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Leveraging ANN and LDA Classifiers for Characterizing Different Hand Movements Using EMG Signals

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Abstract
The analysis of electromyographic (EMG) signals has expedited the use of a wearable prosthetic arm. To this end, pattern recognition-based myoelectric control schemes have shown the promising results; however, the choice of classifier and optimal features is always challenging. This paper presents the comparative analysis of classifiers for multiple EMG datasets including (1) the publicly accessible NinaPro database which provides data recorded for 52 hand movements collected from 27 subjects out of which twelve finger movements were classified, and (2) the data collected from ten healthy and six amputee subjects for 11 different hand movements. The classification results of artificial neural networks (ANN) were compared with those of linear discriminant analysis (LDA) for both datasets separately. For dataset 1, the mean classification accuracy of LDA obtained was 85.41% while ANN showed 91.14% accuracy. Similarly, for dataset 2, the mean classification accuracy achieved with LDA was 93.54% while with ANN, it was 97.69%. Besides, p-values were determined for both datasets which revealed better classification results of ANN as compared to LDA. The overall results of this study show that ANN performed better classification and recognition of hand movements as compared to LDA. The findings of this study offer important insights regarding the selection of classifiers of EMG signals which are critical to evaluating the accurate performance of prosthetic human organs.

Keywords Artificial neural networks · Electromyography · Linear discriminant analysis · Bio signals · Prosthesis

1 Introduction

The technique used to record the electrical activity generated in the human muscles is called electromyography (EMG). This electrical activity helps control the myoelectric prosthetic hand for performing various hand movements. A contracting muscle generates EMG signals which may be collected either with the help of a needle, wire, or surface electrode [1]. Surface electrodes are widely used for acquiring EMG signals by placing these electrodes over the human skin. This technique is called surface electromyography (sEMG). The EMG signals which are stochastic in nature must be accurately recorded and preprocessed in order to achieve the accurate performance of prosthetic hand [2]. The remarkable achievements made in proposing artificial intelligence algorithms and introducing myoelectric interfaces have enhanced the application of wearable prosthetic devices such as prosthetic hand which act as an artificial replacement for disabled or missing organs of a human body [3].

EMG signals have been proposed to be utilized in the operation of prosthetic hand since 1948 [4, 5]. The first myoelectric-based clinical prosthetic hand was introduced at Central Prosthetic Research Institute, Moscow, in 1957–1960 [6]. Thereafter, different control methods were proposed by researchers to make advancements in the control of prosthetic hands. These control methods may be either sequential or simultaneous [3]. Sequential control methods are used in

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commercially available prosthetic devices while research is being performed to develop simultaneous control methods.

The conventional control methods include on–off control which moves the prosthetic hand bidirectionally. The proportional control methods suggest the proportionality of the velocity of a prosthetic movement to the intensity of the myoelectric signal. Finite-state control has been reported to perform better only for the predetermined movements thus unable to perform multifunctional tasks. Separate control positions are required for each movement in case of a direct control method which affects the performance due to disturbance in sEMG [3]. To avoid some of these drawbacks, pattern recognition control methods have been introduced to obtain more useful information from EMG data [7]. Even though the results of the pattern recognition achieved until now are quite satisfactory, its advanced applications require more investigation in order to ensure the natural control of the prosthetic hand.

1.1 Review of Past Studies

The research work on the classification of hand movements started around 1970 [8] which is continued as the advancement in the myoelectric pattern recognition methods [9]. Researchers investigated different classification algorithms over the years with different features extracted which include LDA, artificial neural networks (ANN), *k*-nearest neighbors, fuzzy mean max NN, support vector machine (SVM), log-linearized Gaussian mixture networks (LLGMN), hidden Markov model, Bayes network, backpropagation, and LLGMN-based probabilistic NN among several others [2, 9–11]. Some of these algorithms attained accuracy above 90% but most of them were used to classify only a few movements.

