AR Modeling of Myoelectric Interference Signals During a Ramp Contraction

Tohru Kiryu, *Member, IEEE*, Carlo J. De Luca, *Fellow, IEEE*, and Yoshiaki Saitoh, *Member, IEEE*

***Abstract*— We investigated the time-varying behavior of the autoregressive (AR) parameters in a myoelectric (ME) signal detected during a linear force increasing contraction. The AR parameters of interest were the reflection coefficients, the AR model spectrum, and the prediction errors. We used well-conditioned ME signals for which the complete time record of the motor units firings was available. In addition, the influence of the recruitment of a new motor unit, the conduction velocity of action potentials, and additive broad-band noise were investigated using simulated ME signals. The simulated ME signals were constructed from a selected group of the available motor unit action potential trains. The results revealed that, as the contraction progressed, the AR parameters displayed a time-varying behavior which coincided with the recruitment of newly recruited motor units whose spectrum of the waveform differed from that of the rest of the ME signal. This property of the AR parameters was obscured by the presence of broad-band noise and low-amplitude motor unit action potentials, both of which are more pronounced during low-level force contractions.**

I. Introduction

IT HAS BECOME common practice to use the frequency spectrum of the surface myoelectric (ME) signal as a fatigue index for sustained muscle contractions (see reviews by De Luca [1] and Merletti *et al.* [2], among others). For such analysis, it is important that the ME signal be stationary. This is an important concern because motor units (MU's) may be recruited or derecruited during a contraction due to fluctuations in the force output of the muscle. Such fluctuation may occur even in attempted constant-force isometric contractions.

Previous approaches for analyzing the time-varying aspects of the ME signals have used a linear prediction model. Among them, the autoregressive (AR) model has been used to deal with time-varying ME signals because it emphasizes spectral peaks for time records having a small number of samples [3]. This approach was introduced by Graupe and Cline [4] who attempted to use the surface ME signal for controlling prostheses. Subsequently, Sherif *et al.* [5] studied the behavior of autoregressive integrated moving average (ARIMA) coefficients of the ME signals from the deltoid muscle during dynamic contractions. Recently, Capponi *et al.* [6] represented ME signals, detected from the biceps and triceps muscles, with the time courses of AR coefficients during rapid isometric contractions. The benefit of the AR model in ME signal analysis has been confirmed for applications in prosthesis control [4], [7], functional electrical stimulation [8], and clinical diagnosis [9]. These applications notwithstanding, the problems of applying AR model to time-varying ME signals and the time-varying behavior of AR parameters have not been studied in detail.

The use of AR modeling for physiological interpretation of the behavior of the ME signal has been limited. In an early report, Inbar and Noujaim [9] described the influence of the statistics of MU's firing characteristics to AR parameters. Later, Paiss and Inbar [10] analyzed the AR coefficients of surface ME signals from the biceps brachii muscle to monitor localized muscle fatigue. They reported that the first AR coefficient could be used to monitor local fatigue. However, they did not describe it in terms of recruitment order of MU's. More recently, Kiryu *et al.* [11] achieved a less biased estimation of AR coefficients for surface ME signals of the masseter muscles performing a rapid open-close movement. They described the correlation among the firings of MU's and the levels of the reflection coefficients (one of the indexes of AR parameters), especially the third reflection coefficient, during dynamic movement. However, because their work was limited to a muscle-structured computer simulation, physiological interpretations were not possible.

In order to further investigate the physiological interpretation of AR modeling, we analyzed the time-varying behavior of AR parameters for well-conditioned ME signals detected during an isometric force-varying ramp contraction.

II. Experimental Procedure

Five subjects volunteered for the experiment. All the subjects signed an informed consent form approved by the local Institute Review Board. The first dorsal interosseous (FDI) muscle was chosen for this study. The hand of each subject was placed in a specially designed device that constrained the FDI to contract isometrically and substantially isolated the force being generated by the FDI. The maximal voluntary contraction (MVC) level was measured for each subject. Each subject was asked to contract the FDI with maximal effort for a period of two to three seconds. Three trials were performed with a rest interval of two minutes between attempts. The highest value was taken as representing the MVC. The subjects were instructed to contract the FDI so as to generate a force-time course which tracked trajectory displayed on a monitor. The trajectory consisted of a ramp (10% MVC/s) for 5 s up to 50% MVC.

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T. Kiryu and Y. Saitoh are with the Department of Information Engineering, Faculty of Engineering, Niigata University, 8050 Ikarashi-2nocho, Niigata-shi, 950-21, Japan.

C. J. De Luca is with the NeuroMuscular Research Center, Boston University, Boston, MA 02215 USA.

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A special quadrifilar needle electrode was inserted into the muscle. ME signals were obtained from three differential combinations of the four wires (75 μm in diameter) exposed in cross-section at a side-port on the cannula of the needle, as well as from the cannula itself. The signals from the side-port wires were amplified with a bandwidth of 1 kHz–10 kHz and were digitized at a rate of 50 kHz. Filtering the side-port wires ME signals reduced the amplitude of motor unit action potential (MUAP) waveform having slower rise-time and produced by muscle fibers distant from the recording site [12]. The ME signals from the side-port wires were decomposed into their constituent MUAPT's by the Precision Decomposition technique to obtain the map of MU firings. The Precision Decomposition technique is a template matching technique which arrives at decisions for identifying the shape of individual MU's by a weighted combination of probability of occurrence and the least-squared signal space distance between the MUAP and an established template. The technique also continuously updates the templates if the shape of the MUAP's is modified slowly. For more details the reader is referred to Le Fever and De Luca [12] and Mambrito and De Luca [13].

