A Method for Real-Time Estimation of Local Muscular Fatigue in Exercise Using Redundant Discrete Wavelet Coefficients

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Abstract—**In this paper, we propose a method to estimate muscular fatigue in exercises with load fluctuations. Muscular fatigue is an important property when evaluating the state of a muscle. However, it is extremely difficult to apply general methods, which depend on the relative changes in the signal power or frequency characteristics of a surface EMG, during exercise. We define two qualitative factors of muscular and neural activity, and by compounding these factors, we define a fatigue coefficient to estimate muscular fatigue. These values can be calculated in real-time. The fatigue coefficient quantifies the influence of the muscular fatigue and is not affected by changes in the load amount. Therefore, it can be used to estimate muscular fatigue, even for non-repetitive actions and unknown load amounts.**

Keywords—surface EMG; muscular activity; muscular fatigue; wavelet analysis; center-of-balance transition; quality factor of muscular tissue activity; quality factor of nervous system activity

I. Introduction

In this paper, we propose a method to estimate muscular fatigue in exercise in real-time. This method is applicable to non-repetitive exercise with load fluctuations.

Muscular fatigue is an important property when evaluating the state of a muscle. To avoid disturbing the exercise, the measurement needs to be non-invasive, passive, and robust to vibrations caused by motion. We believe that surface EMGs (sEMGs) are currently the only way to satisfy such requirements.

The general features of muscular activity can be classified as frequency features and signal power features[1], [2]. Following Piper's [3] description of the relationship between sEMG signal frequency and fatigue, and the finding of Cobb and Forbes [4] concerning the increase in the amplitude of sEMG with fatigue, these relationships have appeared evident. Even though there are multiple researches studying muscular fatigue using categorization via methods or features (e.g. RMS, short-term FFT, mean power frequency, wavelet coefficients) [5]–[17], nearly all depend on one or both of these two general relationships. Common methods using sEMG to estimate muscular fatigue depend on the relative change in the signal power or frequency characteristics of an sEMG under a uniform load condition. However, it is very difficult to identify precise timing with the same load during exercise, especially without repeating the same motion. Even if the precise timing could be identified, the fatigue estimation would be applicable only for the specified load. Because it is normal for a person to lift a heavy weight with difficulty due to muscular fatigue but to lift a light weight easily, the influence of muscular fatigue depends on the amount of the load. Therefore, nothing concerning different load amounts can be claimed.

As mentioned above, current common fatigue estimations using sEMG depend on one of two types of relative change: signal power characteristics and frequency characteristics. However, the results of these estimations are not always the same. Sometimes, results based on signal power denote higher states of fatigue than results based on frequency, and sometimes, the opposite occurs. This means that estimations based on only one characteristic are not sufficient, even though the relationship between the two types of relative changes is unknown. Therefore, a robust method to estimate local muscular fatigue under load fluctuations needs to indicate a single feature value unifying both the influence of power and the frequency characteristics. The estimation values obtained by this method needs to have a high temporal resolution and to be independent or insensible to changes in the load amount.

In this paper, we propose two factors and one coefficient to estimate muscular fatigue. We treat muscular fatigue as a quality of muscular and neural activity. We evaluate the quality factors based on redundant discrete wavelet coefficients[20], and by compounding those two factors, we define a fatigue coefficient.

II. The necessity of high-frequency sampling

Conventionally, the signal characteristics of sEMG are included in a frequency band lower than 500 Hz or 1000 Hz. Therefore, in general, a low-pass filter (LPF) is applied with a cut-off frequency of 1000 Hz in measurements of the surface EMG. Many sEMG measuring instruments have an LPF with a cut-off of 1000 Hz as the default or fixed setting. However, we believe that important signal characteristics are included in the high–frequency bands, which are conventionally discarded.

Fig. 1 shows the time–frequency planes of sEMGs of mimic muscles, which are the result of a discrete wavelet analysis (a multiresolution analysis) with Daubechies' 4-tap (N=2) wavelet. The horizontal axis indicates the time and the vertical axis shows the resolution level (the level of the wavelet decomposition). The color scale shows the value of the wavelet coefficient for the area on the time–frequency plane. These

