Artificial Neural Network Classifier in Comparison with LDA and LS-SVM Classifiers to Recognize 52 Hand Postures and Movements

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Abstract— **Classification of postures and movements of distal limbs based on surface electromyography (sEMG) of proximal muscles is necessary in myoelectric hand prostheses. With increasing the number of movements, classification problem becomes a serious challenge. In this paper, we have used NINAPRO database that contains sEMG and kinematic data of upper limbs while performing 52 hand postures and movements. We evaluated the performance of MLP classifier in comparison with LDA and LS-SVM classifiers using different combinations of features. First by windowing the signal with two different methods, the major part of the signal was selected and eight various temporal features (MAV, IAV, RMS, WL, E, ER1, ER2, CC) were extracted. Then to achieve the best performance of each classifier, they were evaluated with single, double and multiple combinations of features. For MLP classifier, the best average classification accuracy of 96.34% was achieved for first windowing method and using combination of all features. The corresponding accuracy for LDA classifier (with first windowing method and MAV (or IAV) +CC features) was 84.23%. For LS-SVM classifier (with second windowing method and IAV+MAV+RMS+WL features), the best accuracy of 85.19% was obtained.**

Keywords- Extraction of motor commands; Hand prosthesis; LDA classifier; LS-SVM classifier; MLP classifier; Surface electromyography signal

I. INTRODUCTION

In recent decades, the performance of active hand prostheses has improved. These prostheses are commonly controlled by extraction of hand motor commands of amputees using surface electromyography (sEMG) signals. Gradually this technology was developed from controlling one movement, like hand opening and closing, to multifunction prosthesis control which can control several movements. In spite of refinements and appropriate commercial accessibility, the acceptance of these prosthesis is low among amputees. Because these prostheses are not user-friendly and fast enough for daily tasks. Researches mechatronics and robotics have shown that the slow functionality of hand prostheses is not due to its mechanical and electronic properties, but it is related to feature extraction and classification steps to attain motor commands of proximal muscles [1].

There are a lot of works in sEMG pattern recognition. Linear discriminant analysis (LDA) is one of the classifiers that has been frequently used in previous studies. In 2010, Li et al [2] studied on five amputees who had one hand amputation. Subjects performed 10 wrist and hand movements by both of their hands. Mean of absolute values (MAV), zero crossing (ZC), waveform length (WL) and slope sign changes (SSC) features were extracted. They used LDA as classifier. Results showed that intact hand data had better classification accuracy. Average classification accuracy of 93.1% for six movements, and 84.4% for all 10 movements, was obtained.

Support vector machine (SVM) is another classifier which has been used in previous works. Oskoei and Hu [3] in their studies in 2008, used 11 intact subjects while performing 5 movements. They applied SVM classifier and feature sets and compared SVM, LDA and multi-layer perceptron (MLP) classifier. Tenor et al [4] extracted MAV, variance (VAR), WL and Willison amplitude features and used MLP with different number of neurons in hidden layer. They showed that by using surface electromyography, it is possible to classify flexion and extension movements of each finger (10 movements) with accuracy of more than 90%. In 2012, Kuzborskij et al [1] compared four classifiers including k-nearest neighbor (KNN), LDA, MLP and linear and nonlinear SVM. They evaluated these classifiers by seven features and three different window lengths. In this study, classification accuracy did not exceeded from 80% on average.

As mentioned before, there are a lot of studies in motor command extraction using sEMG of proximal muscles to control active myoelectric prostheses. In most of them, the process contains data acquisition, preprocessing, feature extraction, and classification. All of these four stages have significant roles on the final performance. In this paper, we focused on selecting appropriate features for MLP, LDA, and LS-SVM classifiers; and comparing their efficiencies. Furthermore, we have paid attention to other stages to have the best performance.

The rest of this paper is organized as follows: first we introduce the database that we have used, preprocessing methods, extracted features and classifiers. Then, results and conclusions are presented.

II. METHOD

A. Database and Preprocessing

We used the NINAPRO [5] database. This database contains surface electromyogram and kinematics of upper limbs of 27 healthy subjects while performing 52 movements of wrist, hand and finger.