The ME signal from the cannula was amplified with a bandwidth of 10 Hz to 1 kHz and was digitized at a rate of 2048 Hz. We then estimated the AR parameters from the cannula ME signals, which in many ways have properties similar to those of surface ME signals. The AR parameters of interest were the reflection coefficients, the AR model spectrum, and the prediction errors.

III. Spectrum Model and Simulation

A. Spectrum Model

Let us consider a spectrum model of ME signals which emphasizes the relationship between the recruitment order and the power spectrum. For a set of active MU's, M, the time-varying power spectrum of the ME signal, $P_{\mathrm{ME}}(\omega, t)$, is represented by

$$P_{\mathrm{ME}}(\omega,t) = \sum_{m=1}^{M(t)} |E_m(\omega)|^2 |MP_m(\omega,t)|^2 |FR_m(\omega,t)|^2, \quad (1)$$

where $E(\omega)$, $MP(\omega, t)$ and $FR(\omega, t)$ are, respectively, the Fourier transforms of the spatial filter, the MUAP waveform, and the firing train. The spatial filter includes filtering effects related to the anatomical structure of the muscle and, for the purpose of this study, is considered to be stationary. It should be noted that $P_{\mathrm{ME}}(\omega, t)$ is nonstationary mainly because the number of active MU's, M, is a function of time; $M(t)$ increases in a step-wise fashion during a task that requires MU recruitment. Also, it should be noted that MUAP waveform contributes to the global pattern of the ME power spectrum, whereas the firing rate only creates a relative insignificant peak in the low frequency range of the spectrum [10], [14].

B. Physiological Evaluation Using Computer Simulation

In order to study the influence of newly recruited MU's, two important considerations must be studied ahead of performing AR analysis of the ME signals which are detected during force-varying contractions: a) the effect of broad-band noise; and b) the effect of the conduction velocity of the action potentials.

The broad-band noise will arise from random noise present in physiological systems as well as in the detection and recording systems. This noise will be essentially independent of the ME signal. Another source of broad-band noise will be the background activity of low-amplitude MUAP's in the ME signal. The amplitude of additive broad-band noise is not negligible when the muscle contraction level is relatively low, for example, during the early stage of a ramp contraction. This is of particular concern because it has been reported that AR model may show discrepancies for contaminated signals with additive broad-band noises [15]. To remove the influences of the broad-band noise on the AR parameters, we simulated noncontaminated ME signals on a computer. This task was accomplished by selecting the higher amplitude MUAPT's from the decomposed ME signals and using their firing times to estimate the trigger-averaged MUAP waveforms from the cannula ME signal. This time history of the firings of these MUAP waveforms produced a noise-free cannula ME signal.

The conduction velocity (CV) of the ME signal is a necessary consideration because it is well-known that the CV of the MUAP's of MU's recruited at higher force thresholds increases. Therefore, as the force output of a muscle increases, so does the average CV of the ME signal [16]–[18]. We performed two simulations. In the first simulation, the MUAP waveforms were assumed to be time-invariant. That is, they had constant CV's throughout the time sequence. Thus, with this approach, we were limited to studying only the contribution of the individual MUAP waveforms and the map of the MU firings to the ME power spectrum during a ramp contraction. In the second simulation, we wished to investigate the influence of the CV during ramp contractions. This increase in the CV was simulated by a reduction function of the MUAP duration, $R(t)$, as follows

$$R(t) = 0, \qquad 0 \le t < t_s, \quad (2.1)$$

$$R(t) = R_m\left[1 - \left(\frac{t_f - t}{t_f - t_s}\right)^2\right], \quad t_s \le t < t_f, \quad (2.2)$$

$$R(t) = R_m \qquad t_f \le t, \quad (2.3)$$

$$\text{MUAP duration } (t) = \text{MUAP duration } (t_s)[1 - R(t)], \quad (2.4)$$

where R_m is the maximum rate of the decrease ($0 < R_m < 1$), t_s is the time at which MU recruitment occurs, and t_f is the time at which the decrease rate reaches R_m. Then, the time-varying increase rate of the CV, $C(t)$, is calculated by

$$C(t) = \frac{1}{1 - R(t)}. \quad (3)$$

The initial conditions of MUAP waveforms and the map of the MU firings were identical to those used in the first simulation.

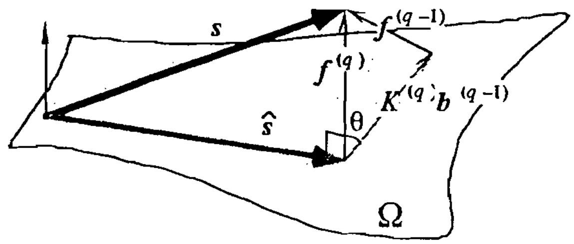

Fig. 1. Geometrical relation of PE vectors. If the minimum norm of the forward PE vector, $f^{(q)}$, is achieved by the LS estimation, $f^{(q)}$ is perpendicular to the subspace Ω that defines the estimate vector, $\hat{s}$. The backward PE vector, $K^{(q)}b^{(q-1)}$, and $\hat{s}$ exist in the same subspace.

