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Multivariate Analysis of Multichannel Surface Myoelectric Signals to Determine Muscular Fatigue

Abstract: Multivariate analysis would be effective in finding the functional change from several variables obtained from multivariate biological signals. We applied this idea to the discrimination of sustained fatiguing contraction from negative ramp contraction. The time-series of eigenvalues were obtained from multidimensional biological variables by the Karhunen-Loève expansion. The results showed that, the first and second eigenvalues came close to each other during fatiguing contraction, whereas only the first eigenvalue was dominant during negative ramp contraction. Moreover, the factor loadings showed considerable difference between fatiguing contraction and negative ramp contraction. As a result, the muscular-fatigue-related functional change could be represented clearly by the time-series of proportions and factor loadings.

Keywords: Muscular Fatigue, Karhunen-Loève Expansion, Eigenvalue, Factor Loading

1. Introduction

The electrocardiogram (ECG) and the electroencephalogram (EEG) are measured with multichannel electrodes, and they are studied by multivariate parameters. Unfortunately, recognizing the actual state of the internal body is difficult. The internal information is not always clearly expressed with a specific signal or a parameter, but it is usually expressed with several signals or parameters. Sometimes, different biological activities are observed as similar behavior from measurable signals or evaluation parameters.

Using orthogonal expansion, we may be able to recognize the state of the internal body based on sophisticated information. Orthogonal expansion is often used in economics, seismology, and meteorology to extract information from multichannel signals. In the field of biological signal analysis, it has been used in the diagnosis from arrhythmia of ECGs [1], the classification of sleep levels from EEGs [2], the discrimination of movements from surface myoelectric (SME) signals, and the prediction of contractile change points in muscle contraction [3].

Our aim is to evaluate muscular fatigue from multichannel SME signals, applying multivariate analysis to some kinds of evaluation parameter time-series. Measuring lactic acid concentration is a direct method [4], but it is an invasive method. On the other hand, SME signals can easily be measured to reflect muscular fatigue, and it is a non-invasive method [5]. Merletti et al. proposed a muscular fatigue index from the cross-correlation between two different kinds of parameters obtained from SME signals [6]. In this paper, we tried to evaluate muscular fatigue using the time-series of eigenvalues obtained by the Karhunen-Loève expansion (KLE) [7] of various kinds of parameters based on multichannel SME signals.

2. Method

2.1 Parameters Evaluating Surface Myoelectric Signals

Parameters for evaluating SME signals are the amplitude, the frequency, and the propagation velocity of a motor unit action potential. The propagation velocity is usually called a conduction velocity (CV).

As an amplitude index, we used the average rectified value (ARV) of a bipolar SME signal $S(t)$ as follows:

$$ARV = \int_{-T/2}^{T/2} |S(t+\tau)|\, d\tau \Big/ T, \tag{1}$$

where t is time, T is the interval for analysis (block), and τ is the local time in each block.

As a frequency index, we used the mean power frequency (MPF) of $S(t)$. The MPF is defined as follows:

$$MPF = \int_0^\infty fP(f)\, df \Big/ \int_0^\infty P(f)\, df, \tag{2}$$

where f is frequency, and $P(f)$ is the power spectrum of $S(t)$ in each block.

Estimating the cross-correlation between two channels of bipolar SME signals, the CV is obtained as follows [8]:

$$CV = D/\tau_{CCmax}, \tag{3}$$

where τ_{CCmax} is a time delay which shows a maximum value for the cross-

correlation coefficient. Note that the distance between the electrodes is D, and that the direction of electrode alignment is parallel to the muscle fibers.

The time-series of multi-dimensional parameters were estimated by the sliding block procedure. That is, the block segmented from the SME signal was shifted along the time axis in constant-interval steps. Therefore, these parameters reflect muscle activity as a function of the block number.

2.2 Analysis by Karhunen-Loève Expansion

In general, information on muscle activity is redundantly distributed among several kinds of parameters. The KLE is suitable to represent such information having several independent components estimated from these parameters. We segmented the time-series of multi-dimensional parameters to evaluate the results of the KLE with the progression in muscle activity. We will call each segment a frame after this. As a result, the evaluation indices were obtained as a function of the frame. The evaluation indices were the proportions and accumulated proportions of the eigenvectors, and the factor loadings.

