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Technical note

Several practical issues toward implementing myoelectric pattern recognition for stroke rehabilitation

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ABSTRACT

High density surface electromyogram (sEMG) recording and pattern recognition techniques have demonstrated that substantial motor control information can be extracted from neurologically impaired muscles. In this study, a series of pattern recognition parameters were investigated in classification of 20 different movements involving the affected limb of 12 chronic stroke subjects. The experimental results showed that classification performance could be improved with spatial filtering and be maintained with a limited number of electrodes. It was also found that appropriate adjustment of analysis window length, sampling rate, and high-pass cut-off frequency in sEMG conditioning and processing would be potentially useful in reducing computational cost and meanwhile ensuring classification performance. The quantitative analyses are useful for practical myoelectric control toward improved stroke rehabilitation.

1. Introduction

Surface electromyography (sEMG) contains rich motor control information from which the user's intention can be identified with appropriate signal processing methods [1]. sEMG signals recorded from residual muscles of amputee subjects have been used for prosthesis control for many years [1]. In recent years, myoelectric control was also used in robot-aided therapy for stroke rehabilitation. Compared with involuntary exercise, voluntary task implementation (triggered or regulated by sEMG signals from stroke subject's paretic limb [2–4]) is a more useful intervention for enhanced therapeutic effect [2–10].

For conventional myoelectric control, sEMG amplitude from a pair of agonist–antagonist muscles is used to control a one-degree of freedom (DOF) movement [1]. In pattern-recognition-based myoelectric control, multiple sEMG electrodes or even high-density electrode arrays have been utilized to ensure recording of sufficient myoelectric control information regarding muscle co-activations [11–13,18,19,22–25]. Recently, myoelectric pattern recognition techniques have also been applied to individuals with neurologic injuries. In a previous study [17], we demonstrated that applying pattern recognition techniques to high density sEMG recordings achieved high accuracies in classification of 20 different movements involving the affected limb of stroke subjects.

In this study, several practical issues related to sEMG signal recording and processing were examined. First, the high density sEMG recording provides a convenient approach to examine the effect of various electrode configurations and number of sEMG channels on the classification performance. After then, the effects of sEMG analysis windows length, sampling rate and filter settings were further examined. Appropriate selection of these parameters may depend on a tradeoff between the classification accuracy and the requirement for implementing a practical system. For example, a longer analysis window would result in lower statistical variance of features and higher classification accuracy, but meanwhile it leads to a larger system delay [11]. Using a low sampling rate may reduce signal resolution and compromise classification accuracy, but dramatically reduce computational burden [16].

Although previous efforts regarding the above-mentioned issues have been made for sEMG classification in amputees or able-bodied subjects [16,19], these issues have not been examined in partially paralyzed muscles after stroke. It is necessary to quantitatively analyze the effect of sEMG signal recording and processing parameters on classification accuracy in individuals with a different nature of injury from amputation (i.e. stroke). The findings from such analyses will be used to determine the optimal parameter values that will facilitate the implementation of pattern-recognition-based myoelectric control for stroke rehabilitation.

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2. Methods

2.1. Dataset description

The dataset was recorded from 12 chronic stroke subjects (8 males, 4 females, 61 ± 10 years), as reported in [17], where the demographic and clinical assessment information for all subjects can be found. The study was approved by Institutional Review Board of Northwestern University (Chicago, IL, USA). Written informed consent was obtained from all subjects prior to the experiment. During the experiment, each subject was comfortably seated and asked to follow a video demonstration and perform 20 functional movements using the affected limb. The 20 movements included wrist flexion/extension, wrist supination/pronation, elbow flexion/extension, hand open/close, thumb flexion/extension, index finger flexion/extension, finger 3–5 flexion/extension, fine pinch, lateral pinch, tip pinch, gun posture and ulnar wrist down/up. Each subject was asked to complete 20 experimental trials, with 5 repetitions of about 3-s muscle contraction of a same movement in each trial. Between the consecutive trials, the subjects were allowed to take a sufficient rest to avoid muscular and mental fatigue.

89 electrodes were used to record high-density sEMG signals in a "monopolar" manner (there was indeed a subtraction of common feedback, namely the mean of all the recording channels, provided to each channel) from the affected arm and hand (Fig. 1) using a Refa EMG recording system (TMS International BV, Enschede, Netherlands). The details of the electrodes placement can be found in [17]. The sEMG signals were collected with a sampling rate of 2 kHz per channel with a band pass filter between 20 and 500 Hz.