In this database, muscle activation was recorded using ten active double-differential OttoBock *MyoBock* 13E200 [6] surface electromyography electrodes. Eight electrodes were placed below the elbow, while two electrodes were placed on the flexor and extensor muscles. These electrodes provide amplified (about 14000 times), filtered (90-450 Hz Band-pass filter [6]) and rectified signals. Each movement lasted 5 seconds and 3 seconds were allowed between movements. After the training phase, ten repetitions of each movement were recorded [5].

In this paper we used data of one subject from NINAPRO database. sEMG signals filtered with low-pass zero phase second order Butterworth filter at 5 Hz (Figure 1). Then two windowing methods were employed. For example, application of these methods on filtered signals of electrodes number 3 and 7, are shown in figure 1. In the first method, the movement was divided to three equal segments and the central segment was selected. According to that each movement lasts five seconds, length of selected signal by this method is about 1.6 seconds. In figure 1, this part is shown with cyan color and pink strip. In the second windowing method, we put one threshold level that is 10% of local maximum and the signal above this threshold was selected. Length of the separated signal by this method is different in each movement. This length can be 0.5, 2 and even more than 4 seconds. Examples of separated signal by this method are shown in figure 1 with green color and pink strip.

B. Feature Extraction

Feature extraction techniques can be divided into three groups: Time domain, Frequency domain and time-frequency features. Because of simplicity and appropriate efficiency of temporal features, these features were repeatedly used in previous studies. In feature extraction step, we extracted MAV that is an evaluation of the mean of absolute values of the EMG signal, integrated of absolute values (IAV), root mean square (RMS) that is the square root of the mean value of the squares of the signal values, WL that is the cumulative length of the waveform over the time segment, energy (E), energy ratio (ER) by two methods and concordance correlation (CC) that quantifies the coincidence of two variables [7, 8]. Definition of these features can be found in table 1.

C. Classification

Classification methods contain LDA, KNN, Gaussian mixture model (GMM), MLP etc. In this work, we considered MLP classifier and compared it with LDA and LS-SVM with RBF kernel [9]. We briefly introduce these classifiers in the following sections.

Multi-Layer Perceptron (MLP): One of the most simple and popular feed-forward neural networks is MLP. Its configuration contains a set of input units, hidden layers (one or more) and one output layer. Each input node is connected to all units in hidden layer and each hidden neuron is connected to the units of the next layer that can be hidden or output layer. Every connection has W weight [7]. Weights are randomly initialized and then fine-tuned during training phase by back-propagation (BP) approaches. To avoid over fitting, it is necessary to choose stopping criteria for the optimization methods and number of neurons in each layer, exactly [1]. In this paper, we used MLP with one hidden layer. Hyperbolic tangent sigmoid transfer function

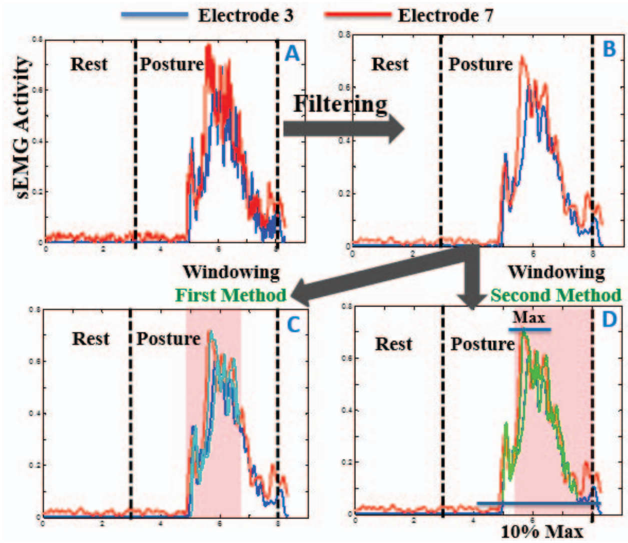

Figure 1. Preprocessing includes Filtering and windowing Methods. It shows preprocessing on signal of electrodes number 3 and 7 (blue and red respectively). A) Raw signals; rest and movement part are separated by dash line. B) Filtered signals. C) First windowing method that divides movement part into three equal segments and takes the center segment. D) Second windowing method that selects signals above the threshold level.

