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Visualization of Motor Unit Activities in a Single-channel Surface EMG Signal

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Abstract

Surface electromyography (sEMG) is a noninvasive method used to capture electrically muscle activity, which can be easily measured even during exercise. The basic unit of muscle activity is the motor unit, and because an sEMG signal is a superposition of motor unit action potentials, analysis of muscle activity using sEMG should ideally be done from the perspective of motor unit activity. However, conventional techniques can only evaluate sEMG signals based on abstract signal features, such as root-mean-square (RMS) and mean-power-frequency (MPF), and cannot detect individual motor unit activities from an sEMG signal. On the other hand, needle EMG can only capture the activity of a few local motor units, making it extremely difficult to grasp the activity of the entire muscle. Therefore, in this study, a method to visualize the activities of motor units in a single-channel sEMG signal by relocating wavelet coefficients obtained by redundant discrete wavelet analysis is proposed. The information obtained through this method resides in between the information obtained through needle EMG and the information obtained through sEMG using conventional techniques.

Keywords: *Motor unit activity, Surface EMG, Needle EMG, Component wave, Redundant wavelet analysis, Wavelet coefficient set.*

1. Introduction

Analysis of muscle activity is useful in many fields, including sports, healthcare, and myoelectric prostheses. Electromyography (EMG) is one method for electrically capturing muscle activity. The basic unit generating muscle activity is the motor unit, and the basic unit of an EMG signal is the motor unit action potential waveform [1, 2]. Therefore, analysis of muscle activity using EMG should ideally be based on motor unit action potential waveforms.

There are two types of EMG: needle EMG and surface EMG (sEMG). Needle EMG can only capture the activity of a few local motor units, making it extremely difficult to grasp the activity of the entire muscle. On the other hand, sEMG can detect a superimposed wave of action potentials of many motor units. However, conventional techniques can only evaluate sEMG signals based on abstract signal features, such as root-mean-

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square (RMS) and mean-power-frequency (MPF), and cannot detect individual motor unit activities from an sEMG signal. Therefore, in this study, a method to capture visually the motor unit activities that constitute muscle activity using only a single-channel sEMG signal is proposed.

2. Methods

Typically, sEMG measurements are conducted at a sampling frequency of approximately 2,000–3,000 Hz. However, such a sampling frequency is insufficient to capture signal changes associated with motor unit action potential waveforms, which are components of an sEMG waveform. Therefore, in this study, sEMG signals were measured at a higher sampling frequency of approximately 10,000–20,000 Hz, which is considerably higher than the conventional settings. A/D conversion circuits capable of withstanding high-frequency sampling and measures to reduce noise are expected to be necessary, but there should be no particular difficulty in other aspects of the measurement.

To capture motor unit action potential waveforms, which are nonperiodic and occur for a short duration, wavelet transform [3] was used, which is better suited for such waveforms than Fourier transform. Multiresolution analysis, the most common type of discrete wavelet analysis, was conducted on the sEMG signals measured at a high sampling frequency. As a result, when the magnitude of the wavelet coefficients was graphed as shading on a time–frequency plane, it was frequently observed that the areas with higher coefficient values flowed from low- to high-frequency bands over time. These flows were also observed in reflexive muscle actions during the onset and relaxation of muscle activity. Therefore, it was predicted that these flows are strongly related to the activities of individual motor units.

However, multiresolution analysis lacks shift invariance. Even a one-sample shift at the start of the analysis can cause the characteristics of the flow to appear or disappear. To overcome this problem, redundant discrete wavelet analysis [4, 5] was conducted such that at every sampling time, all wavelet coefficients with that time as the starting point of the coefficient domain are obtained. In wavelet analysis, a waveform that is similar to the components of the target signal can better extract the features. For the motor unit action potential waveforms in sEMG, Daubechies' N = 2 was selected as the wavelet, because its support is very short and its waveform is similar to the motor unit action potential waveform.