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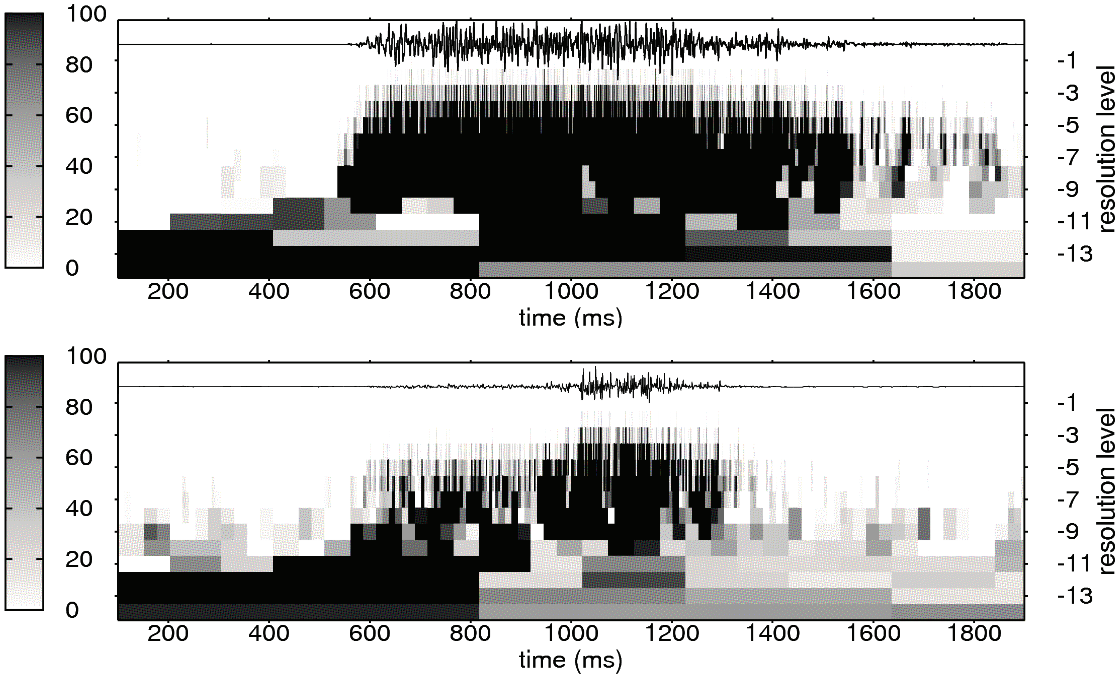

Fig. 1. The time–frequency planes of the sEMGs of mimic muscles (upper panel: orbicularis oris, lower panel: digastric) during pronunciation of the Japanese vowel sequence /u/ and /o/. These panels are the result of a multiresolution analysis with Daubechies' 4-tap (N=2) wavelet. The waves on the upper side of the figures are sEMG signals of the muscles. The sampling rate of each signal is 20 kHz (the LPF is 10 kHz). The maximum value of the color scale is very small with respect to the maximum value of the wavelet coefficients. Therefore, many parts of the planes are filled with black. This is because small wavelet coefficients on high–frequency bands are emphasized, especially level -2 (5000 Hz) and level -3 (2500 Hz).

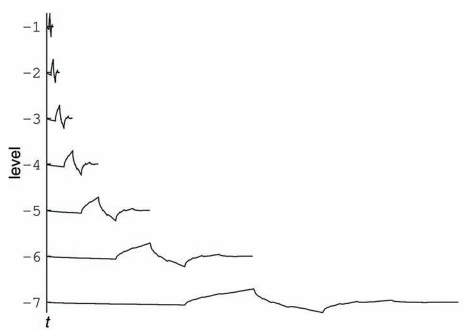

Fig. 2. Scaled waves of the Daubechies 4-tap (N=2) wavelet at a sample time t.

sEMG data are measured at a 20-kHz sampling rate with a 1-kHz low pass filter while the subject pronounces a sequence of two Japanese vowels (/u/ and /o/ including prev– and post–pronunciation).

General conventional sEMG measurements would use a low pass filter with 1000 Hz as the cut-off frequency. This means that those measurements would treat the 5th or lower level wavelet decompositions in Fig. 1. However, the signals in Fig. 1 include important characteristics in the 2nd – 4th level (1250 – 5000 Hz). A particularly important characteristic is the thin striped pattern that appears in the high–frequency band. We believe that these stripes reflect the excitation caused by a nerve impulse.