IV. Time-Varying Spectrum Analysis

A. Time-Varying AR Parameters

Estimation of time-varying AR parameters provides a direct solution for time-varying spectrum analysis. A p-th order AR model is given by

$$s_n = \sum_{i=1}^{p} \alpha_i^{(p)} s_{n-i} + \xi_n^{(p)}, \tag{4}$$

where s_n is a signal sample digitized at time instant n. The linear prediction coefficients, $\alpha_i^{(p)}$ for $i = 1, \ldots, p$, and previous sample sequence, s_{n-i} for $i = 1, \ldots, p$, predict s_n with the residual, $\xi_n^{(p)}$. Although the use of locally quasistationary processing has been shown to be effective for analyzing the ME signals during dynamic contractions [11], for the sake of convenience, we estimated the AR parameters, assuming the ME signals to be locally stationary. In this approach, a set of linear prediction coefficients, $[\alpha_i^{(q)}]$, is estimated in a specific block (interval) segmented from the ME signal, and the ME signal is assumed to be stationary in the block. The sliding block procedure shifts the overlapping block every one sample along the time axis to obtain the time courses of AR parameters.

The time-varying power spectrum obtained by the maximum entropy method (MEM) is expressed as [3]

$$P(\omega) = \frac{1}{\left|1 - \sum_{i=1}^{p} \alpha_i^{(p)} z^{-i}\right|^2_{z=\exp(j\omega)}}. \tag{5}$$

The q-th reflection coefficient (RC), $K^{(q)}$, is defined by the q-th linear prediction coefficient of the q-th order AR model, $\alpha_q^{(q)}$. The order update from q to $q+1$ affects $[\alpha_i^{(q)}]$ and, therefore, the MEM power spectrum, but does not influence RC's of the order below q. RC's up to p-th can be transformed into the p set of linear prediction coefficients, $[\alpha_i^{(q)}$ for $i = 1, \ldots, q$ and $q = 1, \ldots, p]$, and vice versa [19].

B. Prediction Error Analysis

We have shown previously that the prediction error (PE) analysis can be used to analyze the ME signals from the masseter muscle during a rapid open-close movement [20]. This approach has several advantages. Unlike the successive estimation of time-varying AR parameters at every interval, the PE analysis only compares time-varying properties of ME signals with the reference of a sustained contraction, thus resulting in lower computational cost. The PE includes all of the time-varying residual components which the reference AR coefficients cannot predict from time-varying ME signals at every interval.

We represent the equations that will be necessary to understand the PE analysis because the article [20] was written in Japanese. Let the maximum order of the AR model be p, and consider two types of PE vectors: the forward and backward PE vectors, $f^{(q)}$ and $b^{(q)}$, for $q = 1, \ldots, p$, respectively. The time-varying components of both q-th PE vectors at time n in a block have been given by Markel and Gray [19]:

Forward Prediction Error Components (refer to (4))

$$f_n^{(q)} = s_n - \sum_{i=1}^{q} \alpha_i^{(q)} s_{n-i}, \tag{6}$$

where $[\alpha_i^{(q)}]$ is the forward linear prediction coefficients of a q-th AR filter;

Backward Prediction Error Components

$$b_n^{(q)} = s_{n-(q+1)} - \sum_{i=1}^{q} \beta_i^{(q)} s_{n-i}, \tag{7}$$

where $[\beta_i^{(q)}]$ is the backward linear prediction coefficients of the q-th AR filter. The relationship between forward and backward PE vectors is

$$f^{(q)} = f^{(q-1)} + K^{(q)} b^{(q-1)}, \tag{8}$$

where $K^{(q)}$ is the q-th RC.

According to the geometrical interpretation of the least-squares estimation of $[\alpha_i^{(q)}]$, the optimum forward PE vector, $f^{(q)}$, should be perpendicular to the subspace Ω that defines $\hat{s}$ (orthogonality principle) [19], [21]. Fig. 1 shows that

$$f^{(q)} = s - \hat{s}, \tag{9}$$

where $\hat{s}$ is the estimate vector of the observed signal vector s. Since the backward PE vector $K^{(q)}b^{(q-1)}$ and $\hat{s}$ exist in the same subspace, $f^{(q)}$ and $b^{(q-1)}$ are orthogonal with each other in a specific block where the AR filter is designed, for $q = 1, \ldots, p$, in the least-squares estimation sense.