Each component waveform in the target signal being analyzed (in this study, the motor unit action potential waveform in the sEMG signal) has a duration. Therefore, a single point in time that must be treated as the appearance time of the component waveform was first determined. Then, representative positive wavelet coefficients that characterize the component waveform were selected and collected along with the relative time from the appearance time of the waveform. This collected data is referred to as a "wavelet coefficient set," which defines the characteristics of the component waveform. An important point when determining the wavelet coefficient set is that there is no requirement for a computational relationship in multiresolution analysis between the wavelet coefficients contained in the set. The wavelet coefficients are treated as purely indicative of the signal strength in the corresponding time–frequency domain, regardless of the calculation process used to obtain them. This enhances the representability and adaptability of the wavelet coefficient set for the characteristics of various types of component waveforms. In addition, if some coefficients in the wavelet coefficient set characterize the component waveform with negative values, these coefficient values are inverted when collected as element values for the wavelet coefficient set. This makes it possible to define the wavelet coefficient set such that all coefficient values are positive when the collected coefficient values for the wavelet coefficient set match the characteristics of the component waveform.

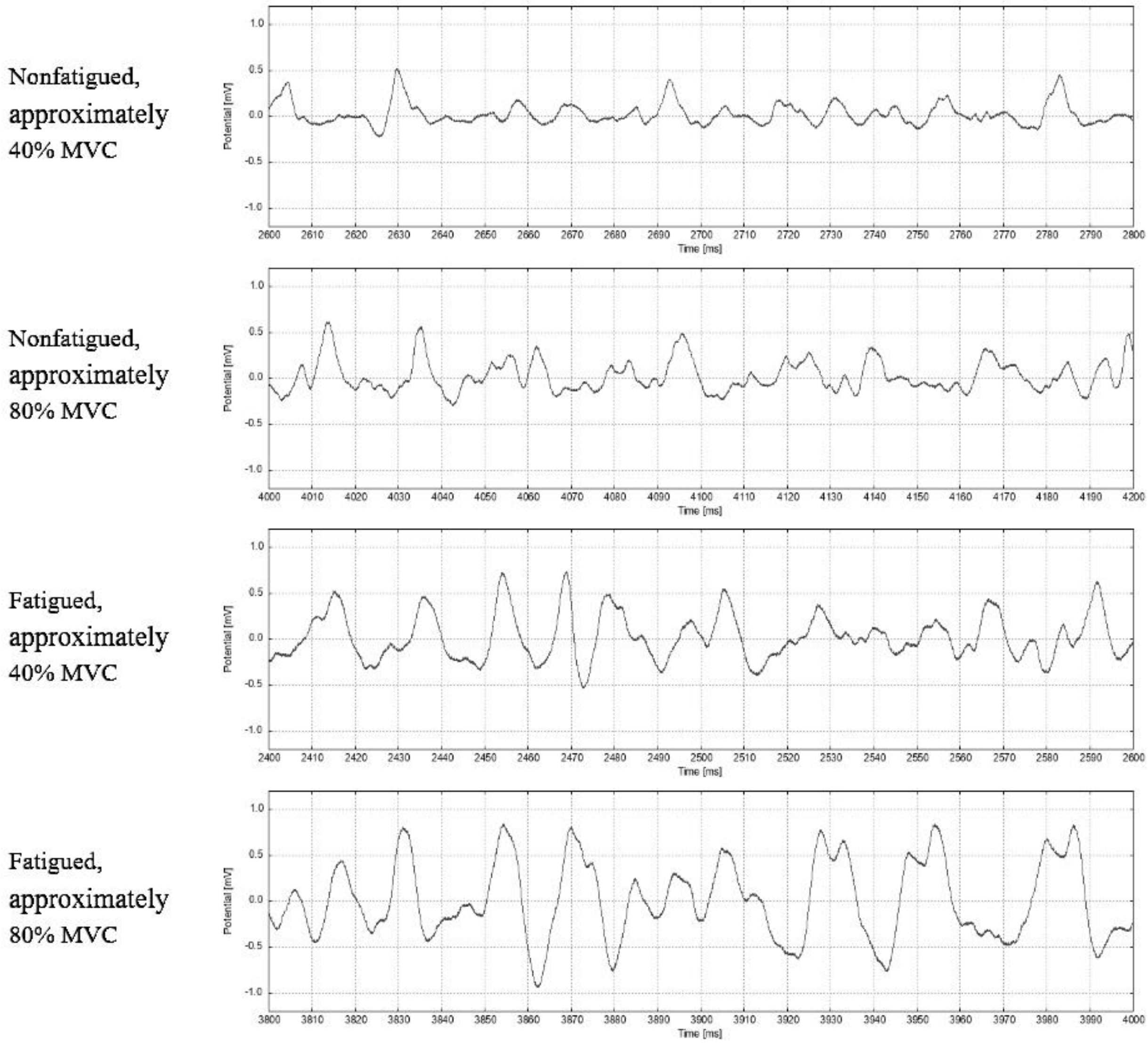

Figure 1. The sEMG signals measured using 20,000 Hz sampling.

All coefficients belonging to the wavelet coefficient set whose appearance time is equal to each sampling time were collected based on the results of the redundant discrete wavelet analysis. If the collected set of coefficient values at a certain sampling time has a high conformity with the motor unit action potential waveform, then all coefficient values in the set will be relatively large positive values. Therefore, these coefficient values can be arranged vertically along the time axis and a contour plot that ignores negative values to visualize the presence of motor unit action potential waveforms as a lump with a waterdrop-like shape can be generated.

3. Results and Discussion

Figure 1 illustrates the sEMG signals recorded from the biceps brachii muscle of a subject using bipolar derivation at a sampling frequency of 20,000 Hz.

The displayed waveforms represent a 200 ms duration for both the nonfatigued and fatigued states, Nonfatigued, approximately 40% MVC

