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Classification of Upper Limb Motions in Stroke Using High Density Surface EMG

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Abstract—**Myoelectric pattern recognition techniques have been developed to infer user's intention of performing different functional movements, which can be used to provide volitional control of assisted devices for people with disabilities. The pattern recognition based myoelectric control systems have rarely been designed for stroke survivors. Aiming at developing such a system for stroke rehabilitation, this study assessed the myoelectric control information remained in the affected limb of stroke survivors using high density surface electromyogram (EMG) recording and pattern recognition techniques. The experimental results from 3 stroke subjects indicate that high accuracies (92.42% ± 5.51%) can be achieved in classification of 20 different intended movements of the affected limb. This study confirms that substantial motor control command can be extracted from paretic muscles of stroke survivors, potentially facilitating their rehabilitation.**

I. Introduction

Stroke is a leading cause of serious, long-term disability in many countries. Approximately 15 million people from all over the world suffer from stroke each year among which 5 million people are permanently disabled [1]. The most common disability following stroke is a physically functional restriction, such as weakness and hemiparesis [1]-[3], which could impact the quality of life for patients after stroke. Specifically, upper limb dexterity is likely to be affected severely, therefore it is crucial to effectively restore the functionality of hand and forearm for stroke survivors, due to the importance of the upper limb in daily activities.

A number of mechatronic devices have been designed as assistive tools for stroke rehabilitation [3], [4]. A practical way for restoration of upper-limb functionality is by providing volitional control of assistive devices to people following stroke [2]-[4].

In myoelectric control systems, surface electromyographic (EMG) signals contain rich information in the form of muscular activities, from which the user's intention can be detected for control purpose [5]. For people following stroke, the myoelectric control has also been reported in robot-aided therapy and can be generally categorized in "on-off" control [4] and proportional control [3]. Such applications are usually implemented to map the EMG of a single weak muscle to a single degree-of-freedom (DOF) of control that is able to trigger the activation of the same muscle.

Recently, pattern recognition techniques have attracted increasing attention in the development of myoelectric control systems [5], which operate on the assumption that the features extracted from EMG signals at given electrode placement reflect the inherent activity patterns of multiple muscles [6]. The use of EMG pattern classification provides us with great opportunity to identify various movements and control more DOFs.

However, there are still great challenges in extending EMG pattern recognition technique to myoelectric control of assistive devices for stroke survivors, due to their neuromuscular impairments [2]. We hypothesize that the intention of stroke survivors to perform various movements could be possibly identified through EMG analysis, although it is difficult for them to perform exact functional tasks with their affected upper limb. In order to assess the feasibility of extracting motor control information for building myoelectric control systems based on pattern recognition techniques, EMG signals were recorded and analyzed from stroke patients using a high density surface electrode arrangement, during their performance of 20 different intended arm, hand, and finger/thumb movements in the affected side.

This report is organized in four sessions. The next session describes the methods of the multichannel surface EMG recording and processing used in this study, followed by a description and discussion of the preliminary experimental results in Session III. Finally, the conclusion and future work are presented in Session IV.

II. Method

A. EMG Measurement

High density surface EMG signals consisting of 89 channels were collected above the upper arm, forearm and hand muscles in the affected side of each stroke subject. A Refa128 EEG/EMG system (TMS International BV, Enschede, Netherlands) was used for the recording.

Fig. 1 illustrates the placement of the electrodes, using the left arm as an example. In order to locate every electrode position conveniently, all of the 89 electrodes were arranged in several groups. A detailed description of the electrode positions is presented in Fig. 1(b). Since both the upper arm and the forearm can be approximately considered as cylinders, there were 80 electrode positions arranged in a grid

