Application of Wavelet Packet Transform on Myoelectric Pattern Recognition for Upper Limb Rehabilitation after Stroke

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Abstract—**Myoelectric pattern recognition applied to high-density surface electromyographic (sEMG) recordings from paretic muscles has been proven to identify various movement intents of stroke survivors, thus facilitating the design of myoelectrically controlled robotic systems for recovery of upper-limb dexterity. Aiming at effectively decoding neural control information under the condition of neurological injury following stroke, this paper further investigates the application of wavelet packet transform (WPT) on myoelectric feature extraction to identify 20 functional movements performed by the paretic upper limb of 4 chronic stroke subjects. The WPT was used to decompose the original sEMG signals via a tree of subspaces, where optimal ones were selected in term of the classification efficacy. The energies in the selected subspaces were calculated as optimal wavelet packet features, which were finally fed into a linear discriminant classifier. The WPT-based myoelectric feature extraction approach achieved accuracies above 94% for all subjects in a user-specific condition, demonstrating its potential applications in upper limb rehabilitation after stroke.**

I. Introduction

The restoration of upper-limb function is of great importance and a challenging task in stroke rehabilitation due to the dexterity of arm and hand. For this purpose, numerous upper-limb robotic devices have been designed as assistive tools for promoting upper limb motor recovery [1]. Some recently developed devices involve interactive control which enables active response to user's intention during the rehabilitation training. Such active approach has proven to be more effective on motor functional improvement in upper limb [2]. Therefore, the implementation of a voluntary control is always preferred in developing robot-aided upper limb rehabilitation after stroke.

Myoelectric control is one of the most commonly reported techniques for voluntary control of assistive devices using electromyographic (EMG) signal [3], which is an electrical manifestation of muscle activation according to user's motor intention. The recent development of myoelectric control of upper-limb robotic systems is mainly based on a simple control strategy that the EMG of a single weak muscle is mapped to a single degree-of-freedom (DOF). Considering the complexity of functional movements performed by multiple muscles of upper limb, it is unfeasible to implement control of multiple DOFs through the single mapping between a muscle and a DOF. By contrast, pattern recognition technique has shown great potential for implementing multi-DOF myoelectric control [2], [4]. The myoelectric pattern recognition has been widely applied to the control of intelligent prostheses for amputees [3]. The use of myoelectric pattern recognition to distinguish intended functional tasks performed by the paretic upper limb of stroke survivors was firstly reported by Lee *et al.* [4]. Our pilot study further demonstrated the feasibility of identifying movement intentions of stroke survivors for control purpose by applying pattern recognition techniques to high-density EMG recordings from paretic muscles [2].

Inspired by our previous finding, further investigation into the myoelectric pattern-recognition methods is demanded for sufficiently decoding neural control information from paretic muscles, with our vision to offer multi-DOF control facilitating the recovery of upper limb dexterity after stroke. Specifically, EMG feature extraction is the prerequisite to myoelectric pattern recognition. A variety of methods for EMG feature extraction have been examined by using both time-domain and frequency-domain analyses [6-7]. However, this task becomes even challenging for stroke survivors due to affected EMG characteristics as a result of their neurological impairments [11]. Therefore, it is crucial to reexamine an appropriate approach that is able to extract separable and repeatable features from the EMG signals under the specifically considered condition (i.e., hemiparesis after stroke). Time-frequency analysis has been reported to provide a better understanding and description of the nature of non-stationary biosignals like EMG in time-frequency domain, thus improving the signal classification as well [12-13]. As a representative method for time-frequency analysis, wavelet packet transform (WPT) was applied to EMG feature extraction in the current study.

Although previous efforts regarding the WPT-based feature extraction have been made for pattern-recognition-based myoelectric control in amputees or able-bodied subjects, the utility of this method has not been examined in partially paralyzed muscles after stroke. The advancement of wavelet packet analysis of a raw EMG signal with high resolution in both time and frequency domains makes it feasible to extract discriminable features highly associated with movement intentions of the paretic upper limb. The findings from the current investigation may be helpful to implement a pattern-recognition-based myoelectric control system designed for rehabilitation training of upper limb after stroke.