Nonfatigued, approximately 80% MVC

Fatigued, approximately 40% MVC

Fatigued, approximately 80% MVC

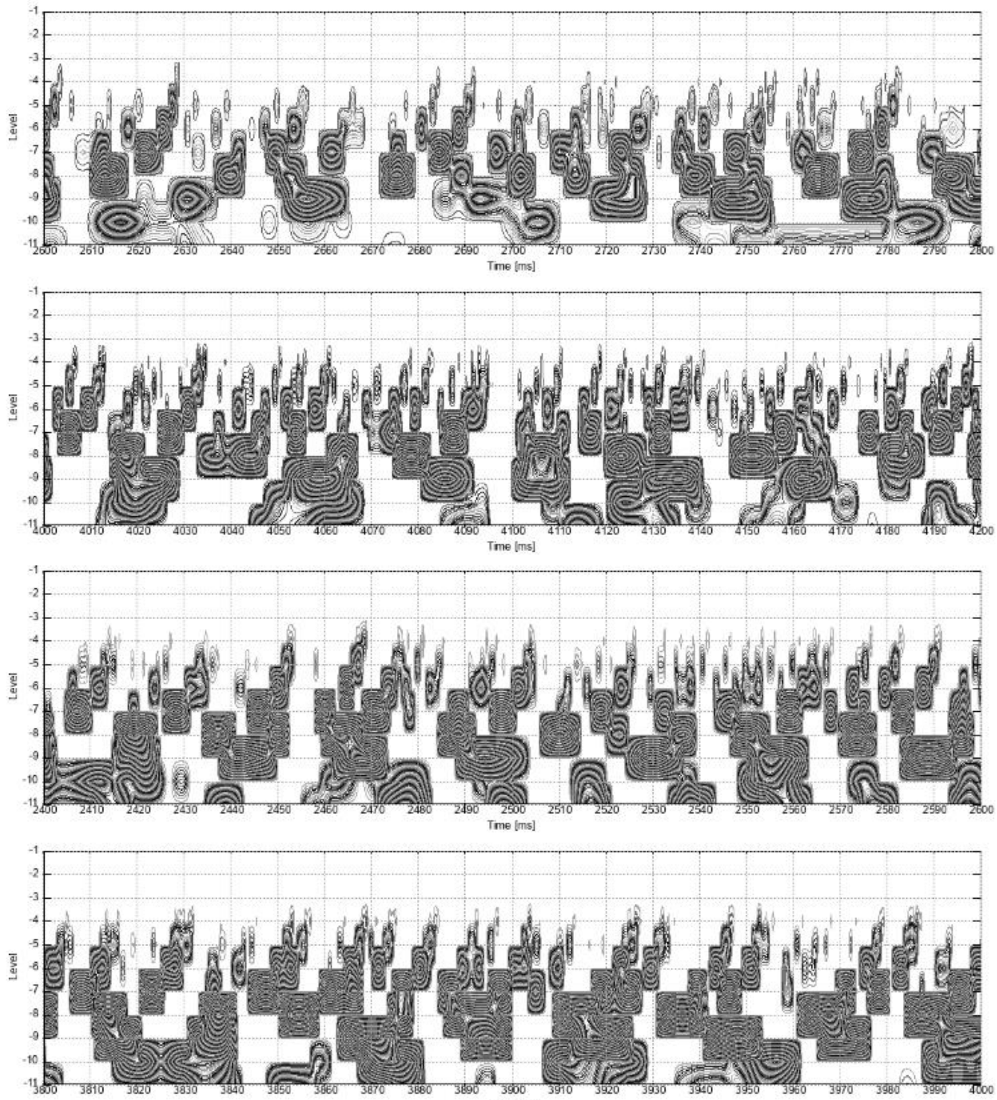

Figure 2. Contour plots of the positive wavelet coefficients obtained from the results of redundant discrete wavelet transform (equal to the H+0 type of wavelet coefficient set).

corresponding to approximately 40% and 80% of maximal voluntary contraction (MVC) loads, respectively. No electrode repositioning or adjustments were conducted during the measurements. Muscle fatigue was induced by engaging in dumbbell exercises for approximately 1 min. These graphs exhibit the expected increase in sEMG amplitude with enhanced force production and the progression of muscle fatigue, in accordance with commonly reported observations [6]. The graphs also demonstrate