Since several kinds of parameters have different units, it is necessary to normalize them so that the mean was set at 0 and the variance was set at 1 during each experimental trial. It was assumed that, in each frame segmented for an experimental trial, the time-series of normalized parameters were locally stationary. Let us define matrix $\boldsymbol{S}$ including several kinds of normalized parameters in a frame as follows:

$$S = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{ni} & x_{ni} & \cdots & x_{nm} \end{bmatrix}, \qquad (4)$$

where x_{ij} is the i-th normalized parameter at the j-th local block in each frame. The variance-covariance matrix $\boldsymbol{R}$ was then calculated from $\boldsymbol{S}$ to obtain eigenvalues and eigenvectors. Eigenvalue decomposition was performed for $\boldsymbol{R}$ by the Jacobi method so that the eigenvalues were sorted in descending order $\lambda_1 > \lambda_2 > \ldots > \lambda_n$.

The factor loading $r_{k;i}$ between the k-th eigenvector z_k and the i-th parameter is expressed as:

$$r_{k;i} = \sqrt{\lambda_k}\, z_{ki} \Big/ \sqrt{\sigma_i^2}, \; for\ k = 1,2,\ldots,n, \qquad (5)$$

where σ_i^2 is the variance in the i-th parameter in a frame, and z_{ki} is the i-th component of z_k. Moreover, the proportion p_k and the accumulated proportion p_{Ak} are given by:

$$p_k = \lambda_k \Big/ \sum_{l=1}^{n} \lambda_l, \qquad for\ k = 1,2,\ldots,n, \qquad (6)$$

and

$$p_{Ak} = \sum_{l=1}^{k} \lambda_l, \qquad for\ k = 1,2,\ldots,n, \qquad (7)$$

in each frame.

2.3 Behavior of Parameters Related to Muscle Activity

The ARV generally increases with a progression in muscle force. Hence, decreasing the number of motor units (MUs) or de-recruitment causes ARV decrease. ARV decrease is also observed during sustained contraction because of fatigue. At the beginning of fatigue, however, the ARV sometimes increases to compensate for the degeneration in muscle force. The de-recruitment of MUs occurs first of all in the fast twitch muscle fibers, and this in turn decreases the CV. In the case of muscular fatigue, the CV decreases exponentially from the beginning of sustained contraction [6]. Since the power spectrum of the SME signal moves toward the lower frequencies because of fatigue, the MPF gradually declines during sustained contraction. Accordingly, it is impossible to discriminate between intentionally reduced muscle force and muscular fatigue by screening the time-series of evaluation parameters.

3. Experiment

3.1 Protocol

Five healthy males participated in our experiments. There were two types of experimental protocols. First, each subject was asked to decrease muscle force from 70% maximum voluntary contraction (%MVC) to 20%MVC at a decreasing rate of -1%MVC/s. We call this negative ramp contraction (NRC). Visual feedback was used for tracking the muscle force, displayed on an oscilloscope. Second, the subjects tried to sustain muscle force at 70%MVC at maximum effort as fatiguing contraction (FC). There might be functional differences between intentionally reduced muscle force and muscular fatigue.

We acquired SME signals of 50 s and 100 s for NRC and FC, respectively. For each subject, a measurement consisted of three successive trials of NRC and then three consecutive trials of FC.

3.2 Measurement

For the tibialis anterior muscle, we measured SME signals and force outputs simultaneously. We could therefore easily estimate muscle fatigue by referring to the measured force output. Each subject was seated in a chair equipped with a force transducer (OG Giken, GT-30), and two seatbelts were used to fix posture. An active four-bar electrode was pasted onto the skin over the tibialis anterior muscle. Each bar was perpendicular to the muscle fibers, and the distance between each bar was 1 cm. The force transducer was attached to the instep of the foot. The positioning of the electrodes is important in estimating the CV from SME signals [9]. For the experiment, we arranged electrodes away from the innervation zone.

The two channels of differential SME signals were bandpass-filtered from 1.6 Hz through 1 kHz and the force output were sampled at 5 kHz.

3.3 Conditions of Signal Processing

There is a tradeoff between the statistical accuracy and time resolution in terms of the block and frame lengths and the shift interval. Considering the rate of decrease of the NRC and the time scale of the FC, muscle activity should change within about 1 s.

Using the fast fourier transform (FFT), the overlapping block length was 204.8 ms (m = 1024 points), and the shift interval was 100 ms (500 points). The hamming window was applied to

estimate $P(f)$, and then MPF was calculated from 10 Hz through 200 Hz of $P(f)$. Note that the ARV was also estimated in each block. Regarding the estimation of CV, we converted the sampling frequency from 5 kHz to 20 kHz using spline interpolation.

The overlapping frame length for the KLE was 2.4 s (24 samples for each evaluation parameter), and the shift interval of each frame was 500 ms (5 samples).