Fig. 2 shows the dilated wavelet forms of the Daubechies' 4-tap wavelet, each of which is used for the wavelet decomposition at each level. When the wave form of the mother wavelet is similar to a wave form of a component of a target signal, the wavelet analysis has better sensitivity on extracting characteristics of the signal. A minimum component of an sEMG is a single wave of a potential change activated by a single nerve impulse. We believe that the wave form of the Daubechies' 4-tap wavelet is similar to the wave form of this minimum component, and this is why the striped pattern is observed.

The disadvantage of the Daubechies' 4-tap wavelet is that analyses using this wavelet have low performance with regards to frequency separation. However, this is not a serious problem because the signal strengths of the individual frequency components are less important in feature analyses of sEMG signals.

The high temporal resolution of the wavelet analysis makes it possible to extract striped patterns from high–frequency bands. Even though short-term FFTs are often used for frequency analyses, it is difficult to extract such stripes using a short-term FFT because the result is smoothed in the analyzing window. The stripes suggest that a wavelet analysis with a high sampling rate might be able to track temporal variations in the muscular activity in more detail than methods using short-term FFTs.

Using features in the high frequency bands with high frequency resolution, we can analyze the muscular activity in detail in terms of the neural activity and the muscular tissue activity in response to nerve impulses. When the increase in the potential caused by a nerve impulse is fast, the high–frequency component is instantaneously included in the sEMG signal and results in stripes on the time–frequency plane. When the increase in the potential caused by a nerve impulse is slow due to fatigue in the muscular tissue, or the increased potential is low due to the weak activity (including the signal being lost via de-noising), the high–frequency components in the sEMG signal are decreased, and the striped pattern is observed in the lower frequency band. This is consistent with the tendency of the frequency distribution of signal components to be shifted to lower frequency during muscular fatigue.

III. Analyzing an sEMG signal

A. Acquiring redundant wavelet coefficients

Based on the discussion in the previous section, we measured an sEMG with a higher frequency sampling rate than that of a standard measurement. The standard sampling rate to measure an sEMG is from 1000 Hz to 3000 Hz, and the cut-off frequency of the LPF is from 500 Hz to 1000 Hz. By contrast, our sampling rate was from 10 kHz to 20 kHz, and the cut-off frequency of our LPF was 5 kHz to 10 kHz. This is approximately 10 times higher than the standard measurement rate[18], [19].

To capture the characteristics of the short-term changes in an sEMG, we analyzed the sEMG signal via wavelet transformation. Multiresolution analysis is a common method for discrete wavelet analysis; however, it lacks shift-invariance. To counter this problem, we calculated and used all the wavelet coefficients at all the sampling times via a redundant wavelet transformation. If we regard each wave on Fig. 2 as an analyzing wave matching a single potential change in a muscular tissue, we can treat each wavelet coefficient at t as the strength of the response in the speed of each resolution level to a nerve impulse arriving at the sample at time t.

De-noising from sEMG signals is an important problem because some components of sEMG are as weak as the noise signal. In particular, to extract the small striped pattern in high frequency bands in Fig. 1, it is important to reduce the white noise. For this purpose, wavelet shrinkage is suitable.[1] We extracted the features of the sEMG signal based on the wavelet coefficients of the signal. This means that we do not need to execute the inverse wavelet transformation to get the sEMG wave. Typical techniques for the wavelet shrinkage are "hard–thresholding" and "soft–thresholding". Hard–thresholding techniques leave noise components in the unmodified wavelet coefficients. To avoid adverse effects on the method described in the next subsection due to the non–uniformity of the remaining noise components, we used a soft–thresholding technique.

B. The center-of-balance transition method

The center-of-balance transition (CoBT) method proposed in our previous studies[18], [23] is a method to treat frequency characteristics and has a better aptitude for extracting small and short-term characteristics than do general methods, e.g., methods based on Mean Power Frequency (MePF) or Median Power Frequency (MdPF)[19].

[1]However, we must be careful not to wipe out weak characteristics in high frequency bands by using a too large threshold.

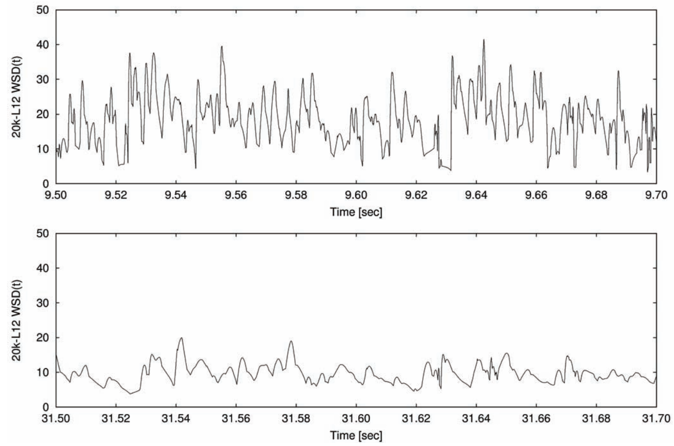

Fig. 3. The Wavelet standard deviation 20k–L12 $WSD(t)$ before and after muscular fatigue (upper panel: before fatigue, lower panel: after fatigue).