The reference AR coefficients of the standard AR filter, $[\alpha_{i,r}^{(q)}]$ and $[\beta_{i,r}^{(q)}]$, should be estimated in a specific locally stationary block, a reference block, in advance. Unlike AR parameters poorly estimated in successive blocks of a time-varying ME signal, the PE components calculated by $[\alpha_{i,r}^{(q)}]$ and $[\beta_{i,r}^{(q)}]$ can treat all of the time-varying residue that reference AR coefficients cannot predict. Now, we can define the PE index, $J_{\mathrm{FBEO}}^{(q)}$ for $q = 1, \ldots, p$, as

$$J_{\mathrm{FBEO}}^{(q)} = 1 - \frac{(f^{(q)T} b^{(q-1)})^2}{|f^{(q)}|^2 |b^{(q-1)}|^2}, \tag{10}$$

where ^{T} denotes the transpose. Then, (10) is rewritten as

$$J_{\mathrm{FBEO}}^{(q)} = 1 - \cos^2 \theta, \tag{11}$$

where θ is the angle between $f^{(q)}$ and $b^{(q-1)}$. The PE index has a value of 1.0 only if the feature in a block is identical to

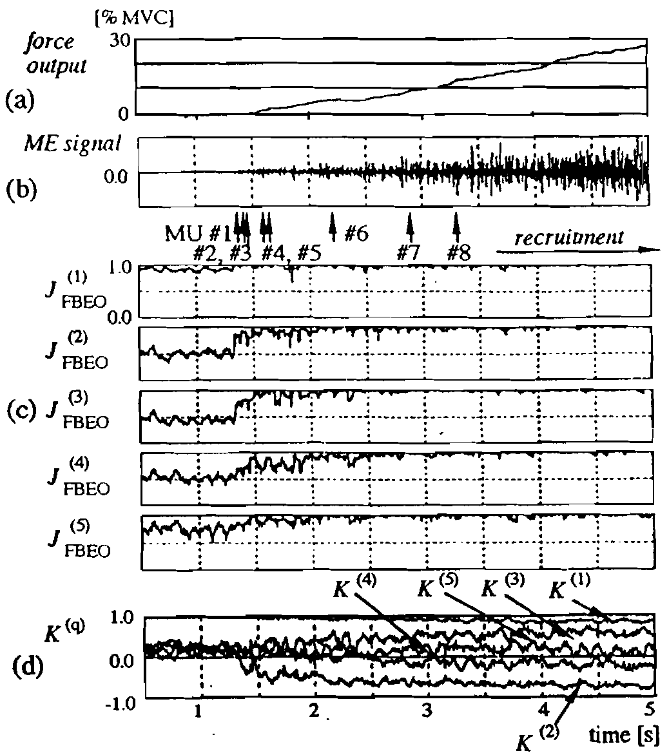

Fig. 2. Time courses of AR parameters for an actual cannula ME signal during a ramp contraction: (a) force output; (b) cannula ME signal with the arrows indicating the location of MU recruitment; (c) time courses of PE indexes, $[J_{\mathrm{FBEO}}^{(q)}$, for $q = 1, \ldots, 5]$; (d) time courses of RC's, $[K^{(q)}$, for $q = 1, \ldots, 5]$. PE indexes and RC's showed the time-varying behavior.

that in the reference block. That is, it shows whether or not the feature in a block is similar to that in the reference block, using $[\alpha_{i,r}^{(q)}]$ of the standard AR filter. It should be noted that $b^{(q-1)}$ is calculated by $f^{(q)}$, $f^{(q-1)}$, and $K^{(q)}$, using (8). The concept of the PE index stems from the similarity function which was proposed by Iijima [22] and has greatly contributed to the development of the optical character recognition.

Since the PE index is evaluated at each order, it can also express a practically required AR order to represent the observed signal in a block of interest. That is, the q-th PE index shows around 1.0 if the practically required AR order is more than q.

V. Results

A. Time-Varying AR Parameters of Original ME Signals

The time courses of AR parameters for an actual cannula ME signal during a ramp contraction is presented in Fig. 2. The force output of the muscle contraction level increased almost linearly, as shown in Fig. 2(a), reaching values of 28% MVC in 5 s. The arrows in Fig. 2(b) indicate the location of MU recruitment as revealed by the Precision Decomposition technique.

The design of standard AR filters for PE analysis was executed in the reference block ranging from 8.88 s to 9.17 s (outside Fig. 2). In this interval, the subject produced a relatively constant force after a ramp contraction of 5 s (see Section II). The PE indexes up to fifth order were calculated for each sliding block of about 50 ms (or 101 samples). The first and second PE indexes reached a value of 1.0 at about 1.3 s, corresponding to the beginning of the contraction. The fourth and fifth PE indexes reached a value of 1.0 at around 2.5 s at which the force level reached around 6% MVC.

The block length for RC's estimation was approximately 70 ms (or 143 samples). The second RC, $K^{(2)}$, which corresponds to $\alpha_2^{(2)}$ of the second order AR model, showed time-varying features from 0.0 to -0.8 of the value. However, the RC's over the fourth order were too random to evaluate. Comparing RC's with the times at which the MU's were recruited, we found that they did not correspond consistently with the times indicated by the arrows in Fig. 2(b).

B. RC's and MEM Power Spectra of Both Original and Simulated ME Signals

We further investigated the time-varying behavior of AR parameters for well-conditioned ME signals and simulated ME signals. AR parameters employed in the subsequent detailed analysis were RC's and MEM power spectrum. The MEM power spectra were obtained in every nonoverlapping interval of 0.25 s (or 512 samples) during a positive ramp contraction, using (5). The AR model of the order 20 was used for the MEM power spectrum because a detailed structure of the power spectrum was required.