4. Results

Figure 1 shows the time-courses of muscle force and evaluation parameters for both NRC (left side) and FC (right side). Two channels of ARVs and MPFs were superimposed on the same graphs. All parameters decreased as muscle force fell for the NRC. The MPF decreased rather exponentially from the early stages of the FC. The ARV, on the other hand, temporally increased the amplitude around the contractile failure point and then reduced. There were no remarkable differences between the evaluation parameters of the NRC and those of the FC, except the ARV.

We investigated four combinations of evaluation parameters: (i) ARV (ch.1), MPF (ch.1), and CV; (ii) ARV (ch.2), MPF (ch.2), and CV; (iii) ARV (ch.1 and ch.2), MPF (ch.1 and ch.2), and CV; and (iv) ARV (ch.1 and ch.2) and MPF (ch.1 and ch.2). These results showed that most information on muscle activity seemed to be concentrated up to z_2. It was observed that λ_1 and λ_2 approached each other during fatiguing phases especially on (iv). Fig. 2 shows the results of proportion time-series for (iv). After this, we focused on the results of the NRC and the FC for (iv).

Figure 3 shows the time-courses of accumulated proportions. The accumulated proportions p_{A2} and p_{A3} were more than 0.8 and almost 1, respectively.

Figure 4 shows the summation of the absolute value for each factor loading. The factor loadings $r_{4;\mathrm{ARV}}$ and $r_{4;\mathrm{MPF}}$ were neglected because λ_4 were very small. The upper part of each graph shows the results of the factor loadings between z_k and ARV, $\Sigma|r_{k;\mathrm{ARV}}|$, and the lower part shows that of $\Sigma|r_{k;\mathrm{MPF}}|$, for

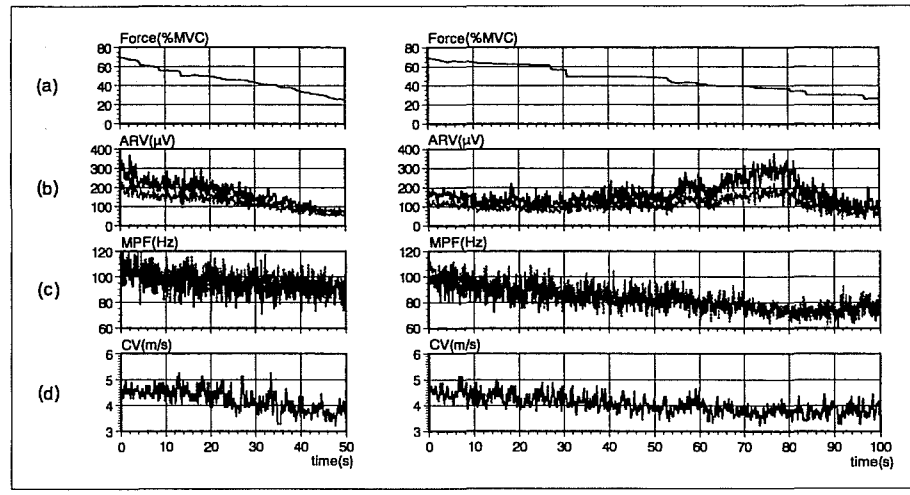

Fig. 1 Time-courses are (a) force output; (b) ARV for channels 1 and 2; (c) MPF for channels 1 and 2; and (d) CV. The left side shows negative ramp contraction, the right side shows fatigue contraction.

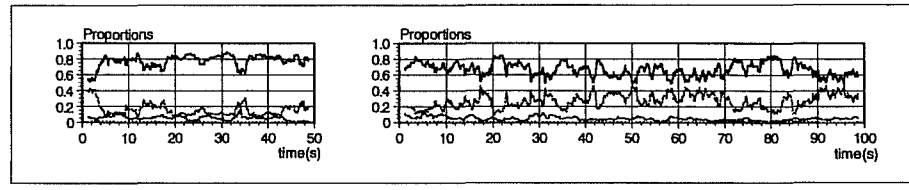

Fig. 2 Time-series of proportions obtained from ARVs channels 1 and 2, and MPFs channels 1 and 2. The left side shows negative ramp contraction, the right side shows fatigue contraction.

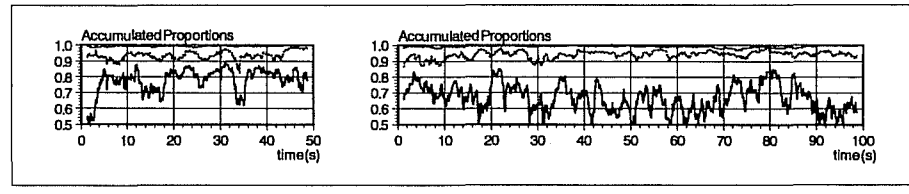

Fig. 3 Time-series of accumulated proportions obtained from ARVs channels 1 and 2, and MPFs channels 1 and 2. The left side shows negative ramp contraction, the right side shows fatigue contraction.