A wavelets' center-of-balance (CoB) is a frequency feature of the wavelet coefficients of an sEMG. It depends on the distribution of the signal power on the frequency axis, such as an MePF or MdPF. The CoB value at t is defined as

$$CoB(t) = \begin{cases} 0 & : \ if \ \sum_{k=1}^{L} |w_{-k}(t)| = 0 \\ \dfrac{1}{\sum_{k=1}^{L} |w_{-k}(t)|} \displaystyle\sum_{k=1}^{L} |w_{-k}(t)| \cdot (2^{L-k} - 1) & \\ & : \ otherwise \end{cases} \quad (1)$$

where $-L$ is the wavelet resolution level of the lowest frequency band used as valid signals, and $w_{-i}(t)$ is the wavelet coefficient of level $-i$ whose starting time of its rectangular region on the time–frequency plane is t. On our algorithm to get a CoBT[24], the calculation steps outputting a CoB value at each sampling are executable with a time complexity of $O(1)$.

The CoB values depend on the sampling frequency "$\langle freq \rangle$" and the lowest decomposition level "$-\langle lvl \rangle$". Therefore, when we specify an analysis, we use the notation "$\langle freq \rangle$–L$\langle lvl \rangle$" (e.g., "20k–L12 CoB" for the CoB with a lowest level of -12 on a 20-kHz sampling). Hereafter, when we need to denote the specification clearly, we will use this form of modifier for the feature values.

IV. Changes in the signal characteristics that depend on muscular fatigue

A. Distribution of the wavelet coefficients on the frequency axis

The more a muscular tissue is stimulated by neural impulses, the more complicated the sEMG will become via the synthesis of the potential changes. To estimate the complexity based on the distribution on the frequency axis, we propose an evaluation value called the wavelets' standard deviation (WSD). Even though it includes the term "standard deviation", it is not a statistical standard deviation; however, the structure of its formula is similar to the formula of a standard deviation.

The WSD at t is defined as

$$WSD(t) = \begin{cases} 0 & : if \ \sum_{k=1}^{L} |w_{-k}(t)| = 0 \\ \sqrt{\frac{\sum_{k=1}^{L} (|w_{-k}(t)| \cdot ((L-k) - CoB(t))^2)}{\sum_{k=1}^{L} |w_{-k}(t)|}} & : otherwise \end{cases} \quad (2)$$

where $w_{-1}(t), \ldots, w_{-L}(t)$ are the wavelet coefficients at time t (see Sec.III-B) and $CoB(t)$ is the CoB at time t. If we take $CoB(t)$ to be the average and $|w_{-k}(t)|$ to be the frequency, the formula's structure is the same as a standard deviation. Of course, $WSD(t)$ is not a statistical measurement because $CoB(t)$ is not a statistical average.

Fig. 3 shows the traces of $WSD(t)$ at the 200-ms width of the sEMGs in Fig. 4. The upper graph is the trace in the 1st trial (without muscular fatigue), and the lower graph is the trace in the 3rd trial (with muscular fatigue). Even though the subject repeats the same motion, the amplitude of the $WSD(t)$ with muscular fatigue is smaller than the amplitude without fatigue, and the wave becomes smoother.

B. Characteristics of Impulses in the CoBT

The influence of muscular fatigue appears not only on the muscular tissues but also on the nervous system. The influence of fatigue on the nervous system reduces the frequency of neural impulses and causes the power of the impulses to decrease. Such changes cannot be extracted independently of the sEMG because the sEMG is the result of the neural impulses acting on the muscular tissues.

However, the CoBT of the sEMG measured with a high sampling rate has many impulse components (see the striped pattern in Fig. 1). Each impulse is thought to result from the arrival of a neural impulse. When the nervous system is active without fatigue, multiple neural impulses will arrive at the muscular tissues and cause steep changes in the potential. They will also generate multiple strong impulses in the CoBT. Conversely, when fatigued, the frequency of the impulses in the CoBT will decrease, and the power of the impulses will weaken.