that in situations where muscle fatigue cannot be disregarded, amplitude-based force evaluation measures such as RMS are not suitable. For example, the amplitude of the sEMG signal at 40% MVC under fatigued conditions is larger than that at 80% MVC under nonfatigued conditions.

When a single motor unit action potential waveform is measured using bipolar derivation, it is often observed as a pair of waveforms, one original and one inverted. With this in mind, Figure 2 presents contour plots on a time–frequency plane depicting the coefficient values obtained from the redundant discrete wavelet analysis (with denoising by soft thresholding [7, 8]) of the signals in Figure 1 within the range of positive

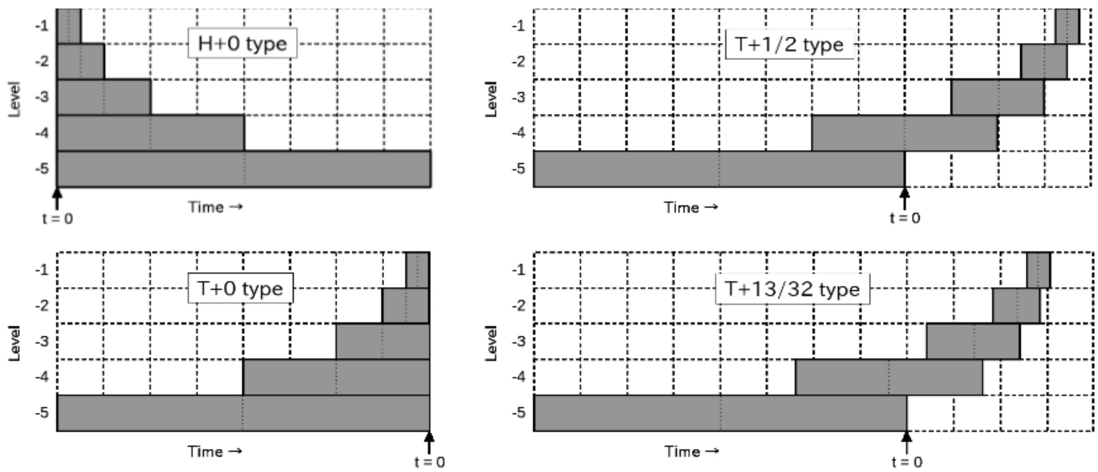

Figure 3. Some simple types of wavelet coefficient set.