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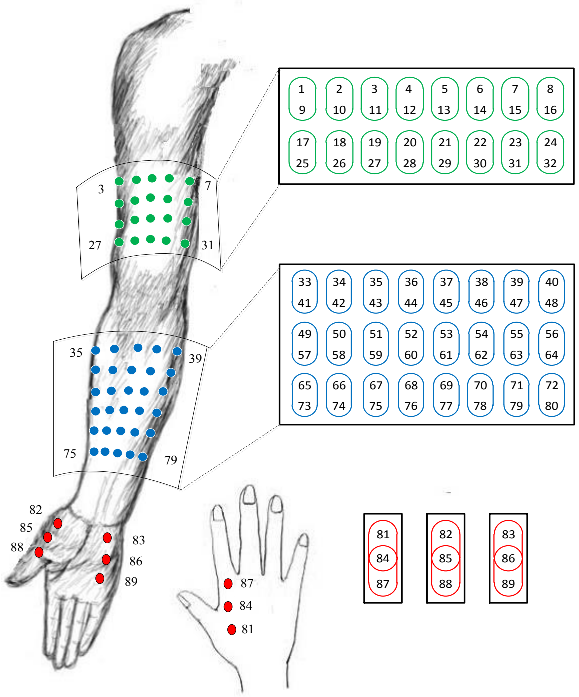

Fig. 1. Illustration of the electrode placement for 46-channel bipolar surface EMG signal recordings derived from previous 89-channel monopolar surface EMG database.

II. Methods

A. Dataset Description

The dataset used in this study was selected from a database recorded in our pilot study [2], which was approved by the Institute Review Board of Northwestern University (Chicago, IL). This database included high-density surface EMG recordings from chronic stroke subjects with hemiparesis during their performance of different functional movements involving the affected upper limb, notably the affected hand. The data of four stroke subjects (labeled as Sub1-Sub4, corresponding to the subject index 1, 3, 9 and 10 in [2]) were preliminarily selected to form the dataset for testing the myoelectric pattern recognition methods in this study. The detailed demographic and clinical measures for experimental subjects can be found in [2]. All subjects gave their informed consent before the experiment.

During the experiment, each subject was instructed to perform 20 functional movements using the affected upper limb, namely 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. A video demonstration of each movement was also shown as a guide for subjects to follow and perform the movements. The experiment protocol comprised of 20 trials, each trial consisting of 5 repetitions of the same movement pattern. For each repetition, the subject was asked to hold the muscle contraction for roughly 3 s and then relaxed for a rest period of 5-20 seconds.

The high-density surface EMG signals in the original database were recorded via 89 monopolar surface electrodes placed on the affected upper arm, forearm and hand muscles. A Refa EMG recording system (TMS International BV, Enschede, Netherlands) with built-in band-pass filter between 20 and 500 Hz was used for multi-channel EMG recording at a sampling rate of 2 kHz per channel. Due to the advantage of using bipolar (i.e., single differential) EMG recording to improve myoelectric classification performance and its indeed more clinical relevance, the 46-channel bipolar surface EMG data were produced from the original 89-channel EMG recordings. The detailed information about the electrode formation and single spatial differential filter was shown in Fig. 1.

B. Data Segmentation

The onset and offset of a voluntary EMG activity segment corresponding to each repetition of muscle contraction needed to be determined first, for all the movement patterns. Such information has already included in the database by [2], and was directly applied to the selected dataset.

For each repetition of muscle contraction, the EMG activity segment in a form of multiple channels was further segmented into a series of overlapping analysis windows with a window length of 256 ms and an overlapping rate of 75% for two consecutive windows. Consequently, the following feature extraction and classification procedure was performed on these analysis windows.

C. Feature Extraction using WPT

The WPT was a generalized version of classical wavelet decomposition method that offers a multi-resolution and time–frequency analysis of non-stationary signals, especially biomedical signals. The WPT is able to split a signal into a detail and an approximation. The approximation and detail obtained from the top-level can be further split into a new detail and a new approximation, and this process can be iteratively performed to a targeted depth. Consequently, the WPT generates a binary tree structure of subspaces spanned by a set of bases, to which a signal can be mapped for multi-resolution analysis. Such characteristics allow WPT to be successfully applied to feature extraction in the fields of pattern recognition and machine learning [9-10].

The WPT using 5-order symlet wavelet was first applied to each channel of an analysis window for EMG feature extraction according to [11]. For WPT analysis, the depth of WPT is an important factor. It is acknowledged that a small depth cannot yield sufficient resolution for extraction effective features, whereas a large depth leads to much more computational complexity. By considering this trade-off, the WPT depth of 3 or 4 has been recommended by previous studies [11]. The WPT depth of 4 was finally chosen after some pretests in term of classification performance. After the WPT, the energy values of all subspaces were calculated as features, where the energy of each subspace was defined as a logarithmic value of the summation of all wavelet packet coefficients in the subspace.