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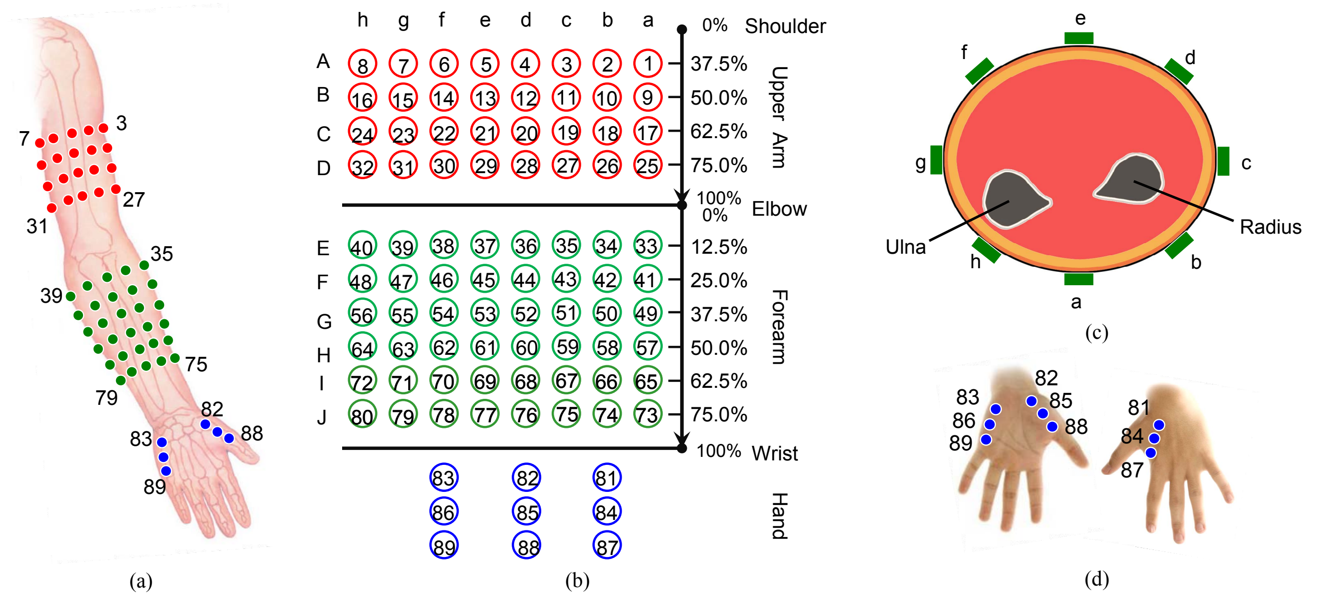


Fig. 1. The electrode placement for 89-channel EMG signal recordings: (a) Schematic diagram of electrode placement with numbers indicating the index of EMG channel. Only the electrode positions on the anterior aspect of upper arm, forearm and hand are visible. (b) Electrode arrangement in a grid formation with 10 round groups and 8 lateral line groups. The open circles with channel index number inside represent the surface EMG electrodes. (c) The cross section of forearm through round group H in the middle of forearm. (d) The positions of 9 electrodes targeting three hand muscles respectively.

formation with 10 round groups labeled with uppercase letters from "A" to "J", and 8 lateral groups labeled with lowercase letters from "a" to "h". The round groups labeled from "A" to "D" were placed on the upper arm at a location from 37.5% to 75% for every 12.5% of the entire distance from the greater tubercle of the humerus to the medial epicondyle of the humerus, respectively. Similarly on the forearm, the round groups labeled from "E" to "J" were placed at a location from 12.5% to 75% for every 12.5% of the entire distance from the medial epicondyle of the humerus to the styloid process of the ulna, respectively. In each round group, 8 electrodes were equally spaced around the circumference of the arm, and each of them also belonged to a different lateral group, as shown in Fig. 1(c). The electrodes in lateral group "a" were placed in a line formation which was along the center of the posterior side of the upper arm or forearm, whereas the lateral group "e" was along the center of the anterior side of the upper arm or forearm. On the hand, the remaining 9 electrodes were divided into 3 groups (with 3 for each), which were placed to target the first dorsal interosseous (FDI), thenar group and hypothenar group muscles, as shown in Fig.1(d). The size of each individual electrode is 8 mm in diameter while the recording surface is 3 mm in diameter. After the recording surface was filled with conductive gel using a syringe, the electrode was then attached to the skin using a double-sided adhesive disc. The center to center distance between two consecutive electrodes depends on the size of the arm. Generally, the distance between two round groups is approximately 10 mm, and the distance between two lateral groups is approximately 15 mm. The surface EMG signals were sampled at 2 kHz per channel. All the 89 channels of surface EMG signals were able to be continuously monitored through the entire procedure of the experiment.

B. Experimental Protocol

Three subjects with chronic stroke, one female and two males, participated in this study. The study was approved by the Institutional Review Board (IRB) of Northwestern University. All the subjects gave their consent forms before the experiment.

Each subject was seated upright on a chair with the elbow in flexion of about 90° and allowed to put their forearm on a height-adjustable table, to have the upper-limb rest entirely. The subject was asked to perform 20 functional movements as listed in Table I. During the experiment, a video of each movement performed by an intact individual served as the demonstration for guiding the stroke subject to perform (or intend to perform) each movement, although sometimes it was difficult for the stroke subject to smoothly or successfully perform a fine task by the affected upper limb.

The experiment comprised of 20 trials. Each experimental trial contained 5 repetitions of one movement. For each repetition of a movement, the subject was asked to comfortably implement the task with muscle contraction at a moderate force, to hold the implementation for 3 seconds and then to relax for a rest period of 5-20 seconds between repetitions. The subject was allowed to rest for 3-5 minutes between trials to avoid muscular and mental fatigue.