coefficients. These plots are equivalent to the contour plots generated using the H+0 type of wavelet coefficient set, which belongs to the category of wavelet coefficient sets with a simple structure as described in [9]. Establishing a relationship between the depicted contours in these figures and the motor unit action potential waveforms is challenging. Consequently, capturing motor unit activities using coefficients derived from redundant discrete wavelet analysis or its near-equivalent analysis, which is based on the H+0 type of wavelet coefficient set, can be considered nearly impossible. This task becomes even more demanding when attempting to use the results of multiresolution analysis, which provides less informative data compared to redundant discrete wavelet analysis.

The transition of strong regions in the signal on the multiresolution analysis results, as mentioned in the previous section, is similar to the T+1/2 type of wavelet coefficient set described in [9]. The T+1/2 type exhibits considerable preservation of computational relationships in the multiresolution analysis between wavelet coefficients. However, within the range examined at 1/32 intervals, when the computational relationships were disregarded and the wavelet coefficient sets of the T+x group were investigated, the T+13/32 type appeared to be the most optimal. See Figure 3 for each structure of the wavelet coefficient sets. Figure 4 illustrates the contour plots of the sEMG signals in Figure 1 using the T+13/32 type of wavelet coefficient set. Unlike the H+0 type, the T+13/32 type exhibited numerous distinct lumps with a waterdrop-like shape.

From the figure, the lumps with a waterdrop-like shape exist in a group limited to a certain extent in the higher frequency range, as well as in a group where the lumps extend across a wider frequency range, starting from a frequency range comparable to the former group and extending to a lower-frequency range. Thus, on the basis of this characteristic, the former group corresponds to motor units classified as fast-twitch fibers, while the latter group corresponds to motor units classified as slow-twitch fibers.

The results of investigating whether the waterdrop-like lumps truly capture the motor unit action potential waveforms are presented in Figure 5. When the wavelet coefficients from the entire frequency range are inversely transformed disregarding the lumps, the resulting waveforms differ significantly from the motor unit action potential waveforms. However, when the wavelet coefficients extracted based on the lumps are inversely transformed, the resulting waveforms exhibit the characteristics of motor unit action potentials. The waveform obtained at time (1) indicated in the figure represents rapid changes and can be identified as fast-twitch fibers. On the other hand, the waveform obtained at time (2) displayed in the figure represents slower changes compared to the waveform at time (1) and can be identified as slow-twitch fibers.

The graphs using contour plot on Figure 4 are visualization figures of motor unit activities. The changes that are dependent on muscle exertion force and muscle fatigue based on Figure 4 were examined. Unless otherwise specified, references to graphs in the following text will pertain to the graph on Figure 4.

