Real-time Classification of Finger Movements using Two-channel Surface Electromyography

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Abstract: The use of a small number of Electromyography (EMG) channels for classifying the finger movement is a challenging task. This paper proposes the recognition system for decoding the individual and combined finger movements using two channels surface EMG. The proposed system utilizes Spectral Regression Discriminant Analysis (SRDA) for dimensionality reduction, Extreme Learning Machine (ELM) for classification and the majority vote for the classification smoothness. The experimental results show that the proposed system was able to classify ten classes of individual and combined finger movements, offline and online with accuracy 97.96 % and 97.07% respectively.

1 INTRODUCTION

The electromyography signal has been used widely to control the upper-limb prosthetic robot to recover the quality of life of the amputee. Many attempts have been made to decode the hand movements as the control sources of the hand robot (Oskoei and Huosheng, 2008): (Sang Wook et al., 2011); (Micera et al., 2010). The dexterous control system should involve not only the hand movements but also the finger movements (Tenore et al., 2009); (Khushaba et al., 2012). Some efforts have been done to recognize the finger movements. Tenore et al decoded ten classes of the individual finger movements by using up to 32 sEMG channels with accuracy ~ 90% (Tenore et al., 2009). In addition, Al-Timemy et al (Al-Timemy et al., 2013) classified 15 individual finger movements and achieved 98 % accuracy by using 6 sEMG channels.

The use of few numbers of electrodes in a finger recognition system without compromising the decoding accuracy is a challenging task. Tsenov et al used two sEMG channels for 4 class finger movements i.e. the thumb, index, middle finger and hand closure with the best accuracy was nearly 93 % in offline classification (Tsenov et al., 2006). Moreover, Khusaba et al classified 10 classes of individual and combined finger movements which consisted of five individual finger movements by using two sEMG channels (Khushaba et al., 2012). This work could achive 92% and 90 % of accuracy for the offline and online classification respectively.

To achieve good classification results, it demands the proper and right decoding methods. Tsenov employed time domain feature extractions and Artificial Neural Networks (ANNs) to process the sEMG signals from two channels (Tsenov et al., 2006). This recognition system gave a good accuracy in offline classification but no evidence in online classification. In addition, this system only decoded for finger movements which were only three individual finger movements and one hand close. More finger movements are needed in real-time application.

The best improvement was proposed in (Khushaba et al., 2012). The sEMG signals from two channels were extracted by using time domain features and reduced by Linear Discriminant Analysis (LDA) and then classified by using Support Vector Machine. The final results were refined by using a Bayesian fusion vote. Ten classes of individuated and combined finger movements were able to recognize with 92 % offline classification accuracy and 90% online classification accuracy.

The achievement attained by previous system is good but not good enough for the implementation in real-time application. Many attempts should be made to achieve more accurate system recognition. For that goal, this paper proposes the novel recognition system which uses two sEMG channels

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in recognizing the individual and combined finger movements. A number of features are extracted by using time domain feature extraction and then reduced by using Spectral Regression Discriminant Analysis (SRDA) (Cai et al., 2008). SRDA is an extension of Linear Discriminant Analysis which is fast and able to work on a large dataset.

Extreme Learning Machine (ELM)(Huang et al., 2012) is used for classification. ELM is generalized" single-hidden-layer feedforward networks (SLFNs) whose hidden layer does not need to be tuned. It needs fewer optimization constraint, has better generalization functioning and faster learning time than SVM (Huang et al., 2012). This combination, SRDA and ELM along with the majority vote (Chan and Green, 2007), provide a fast and an accurate classification system for individuated and combined finger movements.

2 METHOD

2.1 Experiment Procedures

The data in this work were acquired from six subjects, one female and five males. All subjects were normally limbed with no muscle disorder. To avoid the effect of position movement on EMG signals, subject's arm was supported and fixed at certain position as decribed in fig. 2.(Khushaba et al., 2012).