D. Feature Selection using Best Basis Selection

For each channel of an analysis window, the features extracted from all subspaces arranged in the binary tree structure were regarded to carry redundant information due to the signal overlap across levels. A great number of redundant

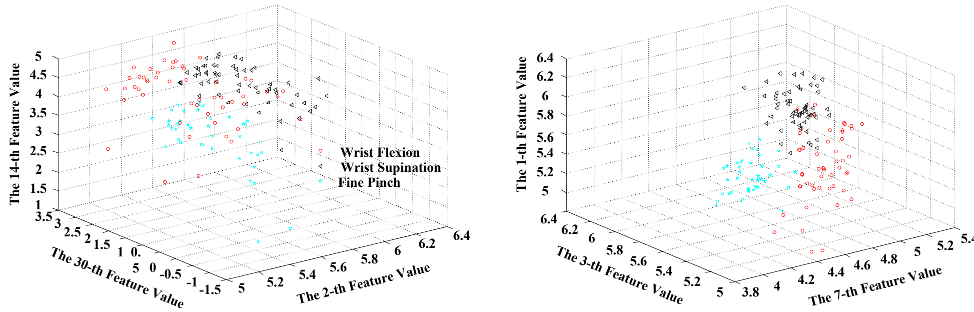

Fig. 2. Comparing the effect of FCSI index values on separability. Three upper-limb movements (wrist flexion, wrist supination, fine pinch) in the 18-th channel from subject 2 are selected to produce the scotter plots. The three-dimensional coordinate axes stand for feature value of the selected index of subspaces(labeled from 1 to 30 due to four levels of WPT) from binary structure of WPT, respectively. (a) three features with lower FCSI index value (b) three features with higher FCSI index value.

features were likely to lead high computational cost and to compromise classification performance. Therefore, a feature selection procedure relying on the selection of the best bases was further performed, involving a criterion of best distinction among classes [12]. In this study, Fisher's class separability index (FCSI), described in [13], was employed as a criterion for best basis selection, which is introduced below.

Suppose that $f_{n,j}^{k}$ represents the energy feature from a basis derived from the n-th channel ($1 \leq n \leq N$, here N=46) of the j-th sample/analysis window ($1 \leq j \leq J_k$) belonging to the k-th class ($1 \leq k \leq K$, here K=20). The mean and standard deviation of these features for the basis can be calculated as:

$$\bar{m}_n^k = \frac{1}{J_k}\sum_{j=1}^{J_k} f_{n,j}^{k}, \quad (1)$$

$$s_n^k = \sqrt{\frac{1}{J_k}\sum_{j=1}^{J_k}(f_{n,j}^{k} - \bar{m}_n^k)^2}. \quad (2)$$

Thus, the FSCI for the basis was finally defined as:

$$\mathrm{FCSI} = \sum_{p=1}^{K-1}\sum_{q=p+1}^{K}\frac{(\bar{m}_n^p - \bar{m}_n^q)^2}{s_n^p + s_n^q}. \quad (3)$$

where p and q represent the indices of two different classes. Generally, a higher value of FCSI indicates higher degree of class separability for features extracted from a certain basis.

With the FSCI values derived from all bases, the best bases with highest values could be selected. It should be noted that for the number of selected bases, there was also a trade-off between the computational cost and classification performance. Thus, 12 bases with the highest FCSI values were optimally selected to produce 12 wavelet packet energy features for each channel. For an analysis window with 46 channels, these energy features from all channels were finally concatenated to form a 552-dimensional feature vector.

E. Feature Dimensionality Reduction and Classification

Even though a feature selection procedure based on the best basis selection algorithm was performed to optimally select 12 features from each channel, the high-density surface EMG recordings still resulted in very high-dimensional feature vectors (i.e., 552-dimensional feature vectors). In this case, feature dimensionality reduction is of great necessity to ensure the generalization capability of a classifier [14]. Taking into account the ULDA function of minimizing within-class distance and maximizing between-class distance by an optimal transformation, ULDA was used to reduce the feature dimension [15].

A linear discriminant classifier (LDC) was employed in this study for the pattern classification. The LDC is able to model the within-class density of each class as a multi-variant Gaussian distribution and gives decisions of unknown samples by using the maximum *a-posteriori* probability (MAP) rule and Bayesian principles. The LDC was used due to its ease of implementation and efficient classification performance [2], [4].