The time course values of RC's and the MEM power spectrum of another cannula ME signal are presented in Fig. 3. Unlike Fig. 2, the time courses of RC's (Fig. 3(c)) did not demonstrate the time-varying behavior. In our experiment, two of the subjects showed the time-varying behavior of AR parameters, the others did not. Furthermore, it was difficult to identify the correlation between random peaks and the recruitment order by modifications in the MEM power spectrum (Fig. 3(d)). The difference between the results of Figs. 2 and 3 seems to be caused by the influence of the low-amplitude MUAPT's and random noise.

Producing noise-free ME signals by computer simulation, we evaluated the influences of MU firings and the time-varying CV's, removing the low-amplitude MUAPT's and the random noise. The map of MU firings was the same as that indicated in Fig. 3(b). The MUAP waveforms of individual MU's, shown in Fig. 4, were recovered from the cannula ME signal by trigger-averaging with the firing times of the MU's. The numbers of samples ranged from 97 to 358 for individual MU's of Fig. 3, whereas it was from 8 to 74 for those of Fig. 2. Thus, we used the data of Fig. 3 for the computer simulation.

Figs. 5 and 6 show the results of simulated ME signals. Fig. 5 presents the results of the first simulation where the CV's were assumed to be time-invariant. The ME signal of the second simulation contained the same MUAP's as those in the first simulation but with time-varying CV's (Fig. 6(b)). Although the time-varying behavior of AR parameters was difficult to recognize in Fig. 3, it was moderately apparent in Figs. 5 and 6.

The behavior of the time courses of RC's revealed a random fluctuation near zero until the recruitment of MU #1 (Figs. 5(b) and 6(c)). The succeeding abrupt change of RC's during the beginning phase of a contraction, from 1.25 s to 2.0 s, was generated by sparse firing of MU #1. As for the effect of

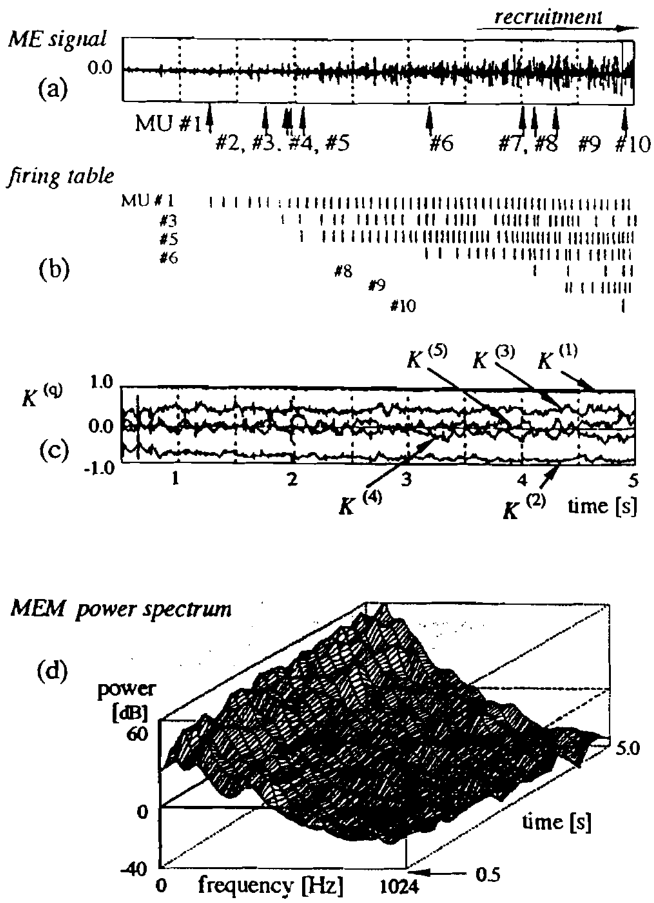

Fig. 3. RC's and MEM power spectrum with respect to time for another cannula ME signal during a ramp contraction: (a) cannula ME signal with the arrows indicating the location of MU recruitment; (b) firing table for the selected MU's; (c) time courses of RC's, $[K^{(q)}$, for $q = 1, \ldots, 5]$; (d) MEM power spectrum change. RC's and MEM power spectrum did not indicate noticeable time-varying behavior.

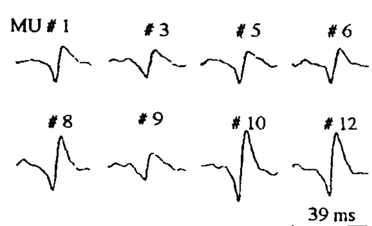

Fig. 4. Selected MUAP waveforms recovered from the cannula ME signal of Fig. 3(a) by trigger-averaging with the firing times of the individual MU's.

the CV change on the time courses of RC's, there was no notable difference between them. Note that Fig. 6(b) shows the time-varying increase rate for the CV's, $C(t)$. The CV's of almost all the MU's were expected to increase by about 30% at 5 s compared to the initial values at the beginning of the recruitment of individual MU's.