Therefore, we use the characteristics of the impulses in the CoBT to evaluate the influence of fatigue on the nervous system. When many strong impulses are observed, the standard deviation of the CoBs in a given time window should be large. The $ICoB(W)$, which is the impulse feature of CoBT in the window W, is defined as

$$ICoB(W) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\ CoB(t_i) - \overline{CoB_W}\ )^2} \quad (3)$$

where W is the time window from t_1 to t_N and $\overline{CoB_W}$ is the average of $CoB(t)$ in the window W.

V. How to Estimate Muscular Fatigue

A. Quantifying the influence of muscular fatigue

In this paper, we define muscular fatigue as the deterioration of the quality of muscular activity. The term "quality" does not denote the static state of the muscle. Even though the influence of local muscular fatigue depends on the load amount, the relationship between the static state, the load amount, and the influence is unknown. The term "quality" denotes the amount of influence of the muscular fatigue on the current local muscular activity.

In our previous studies[18], [19], we proposed a comprehensive feature of muscular activity that was a multiplication of the signal power feature (which tends to reflect muscular tissue activity) and the frequency feature (which tends to reflect neural activity) calculated via the redundant wavelet coefficients. Accordingly, we capture the influence of local muscular fatigue using a compound feature of the muscular tissues and the nervous system.

B. The quality factor of muscular tissue activity

In this paper, we define the muscular tissue efficiency as the quality factor of the muscular tissue activity.

We understand the muscular tissue efficiency based on the reduction in fluctuation of $WSD(t)$. To estimate the amount of fluctuation that occurs in the short term, we use the absolute value of the difference of $WSD(t)$ from the average of $WSD(t-1)$, $WSD(t)$, and $WSD(t+1)$. We define the muscular tissue efficiency, $ME(W)$, in the time window W as the average of the absolute value in the window:

$$ME(W) = \mathop{E}_{t \in W} \left(\left| WSD(t) - \mathop{E}_{i \in \{t-1,t,t+1\}} (WSD(i)) \right| \right) \quad (4)$$

where $E_i(x_i)$ is the average of x_i.

C. The quality factor of nervous system activity

In this paper, we define the nervous system efficiency as the quality factor of the nervous system activity. We use $ICoB(W)$ as the nervous system efficiency, $NE(W)$, in the time window W.

D. Fatigue coefficient

The fatigue coefficient is defined by combination of the muscular tissue efficiency and the nervous system efficiency. That is, the fatigue coefficient $FC(W)$ in the time window W is given by $ME(W) \cdot NE(W)$.

As we show in the following section, Sec. VI, this coefficient is unaffected by the changing load amount without fatigue. Therefore, The fatigue coefficient can estimate the amount of influence of the muscular fatigue on the current sEMG.

However, even if this coefficient has the same value, it does not denote the same statistical fatigue level. If we look at the same value on the same muscle of the same person, a larger load amount would statistically result in more muscular fatigue. If we look at the same load on the same muscle of the same person, a smaller coefficient would result in more fatigue.