TABLE I. NAME, ABBREVIATION AN DEFINITION OF THE TEMPORAL FEATURES. IN DEFINITIONS, IS SAMPLES VECTOR, N IS TOTAL NUMBER OF SAMPLES AND IS TH SAMPLE OF DATA VECTOR. IN DEFINITION OF ER1 AND ER2, IS ENERGY OF TH ELECTRODE. IN CC DEFINITION , , ARE COVARIANCE OF ELECTRODE AND , VARIANCE OF ELECTORDE AND MEAN OF ELECTRODE , RESPECTIVELY.

Name	Abbreviation	Definition
Mean Absolute Value	MAV	$\frac{1}{N}\sum_{n=1}^{N}\lvert x_n\rvert$
Integral Absolute Value	IAV	$\sum_{n=1}^{N}\lvert x_n\rvert$
Waveform Length	WL	$\sum_{n=1}^{N-1}(\lvert x(n)-x(n+1)\rvert)$
Root Mean Square	RMS	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}x_n^2}$
Energy	E	$\sum_{n=1}^{N}x_n^2$
Energy Ratio-First Method	ER1	$\frac{E_i/E_j}{E_j/E_1}=\frac{E_i\times E_1}{E_j^2}$
Energy Ratio-Second Method	ER2	$\frac{\frac{E_i}{E_j}}{\frac{\sqrt{E_i\times E_j}}{E_1}}=\frac{E_i\times E_1}{E_j\times\sqrt{E_i\times E_j}}$
Concordance Corrtion	CC	$\frac{2\sigma_{ij}}{\sigma_i^2+\sigma_j^2+(\mu_i+\mu_j)^2}$

and scaled conjugate gradient back-propagation as training function, were applied. 52 neurons were placed in output layer. The best numbers of neurons for hidden layer were selected at interval of [50,100]. These numbers change with different windowing methods and features.

Linear Discriminant Analysis (LDA): LDA is a popular statistical procedure that maximizes the ratio of between class scatter to within class scatter to obtain the most discrimination. Using LDA for data sets depends on this fact that conditional probabilities of features must have normal distributions [1]. As regarded before, LDA was widely used to classify different movements. The classification accuracy of this classifier is fairly appropriate in trade off the computational complexity and processing time. In other words, this classifier has simple implantation and fast training [10].

Least Square Support Vector Machine (LS-SVM): support vector machines are linear binary classifiers that try to maximize the margin between the two classes. These classifiers reputation is for their capability to use kernel functions [1]. LS-SVM like standard SVM is a kernel based classifier that attempts to find maximum margin between two classes. LS-SVM is an alternative formulation of SVM. LS-SVM leads to a linear programming which is advantageous compared to quadratic programming of SVM [11].

MLP, LDA and LS-SVM are supervised classifiers. So, nine repetitions of 10 movement repetitions were used for training phase and one repetition for testing phase. For 52 movements, a set of 468 entries of training data was made. Selecting one repetition from 10 repetitions of each movements accomplished by 10-fold strategy. For MLP and LDA implantation we used MATLAB functions and for LS-SVM we used LS-SVMlab [12] toolbox.

III. RESULTS

Concordance correlation is not defined for the second windowing method, because of its definition. So, this feature and its combinations were not computed for second windowing method. RMS, E, ER1 and ER2 are from the same kind. Therefore these features were not tested as double combinations. ER1 with second windowing method was not usable for LDA. Considering the results of double combinations of features, we attempted to choose the best multiple combinations of features to achieve the best results. Mean and standard deviation of classification accuracy for MLP, LDA and LS-SVM classifiers are shown in Figures 2 to 4. For the best results, mean and standard deviation of classification accuracy and preprocessing time for each classifier are presented in Table 2.

As shown in Figure 2 and Table 2, for MLP Classifier and for single feature the best average classification of 88.46% with first windowing method and IAV is achieved. Using double features, the accuracy reached 92.69% with IAV+RMS and first windowing method. When we used multiple features the best average classification accuracy of 96.34% with combination of all features and first windowing method was obtained that is the best accuracy between the results of all classifiers.

