A preliminary analysis of analysis window size and voting size with a time delay for a robust real-time sEMG pattern recognition

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Abstract - Myo-electric signals have been widely used in human-machine interfaces because these biosignal directly reflect human intentions to robots. The major difficulty of applying these biosignal in a pattern recognition system in real time is that they are unstable and vary in time. This instability occurs outside of the steady state of the signal, at the beginning and the ending of the motions. For real-time application users, the errors at the beginning of motion can lower the credibility of a pattern recognition system. In this sense, precise classification is the most significant factor for the system; thus the classification accuracy has higher priority compared to other factors.

Generally, a trade-off relationship between the time delay of control commands and the classification accuracy has been known for sEMG users. Since parameters for signal processing can alter the sensitivity (time delay and accuracy) of the system, this study investigates limitations of a pattern recognition system due to transient-state errors. In particular, the performance of the system is analysed with respect to the analysis window size and the voting size of classification. Through an off-line simulation, we propose useful guidelines for the analysis window size and voting size in myoelectric signals for real-time applications.

Keywords - sEMG signal, real-time pattern recognition, optimal parameters and time delay.

1. Introduction

A variety of studies on pattern recognition systems using Electromyogram (EMG) signals have been conducted to extend their usability for various applications such as human robot interaction (HRI), prosthesis device control, rehabilitation robots or human motion analysis. As available myoelectric signals provide increasingly more useful and complex functionality, higher classification accuracy with this biosignal becomes more important in real-time applications. Implementation of a robust pattern classification could give rise to the development of prosthetic control for transradial amputees as well as to a daily human computer interaction (HCI) system like a remote controller for ordinary healthy people. Generally, because sEMG signals of healthy people are stronger than those of stroke patients or amputees, sEMG signals could become useful input sources for HCI system that requires a small number of commands such as a presentation remote controller or game controller and so on [1] [2].

The large challenges of using sEMG signals in pattern recognition applications are their properties of being unstable and varying in time. In other words, these signals show distinctive features, among different people, between morning to night, and even on different days. Thus, this time-varying property of sEMG signals makes successful control of prosthetic devices or other motion controllers in real time difficult. This frequently occurs at the classification for the onset and offset timing of a sEMG signal, which we defined as a transient state session, and is unacceptable because features of the transient state are different from those of a steady state session [3]. In fact, most classification errors generally occurs in a transient state session, not a steady state session. Because continuous classification accuracy is one of the most important key factors for successful online applications, transient errors in the onset and offset should be eliminated properly.

Generally speaking, for the elimination of classification errors, numerous studies on extracting distinctive features and selecting better classifier algorithms have been deeply investigated since sEMG-based applications began to be implemented [4] [5] [6]. Although these types of studies remain highly important in this field, a new approach from a different perspective is required for better performance of an integrated system with myo-
electric signals. Particularly for real-time applications, some parameters of traditional algorithms should be re-investigated for higher accuracy as well as the speed [7] [8]. In addition, an adaptive algorithm for the determination of the onset and offset of muscle contraction with the parameters of processing signals is evaluated by off-line simulation [9].

It has been known that there exists a trade-off relation between the classification accuracy and the speed [10]. Previous studies have attempted to discover the optimal value for analysis window size of signal processing to control prosthetic devices with EMG signals [11] [8]. Although features or classification algorithms could have effect on system performance, the change in the general performance of sEMG signals only with analysis window size was examined in this study. Other research has also attempted to find the optimal control delay for myoelectric prostheses in real time [12].

In traditional pattern recognition systems, two parameters that can change the speed of a system are analysis window size in signal processing and voting size of classification. With fundamental feature-classifier combinations, altering these two variables can have a noticeable effect on the classification speed as well as the classification accuracy. If we consider a significantly higher number of samples when classifying, where the condition in a large voting size, an accuracy will rise but a delay in classification will increase. Thus, for a successful implementation of real-time applications, the precise analysis of system performance with respect to these two variables can be beneficial for the control with sEMG signals.

It is assumed that the sensitivity of the system is varied with two parameters: analysis window size and voting size. The purpose of this study is to reduce transient errors, which originate from the onset of the motion, by varying system sensitivity. The optimal ranges for these two variables so as to maximize the system performance were obtained through off-line simulation. To satisfy user’s comfortness about time delay, the time delay of the system was investigated through pilot study of the actual accuracy that is experienced by actual users. On the basis of the user experiences, the proper time delay and the accuracy were examined in this study. The experimental result can define limitations of the existing classifier to reduce transient errors only by altering analysis window size and voting size.

This paper is organized as follows. In the Section 2, the background of this study, data acquisition, signal processing method and the algorithms of pattern recognition system are introduced. Section 3 describes main proposed methods for data analysis and experiment setup and results are explained in Section 4. Finally, a brief conclusion and future work are mentioned in Section 5.

