Wavelet transform and real-time learning method for myoelectric signal in motion discrimination

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Abstract. This paper discusses the applicability of the Wavelet transform for analyzing an EMG signal and discriminating motion classes. In many previous works, researchers have dealt with steady EMG and have proposed suitable analyzing methods for the EMG, for example FFT and STFT. Therefore, it is difficult for the previous approaches to discriminate motions from the EMG in the different phases of muscle activity, i.e., pre-activity, in activity, post-activity phases, as well as the period of motion transition from one to another. In this paper, we introduce the Wavelet transform using the Coiflet mother wavelet into our real-time EMG prosthetic hand controller for discriminating motions from steady and unsteady EMG. A preliminary experiment to discriminate three hand motions from four channel EMG in the initial pre-activity and in activity phase is carried out to show the effectiveness of the approach. However, future research efforts are necessary to discriminate more motions much precisely.

1. Introduction

The myoelectric signal (MES), recorded at the surface of the skin, and provides information about neuromuscular activity. This has been fundamental to its use in clinical diagnosis, and as a source of control for assistant devices and schemes of functional electrical stimulation. This work seeks to improve the functionality and ease of control of powered upper-limb prostheses using MES.

The complexity of the MES, however, has limited the accuracy with which different classes of activity may be distinguished. Although many control systems have been very successful, they do not provide sufficient information to reliably control more than one function [1]. Unfortunately, these are the requirements to be met. Instead of analyzing the steady-state MES (that produced during effort), Hudgins [3] investigated the information content in the transient burst of MES activity. But from the viewpoint of physiology, there are three phases that should be considered by EMG analyzing method, i.e., pre-activity phase, in activity phase, and post-activity phase. Furthermore, previous works used the analyzing methods such as FFT or other frequency transforms [4, 5], based on the assumption that the EMG signal is stable in the whole process of certain motion [6]. Therefore, it is difficult for those methods to be applied to the initial pre-activity phase of motion, and the final post-activity phase of motion. Now, we introduce the Wavelet transform (WT) as is an effective time-frequency analysis method, to analyze both phases of EMG effectively.

2. Method
An outline of the controller using wavelet analysis and real-time learning method is shown in figure 1. The controller is divided into three units. They are signal analysis unit, adaptation unit, and trainer unit. This paper introduces the wavelet transform into the analysis unit. These units are discussed in detail in following paragraphs.

![Figure 1. Controller System Diagram](image1)

In our experiment, data was acquired from 8 normally-limbed individuals, recording four channels of MES from electrodes placed on the medial side, top, lateral side and bottom of the forearm, as depicted in Figure 2.

Each subject generated five different classes of motion: hand close/open, thumb finger flexion/extension, index finger flexion/extension, palm pronating/extension and palm upper flexion/extension. Each subject produced two sets of data: one comprising transient bursts, and another consisting of steady-state signals. Because this is a prosthetic control problem, the contraction levels are arbitrary as long as they are reasonably consistent, and comfortable enough for the subject to reproduce in daily use without fatigue. Each bipolar channel was acquired used Ag-AgCl electrodes spaced at 2 cm. Each record was 1s in duration (1250 points, sampled at 1250 Hz). In each dataset, 20 patterns were generated in each class, resulting in a total of 100 patterns. This data was evenly divided into training and test sets of 50 patterns, and then motion discrimination by the wavelet analysis and real-time learn methods described in the following section.

3. Wavelet analysis

An EMG signal is time series data. Therefore, it is not easy to infer an operator’s intentions of motion from raw EMG signals. In the proposed method, the Coiflet wavelet was selected as the wavelet basis function. This wavelet exists under the name of Coiflets, but it is indeed constructed by Daubechies at the request of Coifman [7]. Therefore, although Coiflet wavelet and Daubechies wavelet are similar at a certain level, the Coiflet wavelet was indeed different in that it was constructed with vanishing moments not only for wavelet function $\psi(t)$, but also for scaling function $\phi(t)$[9].