The results of using LDA classifier are shown in figure 3 and table 2. For this classifier, with single feature the best average classification accuracy of 78.84% with RMS and first windowing method was achieved. Using double features of IAV (or MAV) +CC and first windowing method this accuracy reached 84.23%. The best average classification accuracy of 84.03% for combinations of all features and first windowing method was achieved.

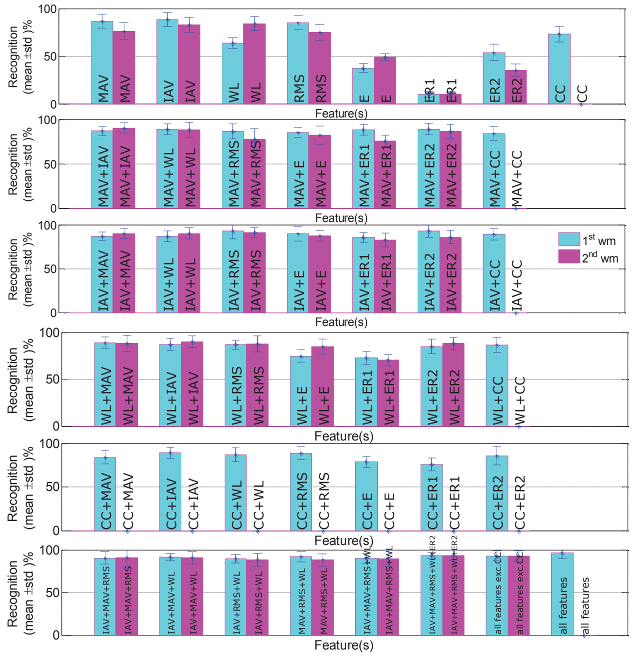

Figure 2. Mean and standard deviation of classification accuracy of MLP classifier for various combinations of features.

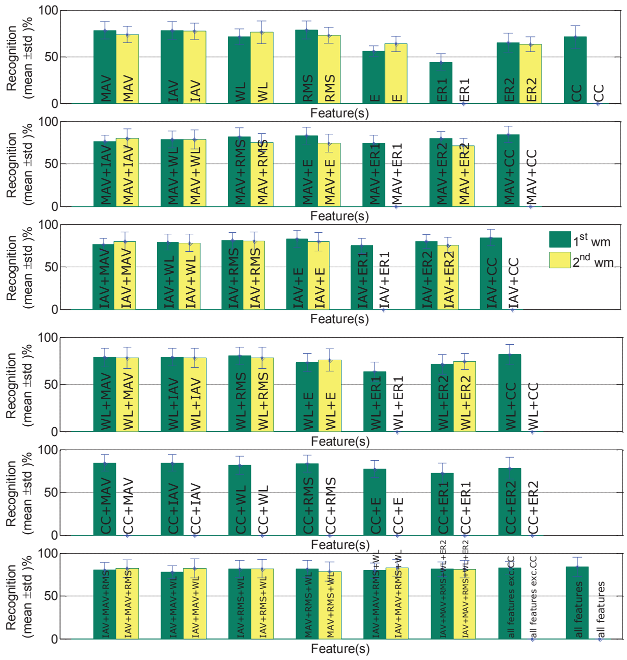

Figure 3. Mean and standard deviation of classification accuracy of LDA classifier for various combinations of features.

TABLE II. AVARAGE MEAN AND STANDARD DEVIATION OF CLASSIFICATION ACCURACY AND PROCESSING TIME (IN SECOND) FOR THE BEST RESULTS OF SINGLE, DOUBLE AND MULTIPLE FEATURES OF MLP, LDA AND LSSVM.