The FlexComp Infiniti™ System from Thought Technology was used to process the signals from two EMG MyoScan™ T9503M Sensors which were put on the subject's forearm as seen in the figure 1. The acquired EMG signals were amplified to a total gain of 1000 and sampled at 2000 Hz.

The collected EMG signals were processed in the Matlab 2012b installed in the Intel Core i5 3.1 GHz desktop computer with 4 GB RAM running on Windows 7 operating system. The signals were filtered by a band pass filter between 20 and 500 Hz with a notch filter to remove the 50 Hz line interference. Finally, the EMG signals were down sampled to 1000 Hz.

Fig. 2 shows ten classes of the individual and combined finger movements consisting of the flexion of individuated fingers, i.e., Thumb (T), Index (I), Middle (M), Ring (R), Little (L) and the pinching of combined Thumb–Index (T–I), Thumb–Middle (T–M), Thumb–Ring (T–R), Thumb–Little (T–L), and the hand close (HC).

The offline classification was performed based on data from the data acquisition. In this stage, the subjects asked to perform a certain posture of a finger movement for a period 5 s and then take a rest for 5 s. Each movement was repeated six times. Therefore 30 minutes of data are collected for each trials and 180 minutes for all repetitions. The data collected were divided into training data and testing data. Four of six trials were training data and the rest were testing data.

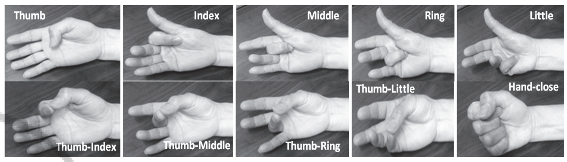

Figure 1: Ten different finger movements.

In the online stage, the subject performed similar activities. The difference is the repetition which is only four times instead of six and all are for testing only. Another difference is the recognition system is performed each 100 ms and then the result is displayed on the screen.

2.2 Proposed Method

The proposed recognition system consisted of two stages, an offline and online classification stages. In the offline stage, the EMG signals were acquired by a data acquisition device from 6 subjects. The filtering and windowing was applied to the collected data before being extracted by using a time domain feature set. To reduce the dimension of the features, SRDA was employed. Then, the reduced data were classified using ELM and refined by using the majority vote. The trained ELM which is produced by the offline classification is stored and used in the online classification stage.

Figure 2: The electrodes placement.

In the online stage, the trained ELM is restored and used to classify the sEMG signals which are captured every 100 ms. The acquired signals are extracted by using time domain feature extractions and reduced their dimensionality by using SRDA.

Then, the reduced features are recognized by the trained ELM and the output classification is refined by using majority vote.

2.3 Feature Extraction

The features were extracted from a time domain feature set which consists of Waveform Length (WL), Slope Sign Changes (SSC), Number of Zero Crossings (ZCC), and Sample Skewness (SS). In addition, some parameters from Hjorth Time Domain Parameters (HTD) and Auto Regressive (AR) Model Parameters were included as used in (Khushaba et al., 2012). All features were extracted by using myolectric toolbox (Chan and Green, 2007) and Biosig toolbox (Schlogl and Brunner, 2008).

The AR model parameters have been proven to be stable and robust to the electrode location shift and the change of signal level (Tkach et al., 2010). Moreover, aforementioned time domain features were windowed by using disjoint window instead of sliding window to keep computational cost low. A 100 ms window and a 100 increments were used to form a system which is suitable for real time application.