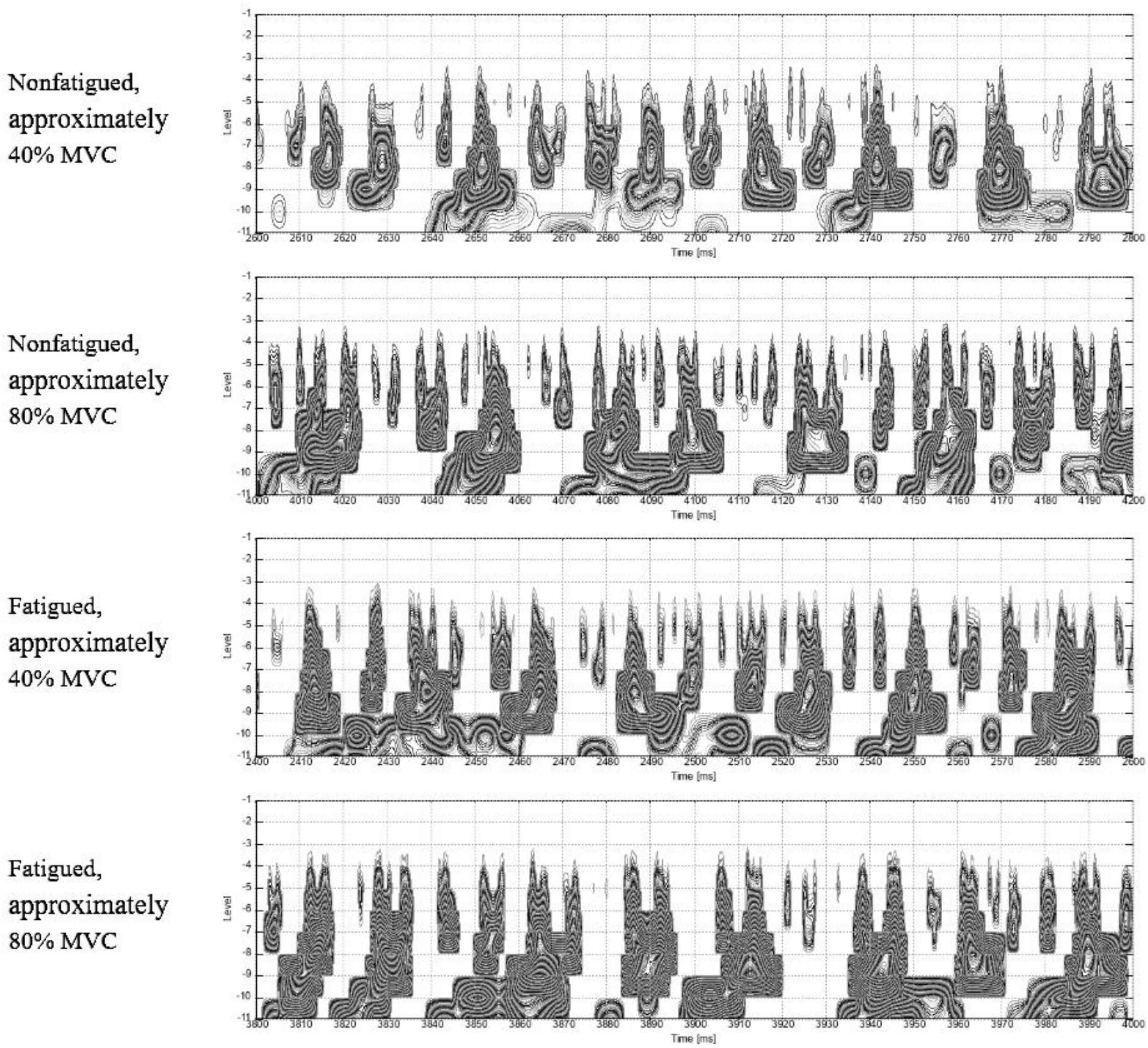

Figure 4. Contour plots of the T+13/32 type of wavelet coefficient set.

When observing the graph variations resulting from the differences in muscle exertion force under nonfatigued conditions, a noticeable increase in the number of lumps representing the activity of fast-twitch motor units accompanies the augmentation of muscle exertion force. Although the activity of slow-twitch motor units also increases, in this case, it can be interpreted that the increase in muscle exertion force is primarily achieved by increasing the number and density of active fast-twitch motor units.