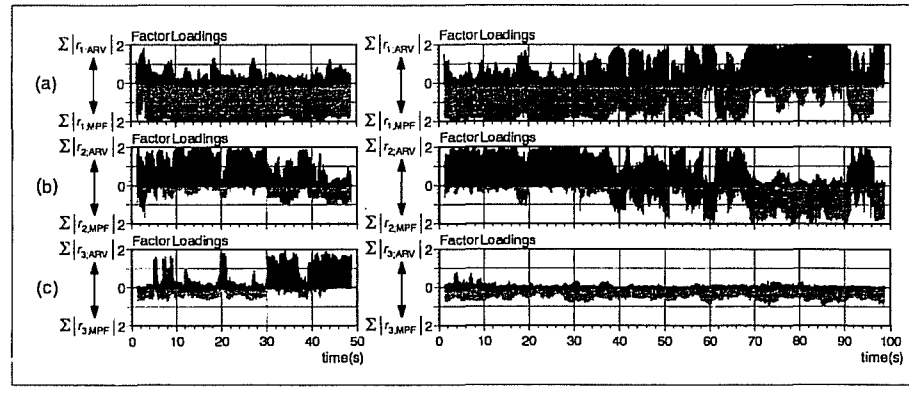

Fig. 4 Time-courses are factor loadings concerned with (a) z_1; (b) z_2; and (c) z_3. The left side shows negative ramp contraction, the right side shows fatigue contraction.

$k = 1, 2, 3$. Note that $\Sigma|r_{k;\mathrm{ARV}}|$ means the summation of $|r_{k;\mathrm{ARV}}|$ channels 1 and 2. During a fatigue-expected-interval (after 60 s at the right side of Fig. 4), $\Sigma|r_{1;\mathrm{ARV}}|$ and $\Sigma|r_{2;\mathrm{MPF}}|$ were high, and $\Sigma|r_{3;\mathrm{ARV}}|$ and $\Sigma|r_{3;\mathrm{MPF}}|$ were low. On the other hand, $\Sigma|r_{1;\mathrm{MPF}}|$ and $\Sigma|r_{2;\mathrm{ARV}}|$ were high during a non-fatigue-expected-interval (for example, before 30 s at the left side of Fig. 4), and then $\Sigma|r_{3;\mathrm{ARV}}|$ was very high when the muscle force was extremely small.

5. Discussion

The contractile change point was able to be estimated by measuring muscle force [10]. However, muscle force was not related to the functional change of muscle activities, because muscle force did not always reflect this. There was an advantage in our method in terms of being able to apply multivariate analysis to various kinds of evaluation parameter time-series.

Evaluation parameters should be selected carefully. Extra fatigue-related parameters, such as the CV in our experiment, sometimes disordered the explicit behavior of evaluation parameters. Perhaps, insufficient accuracy of the CV estimate disturbed the arrangement of fatigue-related information. Consequently, we omitted the CV parameter considering the high computational cost and high attention for locating surface electrodes.

According to Fig. 4, the directions of z_1 and z_2 were opposite during the fatigue-expected-interval and during the non-fatigue-expected-interval. Note that we experimentally determined the suitable combination of ARV (ch.1 and ch.2) and MPF (ch.1 and ch.2). Four of five subjects demonstrated the above features. As a result, the proportions and the factor loadings were effective in allowing muscle activities to be discriminated as a function of time. However, the physiological interpretation of these indices should be studied further.

6. Conclusion

Using the Karhunen-Loève expansion, surface myoelectric signals acquired from the tibialis anterior muscle under two different kinds of muscle activities, negative ramp contraction and fatiguing contraction, were studied as a function of time. The results showed that during a fatigue-expected-interval the first eigenvalue (λ_1) and the second eigenvalue approached each other, and there were high correlations between the first eigenvector (z_1) and the average rectified value (ARV), and between the second eigenvector (z_2) and the mean power frequency (MPF). On the other hand, during a non fatigue-expected-interval only λ_1 was dominant, and there were high correlations between z_1 and MPF, and between z_2 and ARV. Therefore, they were able to be used to estimate muscle activity based on the behavior of proportions and factor loadings, although it was impossible for original evaluation parameters.

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