2.4 SRDA

SRDA is an improvement of LDA which is better than LDA in the computational aspect and the ability to cope with a large dataset (Cai et al., 2008). Let eigen problem of LDA is

$$\bar{X}W\bar{X}^T a = \lambda \bar{X}\bar{X}^T a \tag{1}$$

where $\bar{X}$ (1 x c) is centered data matrix, W is eigenvector matrix (m x m), λ = eigenvalue, a = transformation vector, c = the number of classes, and m = the number of total training data points. Modification of the equation (1) gives:

$$W\bar{y} = \lambda \bar{y} \tag{2}$$

where

$$\bar{X}^T a = \bar{y} \tag{3}$$

The solution of LDA problem by SRDA is to get y by solving eq (2) and then use the y obtained to find a. To solve a, the least square sense could be employed by using:

$$a = \arg\min_a \sum_{i=1}^{m} \left(a^T \bar{x}_i - \bar{y}_i \right)^2 \tag{4}$$

Regularize least square problem of SRDA, we get:

$$a = \arg\min_a \sum_{i=1}^{m} \left(\left(\bar{X}^T a - \bar{y} \right)^T \left(\bar{X}^T a - \bar{y} \right) + \alpha a^T a \right) \tag{5}$$

Derivative of equation (5) gives:

$$\begin{gathered} \left(\bar{X}\bar{X}^T + \alpha I \right) = \bar{X}\bar{y} \\ \Rightarrow a = \left(\bar{X}\bar{X}^T + \alpha I \right)^{-1} \bar{X}\bar{y} \end{gathered} \tag{6}$$

2.5 Extreme Learning Machine

ELM is a learning scheme for single layer feedforward networks (SLFNs). While the network parameters are tuned in classical SLFNs learning algorithms, most of these parameters are analytically determined in ELM. The hidden parameters can be independently determined from the training data, and the output parameters can be determined by pseudo-inverse method using the training data. As a result, the learning of ELM can be carried out extremely fast compared to the other learning algorithms (Huang et al., 2012).

The output function of ELM for generalized SLFNs (for one output node case) is:

$$f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = \mathbf{h(x)}\boldsymbol{\beta} \tag{7}$$

where $\boldsymbol{\beta} = \left[\beta_1, ..., \beta_L \right]^T$ is the vector of the output weight between hidden layer of L nodes and the output node, $\mathbf{h(x)} = \left[h_1(x), ..., h_L(x) \right]$ is the output vector of hidden layer.

The objective of ELM is to minimize the error and the norm of weight:

$$\text{Minimize}: \left\| \mathbf{H}\boldsymbol{\beta} - \mathbf{T} \right\|^2 \text{ and } \left\| \boldsymbol{\beta} \right\| \tag{8}$$

where **T** is the target. For classification purpose, the output function of ELM in equation (7) could be modified to be:

$$\mathrm{f(x)} = \mathbf{h(x)}\boldsymbol{\beta} = \mathbf{h(x)}\mathbf{H}^{\mathrm{T}} \left(\frac{1}{\mathrm{C}} + \mathbf{H}\mathbf{H}^{\mathrm{T}} \right)^{-1} \mathrm{T} \tag{9}$$

where

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}(\mathrm{x}_1) \\ \vdots \\ \mathbf{h}(\mathrm{x}_\mathrm{N}) \end{bmatrix} = \begin{bmatrix} h_1(\mathrm{x}_1) & \cdots & h_L(\mathrm{x}_1) \\ \vdots & \vdots & \vdots \\ h_1(\mathrm{x}_\mathrm{N}) & \cdots & h_L(\mathrm{x}_\mathrm{N}) \end{bmatrix} \tag{10}$$

as well as C is a user-specified parameter and N is the number of the training data. In the equation (10), h(x) is a feature mapping (hidden layer output vector) which can be:

$$h(x) = \left[G(a_1, b_1, x), ..., G(a_L, b_L, x)\right] \quad (11)$$

where G is a non-linear piecewise continuous function such as sigmoid, hard limit, Gaussian, and multi quadratic function.