Classifier	Windowing Method	Feature	Average classification accuracy (%)	Standard Deviation	Processing Time (Sec)
MLP	First	IAV	88.46	7.29	7.95
MLP	First	IAV+RMS	92.69	8.96	8.07
MLP	First	ALL	96.34	6.93	11.33
MLP	Second	WL	84.23	7.57	5.88
MLP	Second	IAV+RMS	91.15	5.3	6.63
MLP	Second	IAV+MAV+RMS+WL+ER2	93.26	6.29	6.19
LDA	First	RMS	78.84	9.55	0.56
LDA	First	IAV(or MAV)+CC	84.23	9.58	0.45
LDA	First	MAV+IAV+WL+RMS+ E+ER1+ER2+CC	84.03	11.17	1.01
LDA	Second	IAV	77.3	8.68	0.27
LDA	Second	IAV+RMS	80.38	10.6	0.3
LDA	Second	IAV+MAV+RMS+WL	82.69	10.3	0.37
LS-SVM	First	IAV	83.57	11	2303.2
LS-SVM	First	IAV+MAV	84.03	12.16	2192.2
LS-SVM	First	IAV+MAV+RMS	84.42	11.6	2165.7
LS-SVM	Second	IAV	80.09	9.73	2624.6
LS-SVM	Second	IAV+RMS	84.82	10.2	1974.1
LS-SVM	Second	IAV+MAV+RMS+WL	85.19	13.32	2369.1

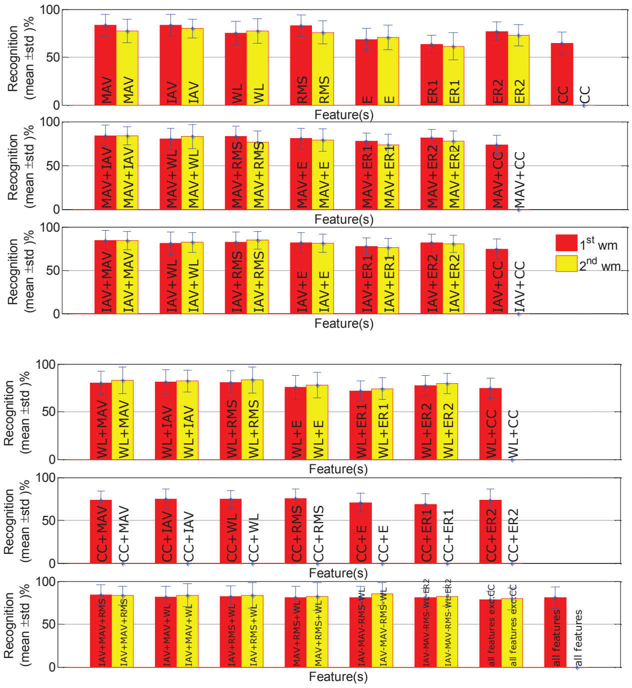

Figure 4. Mean and standard deviation of classification accuracy of LS-SVM classifier for various combinations of features.

For LS-SVM classifier that its results are shown in figure 4 and table 2, the best average classification accuracy 83.57% by using single feature of IAV and first windowing method was achieved. The accuracy of 84.82% was obtained with IAV+RMS and second windowing method. The best average classification accuracy for this classifier was 85.19% by using MAV+IAV+RMS+WL and second windowing method.

IV. DISCUSSION

One of the advantages of this study to most of the previous studies is 52 movements classification that can be valuable in a practical view. This is because with increasing the number of movements, the myoelectric prosthesis will be more user-friendly. This study shows better performance in comparison with previous studies which used this database (like [1]), although some of parameters that are effective in classification accuracy are different. As shown in figures 2 to 4, MLP classifier with double and multiple features indicates high classification accuracies. These accuracies are more than LDA and LS-SVM in most. Although with using single features like E, ER1 and ER2, MLP has worse performance in comparison with two other classifiers. As shown in table 2, processing time in MLP is 210 times less than LS-SVM. Whereas the best average classification accuracy in MLP is about 10 times more than LS-SVM. In average standard deviation for MLP classifier is less than LDA and LS-SVM. Achieving high classification accuracy in MLP needs appropriate determining of parameters and network configuration. Performance of LS-SVM depends on determining its two variable parameters too.

Simple and easy implementation of LDA is its advantage to two other classifiers. Windowing methods and feature extraction procedures used in this study cause that these approaches cannot be usable in online applications. For practical use in hand prostheses this limitation must be solved in future studies.

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