue error $e(n)$ of $x(n)$, (b) are AR power spectrum for $x(n)$ (in dotted line) and $e(n)$ (in solid line), and (c) are autocorrelation functions for $x(n)$ (indicated by dotted line) and the residue sequence $e(n)$ (shown in solid line), where the first 40 autocorrelation lags are obtained.

Table 1. Prediction coefficient a_1 , lower bound of variance estimation (CRLB) and square root of CRLB ($\sqrt{\text{CRLB}}$), for nine subjects. $N = 200$, $p = 9$

Subj.	S1	S2	S3	S4	S5	S6	S7	S8	S9	mean
a_1	-1.179	-.571	-.868	-1.493	-.920	-1.175	-1.404	-.939	-1.055	-1.067
$\text{CRLB} \times 10^2$	.496	.481	.495	.494	.497	.492	.499	.497	.494	.494
$\sqrt{\text{CRLB}} \times 10^1$	.705	.694	.703	.703	.705	.701	.706	.705	.703	.703

Fig.8 Check for invariance and stationarity of the signal. (a) First prediction coefficient a_1 is computed in a smaller window (1s) and advancing interval $\tau = 0.5s$, as in comparison with the estimation of a_1 in (b) which is Fig.5(b).

prediction error in the predictor. The predictor can be used to predict the next samples and provide time series extrapolation. In addition, since the AR spectrum matches the peaks and results in smoothed spectra for small order p (Kay and Marple 1981), the AR model provides a proper estimate for the total power within low frequency band and high one, which is useful for amplitude evaluation.

Conclusion

The AR method is good in modeling short-time sampling data series, and offers a more reasonable resolution over the classical FFT. The fatiguing process, which was produced by weight load on finger, was described by AR modeling of the finger tremor. The adequacy and applicability of the model were discussed. It was concluded that ninth-order autoregressive model appeared to capture sufficiently most information about spectral bands and state underlying the time series.

The calculations for AR parameters demonstrated that the prediction coefficient a_1 decreased continuously during a mass loading. Since the AR parameters are closely related to neuromuscular mechanical system, the variations of the AR parameter is resulted from the parameter variations in the mechanical system. The parameter a_1 is applied to monitor the accumulative fatigue induced by external loads, so that the parameter a_1 can be accepted as an essential index in evaluation of finger muscle state.

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Received: April 13, 1994

Accepted: October 31, 1994

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