If the feature mapping h(x) is unknown to the user, a kernel function can be used to represent h(x). Then, the equation (9) would be:

$$f(x) = \mathbf{h(x)H}^T\left(\frac{1}{C}+\mathbf{HH}^T\right)^{-1}T = \begin{bmatrix} K(x,x_1) \\ \vdots \\ K(x,x_N) \end{bmatrix}\left(\frac{1}{C}+\Omega_{ELM}\right)^{-1}T \quad (12)$$

where

$$\Omega_{ELM} = \mathbf{HH}^T : \Omega_{ELM i,j} = h(x_i).h(x_j) = K(x_i, x_j)$$

and K is a kernel function such that :

$$K(\mathbf{u}, \mathbf{v}) = \exp\left(-\gamma \left\|\mathbf{u}-\mathbf{v}\right\|^2\right) \quad (13)$$

2.6 Majority Vote

The majority vote was used to refine the classification results. It utilizes the results from the present state and *n* previous states and makes a new classification result based on the class which appears most frequent. This procedure produces the finger movement class that removes specious misclassification. Besides majority vote, the transition states in the classification results are removed too. This method gives the recognition system that works in steady state only regardless the transition state.

3 RESULT AND DISCUSSION

The two experiments have been performed, the offline and online classification. In the offline stage, the possibility of adding new channel which was extracted from summing up of two original channels is verified. Next, the best result of the offline stage was utilized in the online classification stage. In the both offline and online stage, the signals were extracted from six subjects with 100 ms windows length and100 increment as recommended in (Khushaba et al., 2012). In addition, the Gaussian kernel based ELM is used as the classifier. It has two importance parameters, C and γ as showed in equation 9 and 12. This paper used the optimized ELM presented in the (Anam et al., 2013) with the $\gamma=2^{-5}$ and $C=2^0$. The majority vote method with 9 decision voting was employed to refine the classification result.

The first experiment was the offline classification. In this stage, the performance of the classification system using only two original signals (ch1, ch2) was compared to the two signals plus the new additional channel from summing up of the both channels (ch1, ch2, ch1+ch2). From six trials across each subject, four trials were used to train the ELM and the rest were the testing data. The classification result is shown in the table 1.

Table 1: The classification results averaged for six subjects.

Subject	Ch1 & Ch2 (%)	Ch1, Ch2, Ch1+Ch2 (%)
1	98.48 ± 2.87	97.10 ± 4.13
2	100.00 ± 0	100.00 ± 0
3	94.95 ± 11.38	96.42 ± 8.26
4	98.61 ± 3.93	98.34 ± 4.02
5	98.89 ± 2.43	98.89 ± 3.51
6	93.81 ± 8.39	96.99 ± 5.49
Average	97.46 ± 2.35	97.96 ± 1.47

Table 1 shows that both configurations achieved good accuracies across six subjects. However, the additional signal of the summation of two channels gave better average accuracy than two channels only even though the difference is not so significant. The significance of the second configuration is depicted in figure 3. Even though both configurations achieve similar accuracy in recognizing the ten finger movements, the standard deviation of second one is better than first one.

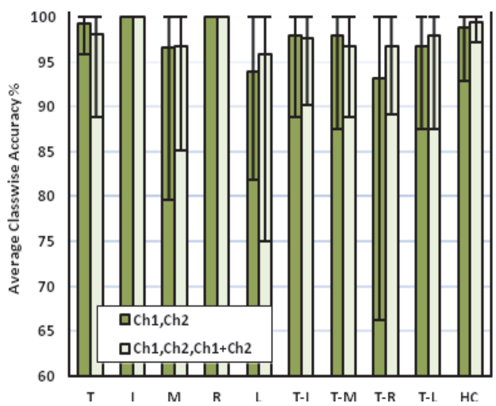

Figure 3: The Average class-wise accuracy in the offline classification.

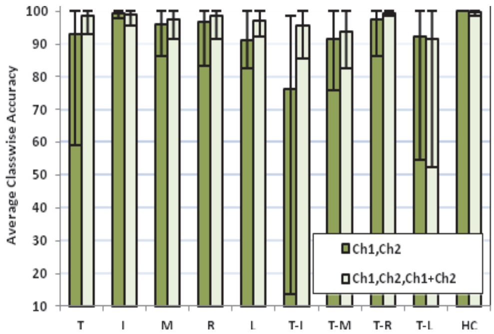

Figure 4: The online classification accuracy.