The MEM power spectra for the simulated ME signals contained sharp peaks due to the limited number of MU's used to construct the ME signals. This detail was seen by comparing the simulation results (Figs. 5(c) and 6(d)) with the actual result (Fig. 3(d)). The third peak of the MEM power spectrum became prominent at about 3 s in Fig. 5(c). In Fig. 5(a), it appears that the third peak may be indirectly correlated to the

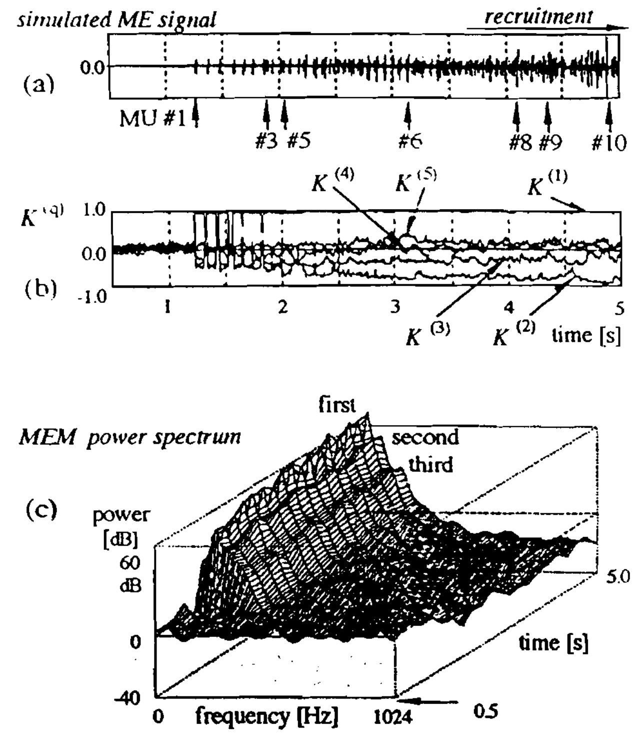

Fig. 5. Results of the first simulation with time-invariant CV's: (a) simulated ME signal with the arrows indicating the location of MU recruitment; (b) time courses of RC's, $[K^{(q)}$, for $q = 1, \ldots, 5]$; (c) MEM power spectrum change. The slight change of RC's appeared after removing low profile MU's and random noise. The third peak of the MEM power spectrum became prominent at about 3 s.

recruitment of MU's, MU #6 and #9. Note that MU #8 and #10 which were recruited at 5 s have sparse firings (Fig. 3(b)), and consequently these MU's did not influence the MEM power spectrum. In Fig. 6(d), the fourth peak of the MEM power spectrum appeared after 4 s, possibly due to the influence of the time-varying CV's. However, the peaks of the early phase did not shift towards a higher frequency at the latter phase.

C. Influence of Additive Broad-Band Noises

An example of the assessments of additive broad-band noise with a computer simulation is demonstrated in Fig. 7. The simulation model employed was a fifth order AR model with time-invariant linear prediction coefficients. The amplitude gradually increased to simulate the profile of an actual ME signal. The additive broad-band noises were Gaussian of zero mean and with five levels of the variance, 0.01, 0.05, 0.1, 0.5, and 1.0. The noise signals were stationary. Fig. 7(b) presents the time course of the signal-to-noise ratio. The time course of the signal-to-noise ratio varied because the signal increased its amplitude as a function of time. The standard AR filters of the PE indexes were designed by the true linear prediction coefficients.

Although the signal was synthesized by the time-invariant linear prediction coefficients, the behavior of estimated AR parameters was time-varying like those of Fig. 2. It is apparent that the noise caused the time-varying behavior of AR parameters. Such behavior occurred when the signal-to-noise ratio was less than 30 dB. This observation was also confirmed

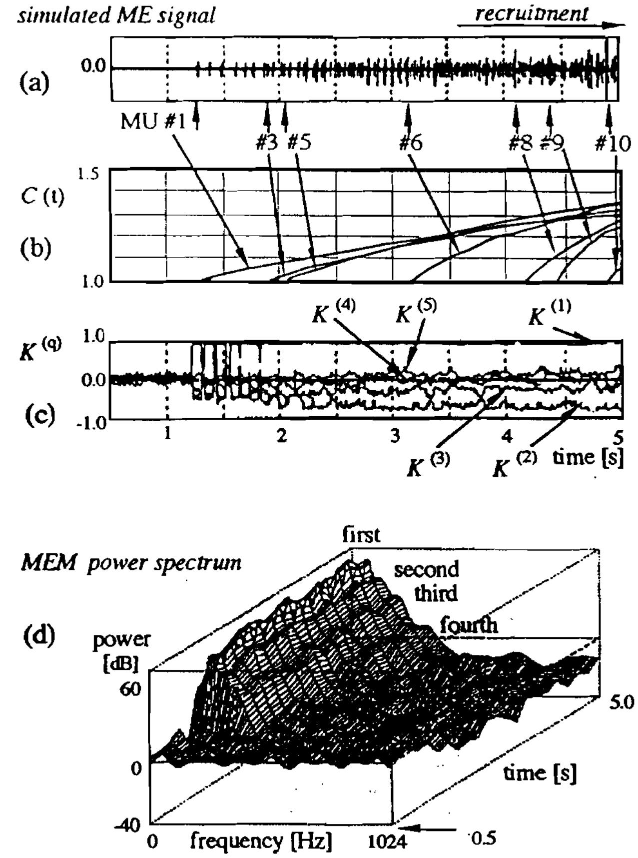

Fig. 6. Results of the second simulation with time-varying CV's: (a) simulated ME signal with the arrows indicating the location of MU recruitment; (b) schedule, $C(t)$, of time-varying CV's for individual MU's; (c) time courses of RC's, $[K^{(q)}$, for $q = 1, \ldots, 5]$; (d) MEM power spectrum change. The change of RC's was the same as that of Fig. 5(b). The fourth peak of the MEM power spectrum appeared after 4 s.