2. Background

2.1 Data acquisition

sEMG signals were recorded using commercial surface electrodes (Trigno Wireless, Delsys Inc.). Eight electrodes were used for sEMG signal acquisition. These electrodes were sequentially placed so as to enclose the circumstance of the proximal forearm as described in Fig. 2. The sEMG signals were acquired at a 1 kHz sampling rate with wireless communication protocols. The signal processing and pattern recognition code were programmed in MATLAB(Mathworks Co.).

2.2 Data processing

Raw signals from each electrode module were processed to analyse their properties. A band pass filter that ranged between 15 Hz and 499 Hz, a squared function, and a moving average filter with a sample size of 150 were applied. This moving average filter size and the range of the band pass filter were determined from the past work [13]. After filtering, the sampled signals were squared to be non-negative property and were also filtered by moving average filter prior to the feature extraction. These filtered signals were transferred to the feature extraction and classifier algorithm.

![Fig. 2: Electrodes attachment to human forearm](image)

![Fig. 3: Flow chart of pattern recognition using sEMG signal](image)
2.3 Feature Extraction

In an EMG-based pattern recognition system, features are usually reflect the properties of the signals. Among a wide variety of features, the mean absolute value (MAV) feature was selected for feature extraction. This has proven to be an appropriate feature when using sEMG signals in pattern recognition systems. As a result, we can compute the feature vectors of each target motion class with following Equation (1), where \( k \) is the number of channels, \( N \) is the total sample size, and \( x_n(k) \) is the \( n \)-th sample for channel \( k \). In this study, the transient session and the early part of the steady state session are included for data analysis. Thus, signals for 1.5 seconds from the beginning, are included to create feature vectors. The onset of each motion is determined by threshold, which is manually set after data acquisition. These obtained signals are plotted in Fig. 4.

\[
x_{MAV}(k) = \frac{1}{N} \sum_{n=1}^{N} |x_n(k)|
\]  

(1)

2.4 Classification

With the extracted features, a single classifier determines the motion class on the basis of the features of the signals. In this study, an extreme learning machine (ELM) classifier [13] was used for data analysis. This classifier was proven to its precise and speedy classification for sEMG feature. The ELM classifier utilized Gaussian probability concept and found the highest probability among motion class. A single classifier found the motion signal that was the nearest feature in trained database. Detail algorithms are well described in [13].

3. Propoesed Methods

3.1 Analysis window size

Classification algorithms make a decision with the window size of analysis. Each feature of the analysis window size was compared by the proposed classifier. This window size can reduce the computation time because not all samples are calculated in the signals. The analysis window size has been shown to be able to affect the processing time in real-time applications [11]. In this experiment, the window size is selectively chosen from a range 100 to 600. Because a larger window size includes more samples from the signals, the transient and random properties of the signal could be reduced. The shift size of one window size to the next window was set to 10ms in this study.
3.2 Vote Scheme

When the classifier algorithm makes a decision, a voting scheme can be applied in the pattern recognition system for high accuracy. There exist numerous types of voting schemes, and the majority vote scheme [14] was implemented in our system. The concept of a majority vote is quite simple: the candidate that receives the majority (i.e., more than half) of the votes wins the election for class assignment. In real-time applications, this type of voting scheme could lead to late decision making but could also provide benefits in terms of accuracy. For example, for a voting size of \( N \), the assignment of class for a given signal is made on the basis of Equation (2), where \( \vec{V} \) represents the voting vector, and each \( x \) is one sample of the signal. Because a voting scheme used more than one sample, the classification decision started after considering a number of samples equal to the voting size. In the case of a voting size of \( N \), without considering analysis window size, with a 1-kHz sampling frequency, \( (N+\tau) \) ms of time delay occurs, where \( \tau \) is the processing time for making a decision for the classifiers [11]. The classification example with a voting scheme is well described in Fig. 1 with two channel signals. Let us assume that the dominant channel simply determines the motion class. If the signal of channel 2 is larger than that of channel 1, the classifier assigns the signal to motion class “1” otherwise, it is assigned to motion class “2”. Naturally, on the basis of the obtained signal, the classifier without a voting scheme might classify the signal as motion class ”1” at the onset of motion, but this miscategorization due to crosstalk of muscles would decrease as the voting size increased.

\[
\text{Class assignment} = \text{mode}(\vec{V})
\]

\[
\vec{V}_i = (x_{i-n+1}, x_{i-n+2}, \ldots, x_{i-1}, x_i) \in \mathbb{R}^N
\]  

3.3 Time Delay

Time delay for decision making differs according to the analysis window size and voting size. To obtain the time delay equation, we utilize the average delay equation from [11]. In this study, the time delay can be calculated with the analysis window size \( T_a \), shift size \( T_s \) and voting size \( N \), and processing time of the classifier \( \tau \) in Equation (3). Time delays with respect to these parameters are shown in Fig. 6. In this experiment, \( T_s \) is fixed to 10ms.

\[
\text{Time Delay} = \frac{1}{2} T_a + \left(\frac{N}{2}\right) T_s + \tau
\]  

3.4 Classification Accuracy

Obtained samples of the target motion signals were evaluated by classifiers with the majority voting scheme. For all of the training data, classification accuracy was calculated in difficult conditions. In other words, each sample was assigned to a motion class and compared with the correct answers. An off-line simulation test for performance accuracy was conducted for the training data.