C. Data Preprocessing and Segmentation

The collected surface EMG signals were first processed with a fourth order Butterworth band pass filter (30-500 Hz) to remove the movement artifacts and noises.

For each movement, the recorded EMG data were composed of 5 active segments corresponding to 5 repetitions

TABLE I

LIST OF THE FUNCTIONAL MOVEMENTS

Index	Movement	Index	Movement
1	Wrist Flexion	2	Wrist Extension
3	Wrist Supination	4	Wrist Pronation
5	Elbow Flexion	6	Elbow Extension
7	Hand Open	8	Hand Close
9	Thumb Extension	10	Thumb Flexion
11	Index Finger Flexion	12	Index Finger Extension
13	Fingers 3-5 Flexion	14	Fingers 3-5 Extension
15	Fine Pinch	16	Lateral Pinch
17	Tip Pinch	18	Gun Posture
19	Ulnar Wrist	20	Ulnar Wrist Up

of muscle contraction. A data segmentation scheme was used to manually determine the onset and offset of the active segments for each movement class. Several signal channels with clear EMG activities and quiescent baseline in between were chosen and then averaged as a single data stream, as shown in Fig. 2. Subsequently, the onset and offset times of each active segment were identified by setting a threshold in a way that the amplitude of the averaged data stream above the threshold indicated the active segment. This resulting segmentation was simultaneously applied on all the channels for the trial.

For each active segment, 89-channel EMG data were further segmented into a series of analysis windows with a window length of 256 ms and a window increment of 128ms. The following EMG feature extraction and pattern classification were then performed on these analysis windows. The overlapped windowing scheme was used to enhance both utilization of limited data stream and continuity of decision output by the classifier.

D. Feature Extraction

For each analysis window, a set of features was extracted to represent the EMG data for classification of intended movements. In this study, a time-domain (TD) feature set consisting of four TD statistics of EMG signals was computed on each of the 89 EMG channels. The TD feature set included mean absolute value (MAV), number of zero crossings (ZC), number of slope sign changes (SSC), and waveform length (WL) of EMG signal. These features were chosen because of their low computational complexity and high classification performance [2]. Thus, these TD features from all 89 channels were concatenated together to formulate a 356-dimensional feature vector for each analysis window.

E. Classification

User-specific classification was conducted to train and evaluate classifiers using the dataset collected from the same subject. There are 5 active segments for each movement. The classification of movements was carried out using the five-fold cross-validation scheme: the EMG data of 4 active segments were assigned as training data, and sequentially the EMG data of the other remaining active segment were referred to as the testing data.

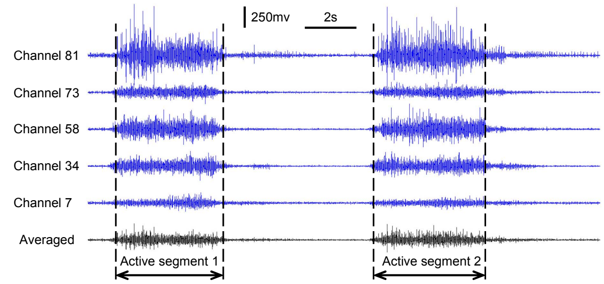
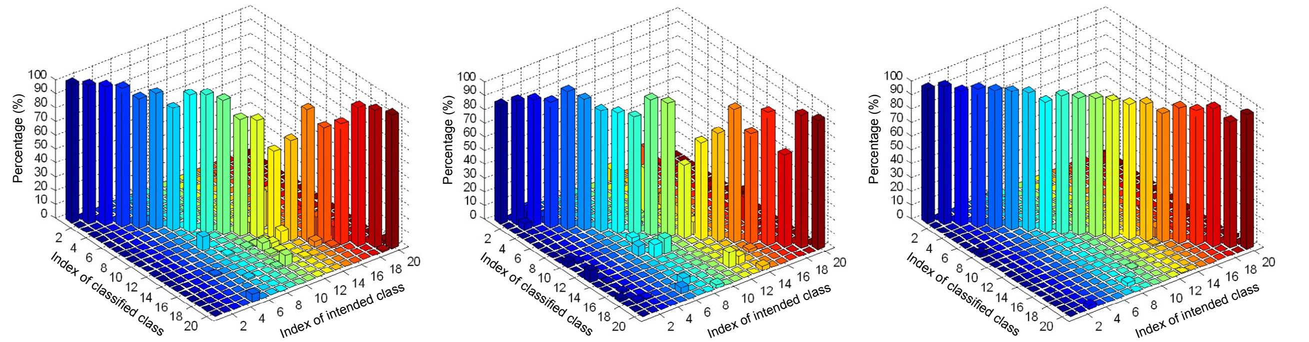


Fig. 2. Filtered surface EMG signals from randomly chosen channels during the movement of hand open with 2 repetitions. Then, the signal of three channels: 81, 58 and 34, are chosen to calculate the averaged signal stream for data segmentation.