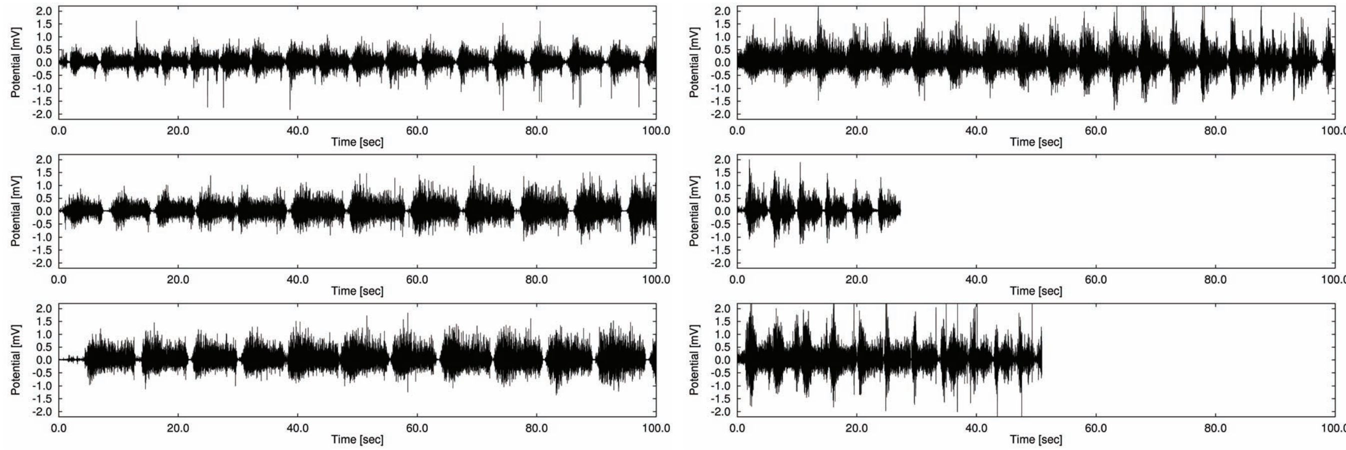

Fig. 4. The sEMGs of the biceps brachii muscle when repeating the motion of lifting and lowering a dumbbell (top panel: first trial, bottom panel: 3rd trial). The left graphs are the sEMGs of subject A who completed the motion for 100 seconds, and the right graphs are the sEMGs of subject B who failed to complete the motion.

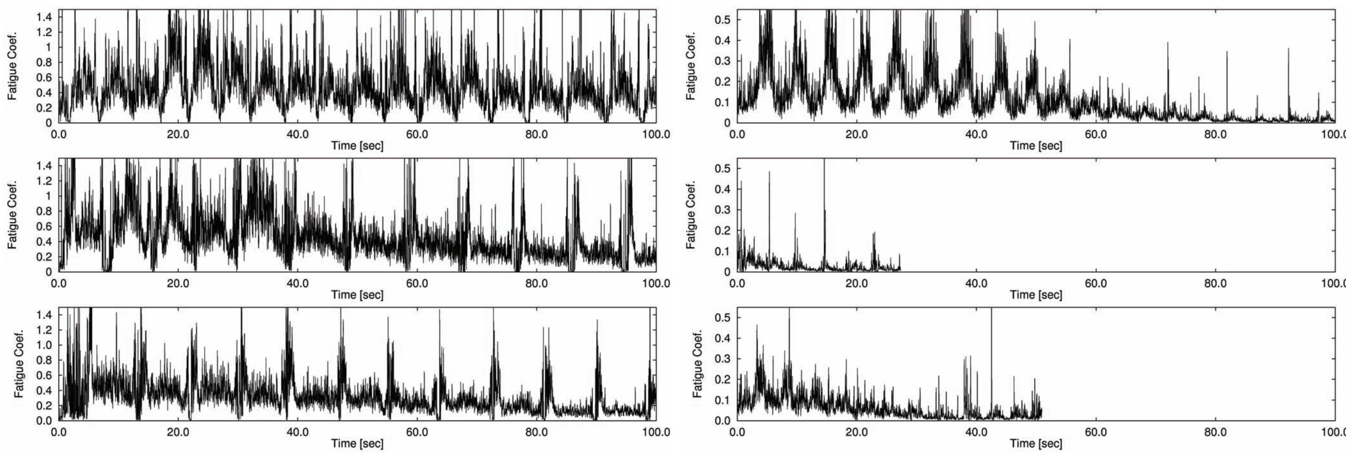

Fig. 5. The fatigue coefficients for the sEMGs in Fig. 4.

VI. Experiments with regards to the fatigue coefficient

A. Repeated lifting of a dumbbell

To analyze the influence of fatigue, we measured the sEMGs of the biceps brachii muscle while a test subject executed the following actions while lifting a dumbbell.

1) The subject maintains an upright posture and lowers his/her hand while holding a dumbbell.
2) The subject lifts the dumbbell by bending the elbow nearly squarely (for approximately 2 seconds), keeps the forearm horizontal (for approximately 2 seconds), and stretches the elbow while lowering the dumbbell (for approximately 2 seconds).
3) The trial repeats the above–mentioned motion for 100 seconds or until the subject can no longer complete the motion. The subject performs 3 trials separated by intervals of a few minutes.

There were 19 test subjects: 10 males in their 20s, 1 female in her 20s, 2 males in their 30s, 3 males in their 40s, 2 males in their 50s, and 1 male in his 60s.

The sEMGs of the subjects' biceps brachii muscles were measured with a sampling frequency of 20 kHz with an LPF of 10 kHz. Fig. 4 shows the sEMGs of two subjects. The three graphs on the left side are the sEMGs of subject A, and those on the right side are those of subject B. Subject A succeeded in completing the motion. However, subject B could not continue the motion for the full 100 seconds. The figure shows an increase in the sEMG amplitude resulting from fatigue, excepting the limitation of the muscular activity of subject B. The weight of the dumbbell might have been too heavy for the muscle mass of subject B.