Pattern-recognition was performed in a user-specific manner, where both training dataset and testing dataset were derived from the same stroke subject. To evaluate

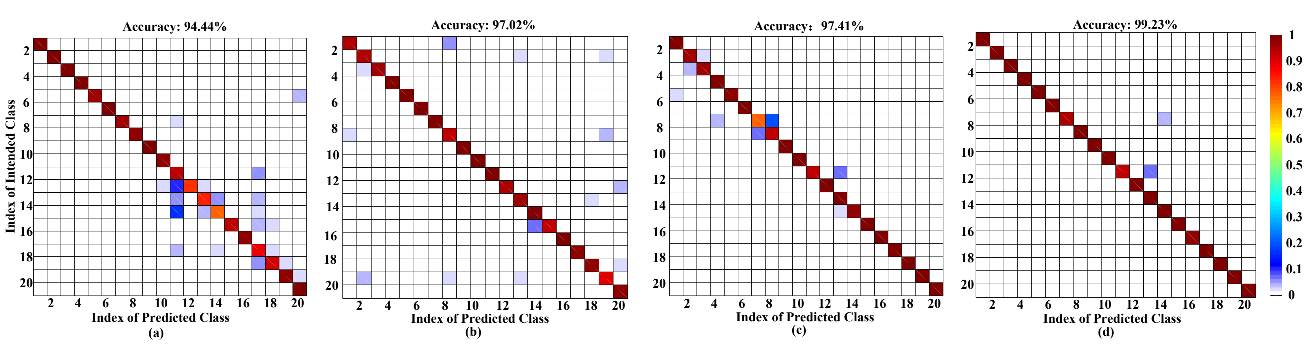

Fig. 3. The class-to-class pseudocolor plot of confusion matrices and classification accuracies derived from (a) Subject 1 (b) Subject 2 (c) Subject 3 (d) Subject 4, using the presented WPT features extracted from 46 channels. Results in confusion matrices are averaged across fivefold cross-validation and expressed as percentages. In each confusion matrix, the main diagonal elements represent the percentages of correct classifications accuracy for each class and others are error rates. The accuracies in the title are calculated by the ratio between the sum of main diagonal elements and the sum of the matrix elements.

classification performance, a five-fold cross-validation scheme was used. The EMG data during any four repetitions of muscle contraction were selected and assigned as training dataset, whereas the EMG data of the remaining repetition of muscle contraction were sequentially used to form the testing dataset. As a supervised pattern recognition procedure, the best basis selection and feature dimensionality reduction were determined only with training dataset, and then were applied to the testing dataset. Finally, the classification performance for each subject was evaluated as overall classification accuracy, which was calculated as the percentage of correctly classified windows over all the testing windows including all movement patterns over five-fold tests.

III. Results

A. Results of Best Basis Selection

Fig. 2 is a three-dimensional scatter plot to show effect of FCSI index values on class separability. Features with three lowest FCSI values (Fig. 2a) did not show good separability across three different classes as compared with features with three highest FCSI values (Fig. 2b). It indicates the effectiveness of WPT-based feature selection via best basis selection approach relying on FCSI.

B. Results of Classification

Fig. 3 depicts the movement pattern classification results in the form of confusion matrix for four subjects respectively. It can be found that high classification accuracies above 94% were achieved for all subjects. Examination of the confusion matrix results revealed that the misclassifications were not consistent among subjects. For example, the movement pattern with major misclassifications for subject 1 was fingers 3-5 extension, whereas it was hand open for subject 3.

IV. Discussion and Conclusion

In this paper, myoelectric pattern recognition based on wavelet packet transform was examined for identifying movement intentions from the affected limb of stroke survivors. In contrast to conventional prosthetic control using EMG signals from neurologically intact muscles, there are many unique challenges in the application of pattern recognition techniques on EMG from stroke survivors for driving assisted devices for rehabilitation purpose. For example, neural control information may not be convoyed sufficiently due to the affected neuromuscular pathway after stroke. Therefore, advanced pattern recognition techniques, especially effective feature extraction methods, need to be performed to sufficiently discover and decode neural control information hidden in the surface EMG recordings from partially paralyzed muscles. The WPT is such a powerful method, which is able to offer flexible time-frequency resolution of a signal, thus facilitating the extraction of many feature components containing discriminable information from a complex biosignal with the aid of best basis selection based on statistical criteria. Taking advantage of such properties of WPT, myoelectric pattern recognition based on WPT was examined for discriminating 20 different functional movements involving the affected limb of the stroke subjects.

The experiment results shows that high classification accuracies can be achieved for all 20 intended upper-limb movements across four subjects by using WPT as the tool of feature extraction. Among all four stoke subjects, the high accuracies above 94% were found. It indicates that the WPT can be applied to myoelectric pattern recognition for upper limb rehabilitation after stroke.

However, the high-density EMG recording is unfeasible to be clinically applied to myoelectric control of assistive devices. Therefore, it's necessary to reduce the number of channels. Considering the power of WPT feature selection based on WPT used in this paper, the potential of extending this approach into EMG channel selection needs to be examined. This remains our future work.

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