In a fatigued state, both the lumps indicating the activity of fast-twitch motor units and those indicating the activity of slow-twitch motor units tend to extend toward lower frequency bands. These changes explain the frequency distribution of sEMG shifts to lower frequencies as muscle fatigue progresses, as is commonly reported [10]. As not all motor units undergo fatigue uniformly, not all lumps uniformly exhibit such extension,

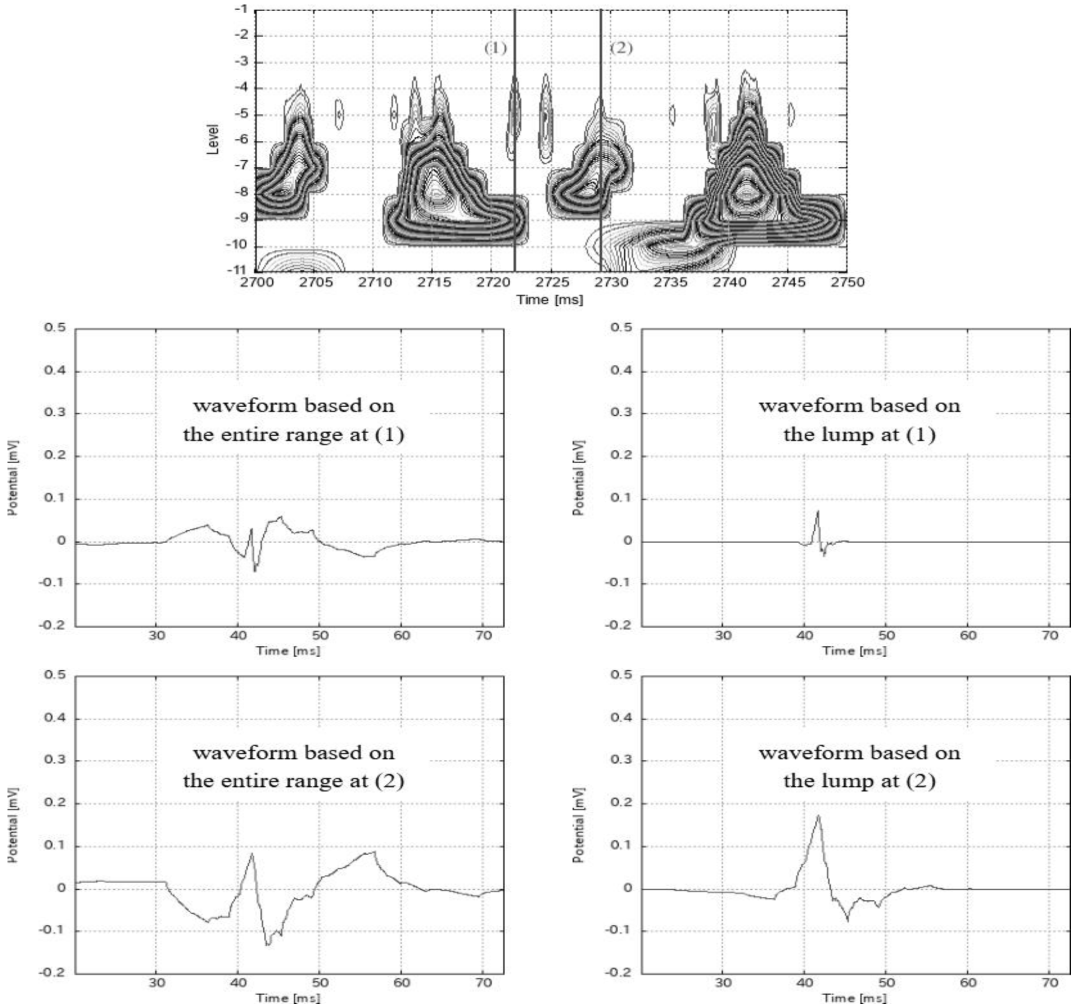

Figure 5. Extracted motor unit action potential waveforms.

but the proportion of lumps extending into the low-frequency range increases. This change in frequency characteristics can be attributed to a decrease in muscle fiber conduction velocity caused by fatigue in muscle fibers.