Fig. 5 shows the fatigue coefficients of the sEMGs in Fig. 4. A subject without fatigue can make large values of the fatigue coefficients. However, after fatigue, a subject can make only small values. On these graphs, roughly two types (high/low) of values are observed. We believe that these types are derived from differences in the fast and slow muscular tissues. If we ignore the high type of values, the lower bound and the amplitude of the coefficients are decreased linearly. This suggests that the amount of influence of the fatigue may be predictable when continuing the same exercise.

The values and the amplitude of the fatigue coefficients in the 1st trial of subject B are smaller than those of subject A. However, the amplitude of the sEMG in the 1st trial of subject B is larger than that of subject A. This is similar to

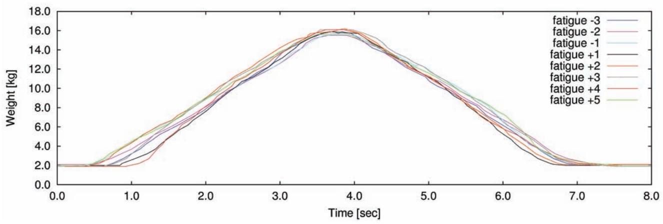

Fig. 6. Change in the weight value for each trial (evaluated with the total weight of the belt and the forearm being 2 kg).

the difference in the sEMG signal before and after muscular fatigue. This difference might simply be caused by individual differences in muscle mass. Or it may be the result of the state similar to muscular fatigue caused by muscle overload. Addressing this question will be included in our future studies.

B. Isometric contraction

Because the muscular tissue efficiency may be affected by changes in the muscle length, we performed the experiment to investigate the relationship between fatigue coefficients and local muscular fatigue in isometric contraction. In this experiment, we measured the sEMGs of the biceps brachii muscle of one of the test subjects during the following trials.

1) The subject stands upright and keeps the forearm horizontal by bending the elbow nearly squarely.
2) Each trial incorporates the weight by pulling the belt on the subject's wrist from below. The power to lift the weight increases over approximately 3 seconds and then decreases over approximately 3 seconds.
3) The trial is repeated 4 times separated by approximately 20 second intervals.
4) Fatigue of the biceps brachii muscle is caused by approximately 1 minute of exercise using a dumbbell.
5) The trial is repeated 5 times separated by approximately 10 second intervals.

Fig. 6 shows the change in the weight value for each trial. However, the value is not equal to the load amount on the biceps brachii muscle because it neglects the activity of the antagonist. The trials are thought to be sufficiently stable because it is difficult to recognize each line on the figure.

Fig. 7 shows the fatigue coefficients of the trials when measuring with a sampling frequency of 20 kHz (the LPF was 10 kHz) . The size of the time window for the calculation was 50 ms (1000 samples). The horizontal line on each graph is an auxiliary line to facilitate recognizing of the change in the coefficients.

For each trial, before fatigue, the fatigue coefficient continuously changes. However, it is independent of the load amount, and its lower bound is quite stable, except for the tendency for the value to slightly decrease in each trial. By contrast, after fatigue, the fatigue coefficients fall well below the auxiliary line. The recovery steps during the short intervals can be seen in the changes in the graphs on the right side of the figure.

Based on this result, we believe that the fatigue coefficients can capture the change in the influence of fatigue in seconds or milliseconds. When we treat the auxiliary line as the threshold, the ratio of the threshold and the amount below the threshold can be used to evaluate the fatigue level (the amount of fatigue expression). Even though it is our idea to evaluate the local muscular fatigue, a method for setting an appropriate threshold value has not yet been established. In addition, our method does not incorporate how the amplitude of the coefficients is reduced by muscular fatigue. These topics will be included in our future studies.

VII. Conclusions

We proposed a fatigue coefficient as a composite evaluation value of the quality of the muscular tissue activity and the nervous system activity. The most significant difference for this coefficient compared to previous studies is that it provides a direct evaluation as opposed to a relative evaluation. In addition, it does not require a base value of the same status (e.g., a load or posture). Therefore, it is applicable to exercises that do not repeat and that change the load amount. Even though the amount of influence of the muscular fatigue depends on the load amount, the reference value for estimating the amount of fatigue influence is independent of the load amount. Further, because it is calculable in real-time[24], the fatigue coefficient can be used to estimate muscular fatigue during exercise.