In this study, the high-density surface EMG recording resulted in 356-dimensional feature vectors for pattern classification. It could be problematic to directly feed classifiers with such high-order feature vectors due to the "curse of dimensionality" [6], which means that high dimensional data is difficult to work with because much more training data is required to get good estimates for classification. Therefore, dimensionality reduction techniques needed to be employed for better classification performance and computational efficiency, before training and testing classifiers. Principle component analysis (PCA) and linear discriminant analysis (LDA) are two well-known linear dimensionality reduction algorithms which have also been designed to improve classification accuracies [7]. We utilized both of them in a two-stage PCA+LDA approach. The first stage was the use of PCA, which employed an orthogonal transformation to convert a set of high dimensional feature vectors into a set of uncorrelated lower dimensional feature vectors called principal components, while preserving as much of the variance in the original high-dimensional feature space as possible. The number of principal components could be chosen less than or equal to the dimension of the original feature space. In this study, forty principal components were chosen to form the PCA transformation matrix, so that the feature vectors were first compressed into 40 dimensions. After that, the LDA was applied on the following stage to find an optimal linear transformation to a lower dimensional feature spaces by maximizing the ratio of between-class scatter against within-class scatter, given a set of high dimensional feature vectors grouped by classes. LDA approach is able to produce feature projections to at most C-1 dimensions, where C is the total number of classes (here, C=20). The introduction of PCA and LDA algorithms can be found in [7]. The transformation matrices of PCA and LDA were calculated respectively based on the training dataset, and then were applied to both the training and testing dataset. Consequently, as the result of PCA+LDA, the dimension of feature vectors was significantly reduced through the projection from the original 356-dimensional space into the resulting 19-dimensional feature space.

Then, the support vector machine (SVM) was used for



(a) Overall accuracy of 92.04% (b) Overall accuracy of 87.11% (c) Overall accuracy of 98.11%

Fig. 3. The three-dimensional bar charts of the confusion matrices of the user-specific classification per subject: (a) Subject 1, (b) Subject 2, and (c) Subject 3. Note that the diagonal elements denote the correct classification rates and the off-diagonal elements represent error rates of misclassification that a movement of one class is classified into another class.

movement classification, with its advantages in dealing with limited data samples, high dimensional and nonlinear pattern recognition. The SVM is a kernel-based approach, which finds a linear separating hyperplane with maximal margin in a higher dimensional feature space, where the training data are mapped using a nonlinear kernel function. In this work, the library for SVMs (LIBSVM) developed by Chang et al. [8] was used to implement the SVM classifiers, and the radial basis function (RBF) kernel, which was generally used and recommended by LIBSVM software, was chosen to create nonlinear decision boundaries of classifiers.

III. Experimental Results

According to the five-fold cross-validation scheme, each of the five repetitions of one movement was assigned as testing dataset in turn, and the user-specific classifiers were trained on the remaining training data of each subject. The classification results from all the five-fold testing were summarized to generate the confusion matrices for the classification of 20 functional movements. Fig. 3 shows the three-dimensional bar charts of the confusion matrices of the user-specific classification per subject. Generally, the subjects' intention of performing 20 different functional movements can be successfully indentified with the overall classification accuracies of 92.04%, 87.11% and 98.11% for three subjects respectively. The user-specific classifiers were able to distinguish functional movements in stroke with the mean rates of 92.42% ± 5.51% for all three subjects, despite a few movements were partly misclassified into others with low classification rates for Subject 1 and 2, whereas almost all the functional movements performed by Subject 3 were correctly identified with high rates close to 100%.

Based on the use of high density surface EMG recordings, the overall user-specific classification accuracies obtained in this study to recognize 20 movement classes were even higher than the classification accuracies presented in pilot study by Lee *et al.* [2], which utilized 10-channel differential EMG to recognize 6 hand tasks. Thus, the sufficient information associated with the movement intent of stroke survivors can be captured using high density surface EMG measurement. This confirms the rich control information remained in the paretic muscles of stroke survivors and motivates our potential efforts to develop optimal myoelectric control schemes for stroke rehabilitation.

IV. Conclusion and Future Work

This paper presents an initial stage of the work on high density surface EMG recording and processing, towards improved myoelectric control of assisted devices designed for stroke rehabilitation. The preliminary experimental results demonstrate the feasibility of applying pattern recognition techniques on high density surface EMG to reliably identify the movement intent of stroke survivors. Future work will concentrate on the development of advanced EMG feature extraction and pattern classification algorithms to further improve the performance of movement classification. Moreover, considering requirement of a real time myoelectric control system implementation, we will also examine and optimize different strategies of EMG electrode configuration, channel reduction, feature selection and compression, and other related issues.

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