In the Coiflet wavelet formulation process, the following equations must be satisfied

\[
\int dx \psi(x) = 0 \quad \text{for} \quad l = 0, \ldots, L - 1
\]

(1)

\[
\int dx \phi(x) = 1
\]

(2)

\[
\int dx \phi(x) = 0 \quad \text{for} \quad l = 0, \ldots, L - 1
\]

(3)

where $L$ is the order of Coiflet wavelet function, and $\phi(x)$ is a scaling function associated to $\psi(x)$. For a Coiflet of order 6, the corresponding scaling function and wavelet basis function were shown to be smoother and more symmetric than the Daubechies wavelet. This observation indicates that at different resolution, the approximation of polynomial functions can be better achieved. Furthermore, the symmetry property of the Coiflet is desirable in the signal analysis work due to the linear phase of the transfer function. As for the comparison with the Morlet wavelet that was also tested in our laboratory, although the Coiflet method is less flexible in visualizing any frequency of interest, its
The discrete form is useful for digital implementation. These benefits consolidate the utilization of the Coiflet wavelet transform for this study.

The paper uses a normed wavelet coefficient for erasing phase lag as follows:

$$\sum_{n=a}^{Max-a} a Wa b n af n b$$

where $a = Min, Min+1, \cdots, Max-1, Max; b = n_a, n_a+1, \cdots, -1, 0$.

In this formula, $Min$ and $Max$ fix the frequency band extracted from EMG $f(.)$. To extract most useful information from the coefficient, the Analysis Unit generates the spectra summation and detects its peak. The spectra summation is defined as formula:

$$st(b) = \sum_{a=Min}^{Max} W(a,b)$$

The condition of the peak decision is that the gradient changes from plus to minus at a certain point and the sign of the gradient does not change in the other points within a definite period of time. Feature vector is generated from the spectra at the peak point $p$.

$$v = (W(Min, p), W(Min + 1, p), \cdots, W(Max, p))$$

When the peak is not found in the frequency strength $st(b)$ through a period defined by $n_a$, the Analysis Unit outputs a zero vector and the Adaptive Unit does not discriminate motion.

For discriminating the operator’s motions, the adaptation unit is used to deal with a feature vector generated by the analysis unit. The controllers must learn adequately the operator’s characteristics to give the control command using nonlinear functions, moreover the mapping relationship is not linear. The adaptation unit uses a feed-forward Neural Network (NN) as the nonlinear function. The Adaptation Unit calculates the output in the NN section from the feature vector. The Trainer Unit makes training data which contains a teaching signal from operator and feature vector from the Analysis Unit, to help the Adaptation Unit learn the operator’s characteristics by supplying the illustrative training data. When the unit receives the teaching signal, the Trainer Unit composes the training data from the feature vector. The obtained new training data is then added to the last position of the total training data set. The learning method employs the Back Propagation Algorithm [10]

### 4. Experiment results

There are 8 participating subjects who are about twenty years old, divided into two groups, male and female, and instrumented with four dry-type EMG electrodes on forearm. The controller is implemented by software in PC to discriminate five motions. The five motion classes are described in section 2. Measured EMG is amplified and sent to the PC through A/D board. In the experiment, the subject operates hand, index finger, palm and thumb flexion and keeps flexion status for a moment then moves to extension, while watching the PC’s monitor denoting the discriminated result and using the keyboard to send teaching signals when the discriminated motion is quite different from that intended. After the training and learning, the experiment enters test mode in which data sets for investigation are collected while the subject exercises the two type motions repeatedly.

Figure 3 shows a part of the experimental results using unsteady EMG measured in the initial pre-activity phase of the index finger flexion. The controller can precisely discriminate the motion in the presence of a weak signal by detecting the peaks of spectra summation from four channels. The frequency spectra described in the second row of figure 3 presents some similar sub-patterns on intensity distribution, the position which can be clearly illustrated by the peak detected, shown in the third row of figure 3. The time of the peak in the spectra summation is delayed slightly as compared to time of the peak in EMG signals.

We have compared the result from the proposed method using the Wavelet transform with one from the previous method using the Fourier transform. Both use an unsteady EMG measured in the initial pre-activity phase of the thumb flexion. Precise discriminating is performed in the proposed
new method in contrast to the occurrence of errors in the previous method. This is because the Fourier transformed initial pre-activity spectra are blurred but the Wavelet transformed spectra are not. Therefore, the proposed method is effective in the initial pre-activity phases.

![Waveform plots](image)

Figure 3. The flow diagram from the measured EMG signal to control command. The results of four channels are shown in a, b, c and d, respectively.

### 5. Conclusion

This work has described a feature set based upon the WT that offers significantly improved accuracy and discriminate motions from the initial pre-activity phase of EMG. In the experiment, the controller discriminated difference motions from four channels of unsteady EMG detected in the initial pre-activity phase and steady EMG. In the future, we will focus on more motion classes.

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