2.2. Data processing and pattern recognition

The collected sEMG signals were processed offline with Matlab (ver. 2012a, the Mathworks, Natick, MA). The onset and offset of each movement repetition were manually determined from the sEMG signal stream. Electromyogram feature extraction was performed for each 256 ms window, incremented in 64 ms segments throughout each movement repetition. The feature set consisted of four time domain (TD) statistics: number of zero crossings, waveform length, number of slope sign changes, and mean absolute value. These measures were calculated for each sEMG signal from the 89 channels [11–15]. Finally, a linear discriminant classifier (LDC) [20] based on the maximum a-posteriori probability rule and Bayesian principle was chosen to get the classification results in a user-specific manner. For each subject, the data from first 4 repetitions were assigned as the training dataset and the data from the last repetition (i.e. the fifth) were referred to as the testing dataset. The classification accuracy was defined as the percentage of correct decisions to total number of testing samples for each subject.

2.3. Practical issues

With the attempt to build a robust myoelectric control system toward improved stroke rehabilitation, the following practical issues were examined sequentially in this study.

2.3.1. Spatial filters

The effect of different electrode configurations on classification performance was examined by implementing 5 spatial filters including single differential filter in transverse direction (SDT), single differential filter in longitudinal direction (SDL), double differential filter in transverse direction (DDT), double differential filter in longitudinal direction (DDL), and Laplace filter (LapD). Each spatial filter corresponded to an electrode configuration (Table 1) comprised of several neighboring monopolar electrodes with different weights.

2.3.2. Channel reduction

To select a clinically applicable small number of sEMG channels, an electrode selection algorithm based on the sequential forward searching (SFS) method [14] was used, which iteratively added the most informative channels till the classification performance was regarded to be acceptable or comparable with that of all the 89 channels.

2.3.3. Window length adjustment

Each pattern decision was produced from an analysis window within the continuous sEMG signal stream. In this study the analysis window length was originally set at 256 ms [17]. It was then adjusted from 64 to 512 ms with a 64 ms increment, and the dependence of the classification performance on the analysis window length was examined.

2.3.4. Re-sampling

The sEMG signals were acquired with a sampling rate of 2 kHz per channel. In this study, the sEMG signals were down-sampled from 2000 to 200 Hz in 50 Hz decrements. The dependence of the classification performance on the reduced sampling rate was examined. In signal down-sampling process, Matlab used a proper anti-aliasing (low-pass) finite-impulse-response (FIR) filter with a cut-off frequency that was half of the corresponding down-sampling rate to the original sEMG data.

2.3.5. Re-filtering

The original sEMG signals were filtered by a system band-pass filter at 20–500 Hz to remove motion artifacts and high frequency noise. To examine the dependence of cut-off frequencies of a high-pass filter on the classification performance, the original sEMG data were digitally re-filtered by a high-pass filter (6th order digital Butterworth filter) with a gradually increasing cut-off frequency from 20 to 120 Hz with a 5-Hz increment, and then the classification accuracy was re-calculated for each new cut-off frequency.

2.4. Statistical analysis

The one-way repeated-measure analysis of variance (ANOVA) was applied on the classification accuracy. The level of statistical significance was set to $p < 0.05$ for all analyses. When necessary, post hoc pairwise multiple comparisons with Bonferroni correction were used. All statistical analyses were completed using SPSS software (ver. 16.0, SPSS Inc. Chicago, IL).

3. Results

3.1. Spatial filtering results

The classification accuracies of different spatially filtered sEMG signals were averaged over 12 stroke subjects (Fig. 2). It was observed that the mean accuracy of 94% was achieved by the unfiltered monopolar (MN) sEMG signals while the accuracy slightly improved with different spatial filters. However, the ANOVA showed that there was no significant difference in classification accuracy among spatial filters (main effect: $p = 0.074$). Relying on the high-density sEMG recordings, the unfiltered MN-sEMG signals still yielded very high-classification accuracy (close to 100%) for some subjects, making it difficult to examine the performance improvement due to the spatial filtering. With this concern, we divided 12 stroke subjects into two groups: one was termed as group A including 7 subjects with unfiltered MN accuracy higher