By estimating the fatigue influence directly, the effective power of muscular activity can be more accurately analyzed. A systematization of the quantitative and qualitative factors in muscular activity will be described in a future paper.

Acknowledgments

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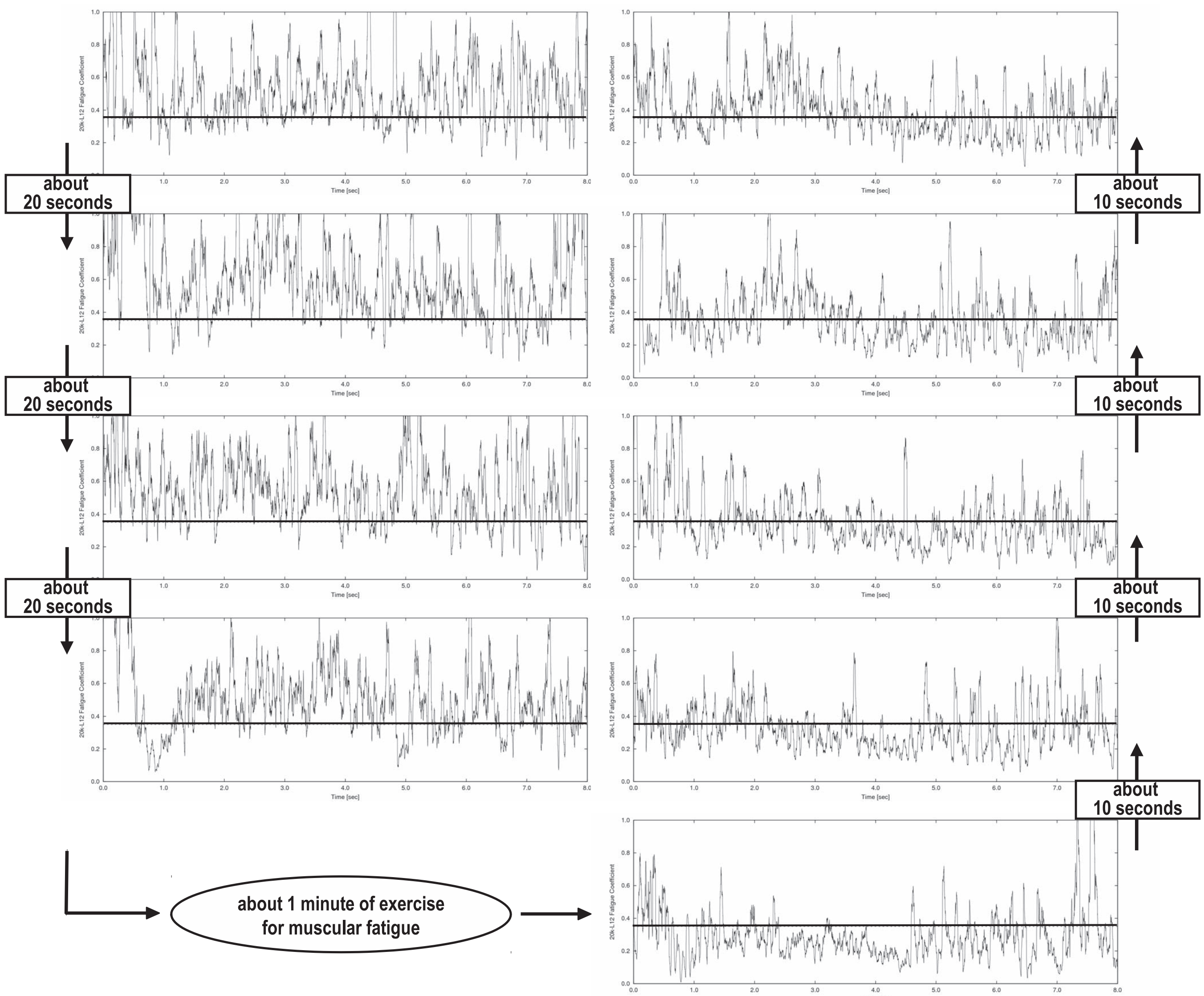

Fig. 7. Change in the fatigue coefficient with each trial. Trials prior to the fatigue action are shown on the left side (top to bottom), and trials following the fatigue action are shown on the right side (bottom to top).

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