The online classification is the second experiments performed. The individual and combined finger movements were recognized in real-time based on the matrix projection of SRDA and the trained ELM kernel from offline stage. In this experiments, the configuration of (ch1, ch2) achieve 93.36 % accuracy while the (ch1,ch2, ch1+ch2) configuration attained better accuracy which is 97.07 %. The performance of finger recognition is depicted in the fig.4 and the table 2.

Table 2: The confusion matrix of the classification results averaged for SIX subjects.

		Intended task (%)									
		T	I	M	R	L	T-I	T-M	T-R	T-L	HC
Classified task (%)	T	98.7	0.1	0.0	0.0	0.0	0.9	0.0	0.0	0.0	0.3
	I	0.0	99.3	0.0	0.0	0.0	0.3	0.0	0.0	0.4	0.0
	M	0.0	0.0	98.0	0.2	0.0	0.0	1.3	0.0	0.0	0.5
	R	0.0	0.0	0.0	99.9	0.0	0.0	0.0	0.1	0.0	0.0
	L	1.1	0.0	0.0	0.0	97.2	0.6	0.0	0.0	0.1	1.0
	T-I	0.5	0.0	0.0	0.0	1.5	95.1	1.0	0.0	1.9	0.0
	T-M	0.0	0.0	0.9	0.0	0.7	1.3	96.1	0.0	0.1	1.0
	T-R	0.0	0.0	0.0	0.0	0.0	0.3	0.5	99.1	0.0	0.0
	T-L	0.0	0.1	0.0	0.0	6.0	0.3	0.7	0.5	92.3	0.0
	HC	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	99.8

Figure 4 shows that the T-L movement is the most difficult one to recognize. It was misclassified to the L movements as seen in the confusion matrix table 2. It was probably caused by the facts that the T-L was composed of Thumb(T) and Little(L) finger movement therefore there is possibility each movement affects the combined movements.

Besides the classification performance, the processing time of the real-time application has been also tested which the result is presented in table 3. The acquisition, filtering, feature extraction and reduction, ELM and majority vote processing time were record during the experiment. This recognition system took 112.13 ms in average. It is verified that processing time of this system is in between the optimal processing time for real-time myoelectric control, 100-125 ms, as suggested in (Farrell and Weir, 2007).

Table 3: The processing time of the online experiment.

	Processing time (ms)					
Class	Acquiring	Filter	Extraction /reduction	ELM	Vote	Total
T	100	3.9	7.6	0.5	0.1	112.1
I	100	3.5	7.2	0.5	0.1	111.3
M	100	3.5	7.3	0.5	0.1	111.4
R	100	3.6	7.4	0.5	0.1	111.6
L	100	3.7	7.6	0.6	0.1	111.9
T-I	100	3.5	7.3	0.5	0.1	111.4
T-M	100	3.6	7.5	0.5	0.1	111.7
T-R	100	3.6	7.6	0.6	0.1	111.8
T-L	100	3.5	7.3	0.5	0.1	111.4
HC	100	3.5	7.3	0.5	0.1	111.4
Avg	100	3.6	7.4	0.5	0.1	112.1

This promising result could be implemented to the hand exoskeleton to recover the motor function of the patients post stroke. It could move all individual fingers and some combined movements. However, it is aimed for finger extension only. In addition, it would not work properly if the EMG signal of the subject is very weak. Therefore, it could be only applied to the partially paralyzed subject.

Furthermore the proposed system could be implemented to the prosthetic hand device. It is promising because it used few electrodes which enhance the user's comfort. However, it needs more validation for amputee subjects.

4 CONCLUSIONS

The two channel sEMG signals were used in this paper to recognize the ten individual and combined finger movements. The extracting more feature from summation of the signals from the two channels improves the classification accuracy in both offline and online classification system. By using this combination, the recognition system was able to achieve in average 97.96 % in offline and 97.07% in online one. These results show the feasibility of the proposed system in classifying ten different finger movements.

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