4. Experimental Results

4.1 Experiment

This study was performed on three healthy subjects who were not trained with their sEMG signals before the experiments. For each subject, the performance of the system was evaluated with a broad range of analysis window sizes and voting sizes and a spectrum of classification errors and time delays for recognition. They performed three sessions, which included five repetitions of a data acquisition for each motion.

The sEMG signals with a total of ten target hand configurations (wrist flexion, wrist extension, radial deviation, ulnar deviation, pronation, supination, rock motion, paper motion and two types of scissors motion) were recorded five times for each configuration. A motion cue was visually delivered to the subjects through a computer screen. Among ten types of motions, once the picture of a randomly chosen motion was displayed on the screen, the subject began to imitate that motion immediately. The subject had to maintain each motion for three seconds to record each motion and take a rest for three seconds between two motions, as shown in Fig. 1.

When obtaining the signals of the subjects, subjects were provided with visual feedback with a compass-type plot. This type of visual feedback is intuitive with the combinations of the radial placement of electrodes on the forearm. They could tune their signal by a normalized compass plot because the each direction of the compass was synchronized to the place where the electrode was attached to their forearm. Data acquisition with a visual guide could be used to help the subjects concentrate in training session.

4.2 Data Analysis

The purpose of data analysis is to find the optimal analysis window size and voting size to minimize the transient state errors at the beginning of motion with proper time delay. Therefore, transient errors and performance accuracy are investigated for a wide range of these parameters to find an optimal range. Classification errors are measured for 1.5 seconds from the initial onset of the motion signal, which was determined by the preset threshold criteria. This threshold can be set by manually with training data. In this study, the threshold for the beginning of motion was set to 0.005 for each motion. With
this relationship, an appropriate time delay for applications are investigated by pilot test.

A. Transient errors

For a small analysis window size and voting size (analysis window: 100, voting size: 0), transient errors existed as described in Fig. 7. In this figure, the classifier confused the received signal as being between motion classes “2” and “4” at the beginning of the motion as circled in red line. If the analysis window size and voting size of the system increase, transient errors could be removed properly. As a result, this increase of these parameters raised overall accuracy of system so that the errors are eliminated in the second figure of Fig. 7.

B. System Performance

An off-line simulation for trained data was conducted to calculate the system performance. We collected data from three subjects and calculated the average value with respect to the range of the analysis window size and voting size. The tendency of the classification accuracy with these parameters is briefly shown in Fig. 8. Generally, the system showed better performance with a larger analysis window size and voting size. The classification accuracy improved from 77% to over 90% in Fig. 8. In this figure, voting size larger than 60 improved classification accuracy slightly while analysis window size had positive effects on accuracy over the range from 100 to 600.

4.3 System evaluation pilot test

Five healthy male subjects were participated to control with the Google Earth navigation program, the sEMG-based real-time applications with six commands: up, down, left, right, zoom in, and zoom out. They were asked how much the length of delay that was acceptable to deliver their commands to the system. During experiment, random time delays were applied with varying voting size while analysis window size was fixed to 100. As a result, subjects selected boarderlines of time delay between comfortness and uncomrtness. Average boarderline was equal to 0.460 seconds from this experiment and at the average accuracy at this conditions were equal to 88%. However, subjects felt satisfied with system if the classification accuracy was high. In this sense, accuracy was a higher priority than the speed of classification for real-time applications for healthy people. This result are quite surprising because the optimal delay for control the prosthesis has been known range from 100ms to 125ms [12]. This gap might originated from the difference of target applications and their users. From this pilot study, users did not feel discomfort the applications which need not rapid classification speed but high accuracy until time delay became 0.5 to 0.6 seconds.

5. Conclusion

For robust and successful online pattern recognition applications using sEMG signals, the optimal parameters for data processing for sEMG were investigated through an offline simulation. Because the time delay of the con-
control command and classification accuracy have a trade-off relationship, this research attempted to find an acceptable range of analysis window size and voting size for users of myoelectric signals. From the pilot test, the elimination of transient errors is more important than the time delay in real-time applications. The users were satisfied with a longer time delay if the system showed high quality accuracy. The spectrum of classification accuracy with respect to the window size and voting size were analysed.

This results demonstrate the viability of an implementation of an EMG-based pattern recognition system to reduce transient errors without changing features or classifying algorithms. An inevitable time delay for the proposed classifier is common limitation of current EMG-based applications with a single reference classifier. From the pilot study with real-time applications, time delay of 0.5 s to 0.6 s is approximately the limit at which users feel inconvenience when using the proposed pattern recognition system.

For future work, for a successful myoelectric control for various real-time applications, the proposed methods with different classifiers or algorithms should be deeply investigated with a large number of subjects. In addition, transient state signal should be reduced without increasing time delay to well exploit the early generation feature of sEMG signals.

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