As fatigue progresses, motor units experience a decrease in the magnitude of force that they can generate. Therefore, to maintain the same muscle force as when not undergoing fatigue, it is necessary to compensate for the decreased force output of the fatigued motor units by activating a larger number of motor units, similar to increasing muscle force. This observation is supported by the similarity between the changes observed in the transition from the graph of approximately 40% MVC without fatigue to the graph of approximately 80% MVC without fatigue, and the transition to the graph of approximately 40% MVC with fatigue. However, in the graph of approximately 40% MVC with fatigue, there is a prominent presence of lumps of fast-twitch motor unit activity indicating a tendency toward fatigue, and the proportion of slow-twitch motor unit activity appears to increase. The progression of fatigue in motor units is faster in fast-twitch fibers than in slow-twitch fibers. Therefore, when it becomes difficult to achieve a sufficient increase in muscle force output solely through increased activity of fatigued fast-twitch motor units, an attempt is made to obtain the necessary muscle force output by compensating through an increased proportion of activity of slow-twitch motor units, which experience a slower fatigue progression compared to fast-twitch fibers. The graph of approximately 40%

MVC with fatigue indicates this situation.

To further enhance the muscle force output, efforts were made to increase the combined force generated by the motor units by increasing the density of motor unit activity and strengthening synchronization, ensuring the attainment of the required force output. This phenomenon can be observed as a fusion of force summation on a visualization figure using a contour plot. In particular, in a fatigued state where the muscle force output needs to be increased, simultaneous activation of numerous motor units, encompassing both fast- and slow-twitch fibers, occurs. In the graph depicting approximately 80% MVC with accompanying fatigue, large clusters characterized by fused motor unit activity consistently appear, indicating the occurrence of synchronized activity approaching the limits of the muscle force output. This phenomenon can be observed as the fusion of lumps on a visualization figure. In particular, when attempting to increase the muscle force output in a fatigued state, a synchronized activity of numerous motor units, involving both fast- and slow-twitch fibers, occurs.

In the graph of approximately 80% MVC during muscle fatigue, a high occurrence of large clusters formed by the fusion of multiple motor unit activities can be observed. By considering the muscle force generated when all motor units belonging to the muscle are synchronized, it becomes apparent that obtaining a greater muscle force beyond that level is impossible. Therefore, this graph, with its high proportion of large clusters, indicates a state where muscle activity is approaching the limits of force generation.

4. Conclusion

The proposed method provides a means of analyzing muscle activity from the perspective of motor unit activity, which separates fast- and slow-twitch motor units, and is difficult to achieve using conventional techniques. The information obtained through this method resides in between the information obtained through needle EMG and the information obtained through sEMG using conventional techniques. Although sEMG is less precise compared to needle EMG and does not allow for the identification of individual motor units, it provides a means to analyze in detail the accumulation of many motor unit activities that contribute to muscle activity. Because the method only requires single-channel sEMG information, the combination of information from multiple channels can be effectively used for more advanced muscle activity analysis if available.

The relationship between sEMG signals and muscle fatigue has been the subject of a great deal of research over the years (*e.g.*, [11-22]). To capture accurately the effect of muscle fatigue on muscle activity, it is necessary to assess the fatigue status of muscle fibers and the changes in motor unit activities resulting from muscle fiber fatigue. This method can provide a new perspective on muscle fatigue analysis based on sEMG signals.

This method does not use machine learning inference to obtain features. It can be classified as a kind of simple signal processing, and the obtained features (lumps and wavelet coefficients that form them) can be considered high-quality raw characteristics of sEMG signals, surpassing abstract features such as RMS or MPF. Therefore, by using these features as input parameters for machine learning in systems using sEMG signals, it is expected to achieve higher quality learning compared to parameters based on RMS, *etc*. This is because these features directly capture motor unit activities, which are the basis of muscle activity, and contain information that would be lost with abstract features.

While the underlying data visualization can be acquired in real-time using the proposed method, the display speed is too fast for human recognition even if visualized in real-time. To use real-time processing, it is necessary to detect mechanically motor unit activity in real-time and apply it directly or aggregate the information to a level recognizable by humans. The methods for mechanical detection and their applications will be presented in a separate paper due to space limitations.

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