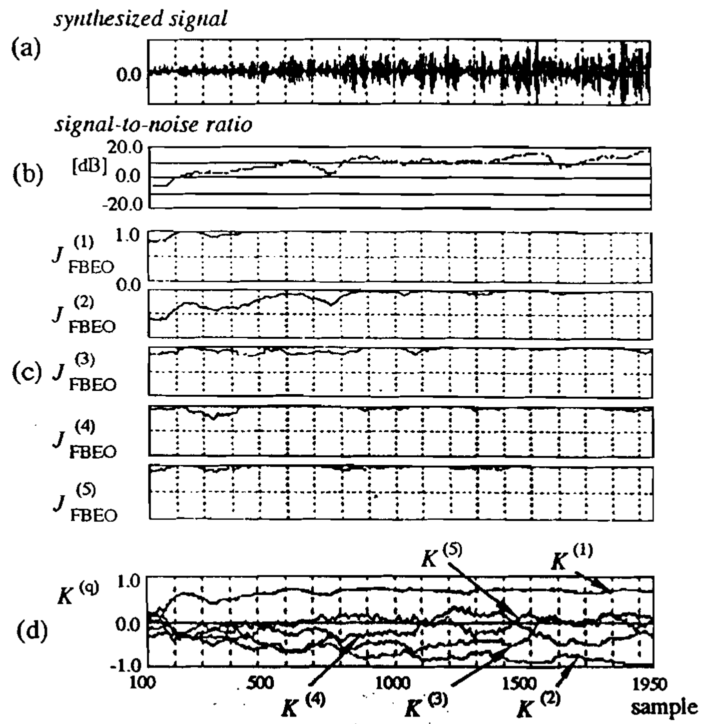

Fig. 7. Influence of an additive broad-band noise on AR manifestations: (a) synthesized signal with the additive broad-band noise; (b) time course of the signal-to-noise ratio; (c) time courses of PE indexes, $[J^{(q)}_{\mathrm{FBEO}}$, for $q = 1, \ldots, 5]$; (d) time courses of RC's, $[K^{(q)}$, for $q = 1, \ldots, 5]$. The RC's were 0.7184, −0.9078, −0.4244, −0.0300, and −0.0186. These values were used to design the SDF's. The amplitude was multiplied by $n/1500$ at the time index n. The noise was Gaussian type with zero mean and the variance of 0.01. The block of 101 samples in length was shifted every one sample. The behavior of estimated AR parameters was time-varying like those of Fig. 1.

by adding the broad-band noises with different variances to the simulated ME signals in Figs. 5 and 6.

VI. Discussion

A. Contribution of MU Firings to AR Parameters During Recruitment

When we analyzed well-conditioned ME signals, for which the complete map of the MU firings was available, we found that the time-varying behavior of RC's and MEM power spectra during a ramp contraction were not directly related to the occurrence of MU recruitment (Figs. 2 and 3). However, when the low-amplitude MUAP's were removed in the computer simulations using the data of Fig. 3, the MEM power spectrum revealed the significant peaks related to the MU recruitment during the latter phase of a contraction (Figs. 4 and 5), but not in the RC's. This difference is most likely due to the nonlinear relationship between MEM power spectrum and RC's (refer to (5)). Another concern was the firing rate of each MU's. In Fig. 4, MU #9 had a dense firing and a similar waveform to those of MU #1, #3, and #5, whereas MU #8 had a sparse firing and a different waveform to the previous ones. The difference in MU firings seemed to produce the prominent contribution of MU #9 and the minor contribution of MU #8 to the MEM power spectrum profile. It appears that recruited MUAP waveforms which have more prominent firing rates contribute noticeably to the ME power spectrum [10].

B. Contribution of CV's to AR Parameters During Recruitment

When the CV's were increased by 30% above the initial values, the magnitude of MEM power spectrum in the higher frequencies increased only during the latter phase of a contraction (Fig. 6(d)). This makes sense because increasing CV's shortens the duration of MUAP waveforms. The influence of increasing CV's, as well as the effect of MU firings, was not identified in the time courses of RC's, apparently due to the nonlinear relationship between MEM power spectrum and RC's. Even supplemental simulations where the CV's increased by 40% above the initial values, RC's demonstrated only a slight decrease of the absolute values. However, such a dramatic increase in the value of the CV is not physiologically realistic. (For example, Sadoyama and Masuda [16] measured the time course of the CV's of individual MU's during a recruitment task in the biceps brachii and reported that the CV's of individual MU's increased by 20% during a contraction which spanned from 0 to 100% MVC.)

C. Low-Amplitude MU's and Broad-Band Noises

The almost time-invariant behavior in Fig. 3 might be caused by the low-amplitude MUAP's with the dense firing.

That is, a slight change of RC's appeared for the simulated ME signals, after removing low-amplitude MU's and random noise (Figs. 5(b) and 6(c)). However, the remarkable time-varying behavior seen in Fig. 2 was not identified due to the following reasons. Firstly, the above-mentioned influences of MU recruitment were noticeable only during the latter phase of a contraction on the computer simulations. Secondly, as seen in Fig. 7(d), the increase of the signal-to-noise ratio produced the increase of the absolute values of RC's (Fig. 7(d)). This additive broad-band noise effect was noted in ME signals regardless of the differences in frequency components of recruited MUAP's, especially in the early phase of a contraction. In this case, it was difficult to identify whether the time-varying behavior was produced by the additive broad-band noise or by the different frequency components of later recruited MUAP waveforms. This fact has been at times ignored by previous researchers.

D. Dealing with ME Signals During an Early Phase of a Contraction

We conclude that if the ME signal consists of predominantly high-amplitude MUAPT's and it does not contain additive broad-band noise, a high order AR model and the MEM power spectrum may identify the occurrence of higher threshold MU recruited during the latter phase of a positive ramp contraction. Although ARMA modeling is generally recommended for a noisy signal [15], estimation of ARMA parameters is not cost effective because it is difficult to determine the optimum order in advance. The high order of the AR process can effectively represent the ARMA process [23].

However, such application will have limited use because most ME signals detected with a surface electrode or a cannula electrode will contain low-amplitude MUAPT's which tend to be representative of MU's recruited at lower force threshold. In this case, the PE index can serve as a quality check to verify if the time-varying AR parameters correspond to physiologically realistic variations due to the MU recruitment because it indicates noticeable behavior in the presence of additive broad-band noise. The PE index is also effective because it can deal with the time-varying residue that RC's and MEM power spectrum can not treat and has low computational cost.

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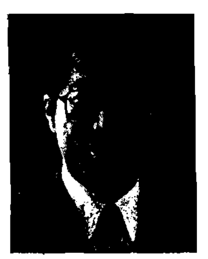


Tohru Kiryu (M'81) was born in Niigata Prefecture, Japan, in 1952. He received the B.E. and M.E. degrees in electronics engineering from Niigata University, Niigata, Japan, in 1975 and 1977, respectively and the Dr. Eng. degree in computer science from Tokyo Institute of Technology, Tokyo, Japan, in 1985.

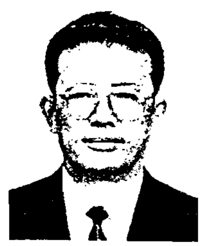
From 1977 to 1978, he was an Assistant at the school of dentistry of Niigata University. Since 1978, he has been with the Department of Information Engineering, Niigata University as an Assistant, where he is now a Professor. From June 1990 to March 1991, he studied at the NeuroMuscular Research Center at Boston University as a Visiting Scientist. He has been working on biomedical signal processing, especially time-varying spectral analysis, time-varying parameters estimation using nonstationary models and nonstationary stochastic process. For applications, his recent interests have been in myoelectric signal analysis during dynamic movements, muscular fatigue evaluation at a required time, and change points estimation from multidimensional time-series.

Dr. Kiryu is a member of the Institute of Electronics, Information and Communication Engineers of Japan, the Japan Society of Medical Electronics and Biological Engineering and the Japan Prosthodontic Society.

Carlo J. De Luca (S'64–M'72–SM'77–F'86) was born in Italy in 1943. He received the B.A.Sc. degree in electrical engineering from the University of British Columbia, Vancouver, B.C., Canada in 1966, the M.Sc. degree in electrical engineering from the University of New Brunswick, Fredericton, Canada in 1968, and the Ph.D. degree in biomedical engineering from Queen's University, Kingston, Ontario, Canada in 1972.

He joined Boston University in September of 1984. In 1986, he became Chairman ad interim of the Biomedical Engineering Department. From 1986 to 1989, he was Dean of the College of Engineering while maintaining the Directorship of the NeuroMuscular Research Center. Prior to moving to Boston University, he held faculty appointments at Harvard Medical School and Massachusetts Institute of Technology. He is Founder and Director of the NeuroMuscular Research Center at Boston University which consists of a staff of approximately 25 professionals. He has been a consultant of long standing for the Liberty Mutual Research Center. He is coauthor of the book *Muscles Alive* and two monograms. He has published approximately 90 articles and approximately 160 abstracts. His research interests span motor control, rehabilitation medicine and engineering, low back pain, and muscle fatigue. He maintains various positions on the editorial board of several journals and scientific review committees.

In 1989, Dr. De Luca, along with two coworkers, received the Volvo Award on Low Back Pain. In 1993, he gave the Wartenweiler Lecture at the ISB XIVth Congress. In 1994, he presented the Stuart Reiner Memorial Lecture at the AAEM Annual Meeting. He is the subject of several biographical references including *Who's Who in America* and *Who's Who in the World.*



Yoshiaki Saitoh (M'80) was born in Niigata Prefecture, Japan. He received the B.E. degree in electrical engineering from Niigata University, Niigata, Japan, in 1963, and the M.E. and Ph.D. degrees in electrical engineering from Hokkaido University, Sapporo, Japan, in 1965 and 1970, respectively.

In 1965, he joined the staff of the Department of Electronics, Niigata University, as an Instructor. Since 1980, he has been a Professor in the Department of Information Engineering at Niigata University. His recent research interests include measurements and stimulation of the human organs, hyperthermia systems, electrocardiogram data compression, and other biomedical signal processing.

Dr. Saitoh is a member of the Institute of Electronics, Information and Communication Engineers of Japan and the Japan Society of Medical Electronics and Biological Engineering.