Initially, Hudgins demonstrated the use of time domain features, which include mean absolute value, waveform length, zero crossing, and slope sign change, extracted from EMG signals. These signals were generated as a result of muscle contractions for the classification of hand movements. A nonlinear ANN classifier was proposed to differentiate four different movements [12]. Although both linear and nonlinear classifiers result in good classification accuracy, however, LDA is more widely used because of its good classification accuracy and computational efficiency. Some other features used for classification techniques include the variance, hamming and trapezoidal window, mean and median frequency, frequency and power spectrum ratio, auto-regressive and cepstral coefficients, histogram of EMG, myopulse percent rate, RMS value, log detector, Wilson amplitude, the variance of central frequency, and many more [13].

In addition to the classical machine learning techniques, some deep learning approaches such as convolutional neural networks (CNN) and autoencoders (AEs) are also used in many applications of biomedical signals including electrocardiography (ECG) [14], electroencephalography (EEG) [15], and others [16–18]. Some studies also demonstrated the use of CNN for the EMG control of hand movements. Park and Lee [19] used EMG signals to introduce a movement decoding CNN which was comprised of an input layer, four convolutional layers, and four subsampling layers and compared its performance with SVM. They concluded that CNN got accuracy above 90% and gave better results than SVM. Atzori et al. [20] used a publicly accessible NinaPro database [21] for sEMG and suggested a multilayer CNN made up of five blocks. This database consists of sEMG data of 52 different hand movements collected from a total of 78 subjects (67 intact and 11 trans-radial amputees). It is composed of three datasets, dataset 1 contains data acquisition of 27 intact subjects, dataset 2 contains EMG data of 40 intact subjects, and dataset 3 contains data of 11 amputees. The CNN introduced by them was a remodeled version of a widely known network called LeNet. The classification results of this network were compared with SVM, LDA, random forest, and KNN for all three datasets which revealed the comparable average classification accuracies to those achieved from these classical techniques, but random forest showed better results than CNN. More complex designed deep networks were conducted to increase the robustness of sEMG-controlled prosthetics. Previous research concluded the superior performance of combined sEMG and intramuscular (imEMG)-based myoelectric system as compared to sEMG only [22]. Kamavuako et al. performed real-time EMG control to demonstrate the difference in the classification efficiency of sEMG and combined EMG [23].

1.2 Study Motivation and Objectives

Though the analysis of electromyographic (EMG) signals has resulted in the use of a wearable prosthetic arm and other human organs; however, the selection of classifier and optimal features has always been challenging. The selection of adequate classifiers is critical to evaluate the accuracy of the performance of prosthetic human organs. In this vein, this study evaluates the relative performance of both ANN and LDA classifiers for classifying EMG signals using two different datasets. The first dataset contains the database 1 of the Ninapro database which includes twelve finger movements while the second dataset includes surface and combined EMG data of ten healthy and six amputee subjects. This study aims at comparing both ANN and LDA and identifying the better classifier in terms of accuracy which could eventually be used to contribute to better control of the prosthetics.

The remaining article is divided into three sections. Section 2 elaborates on the types of data used in this study, data collection and collation, the extraction of features to be used in the study, and the classification methods implemented in the study. Section 3 provides the discussion of the results, whereas the last section concludes the article.

2 Data and Methods

Two different datasets are used for the classification of hand movements. LDA and ANN are used to compare the classification accuracies for each dataset separately. The methodology of both datasets is explained as below.

2.1 Dataset 1

Dataset 1 used in this study is the NinaPro database [21, 24, 25] which is publicly accessible. The database executes kinematic and sEMG data of ten repetitions of 52 distinct hand movements acquired from 27 intact subjects. These movements are presented in Fig. 1. The whole dataset is categorized into four classes including 12 finger motions, 8 hand positions, 9 Wrist angles, and 23 grasping and activity movements. These four classes are subcategorized into three exercises as finger motions, isometric hand and wrist positions (the second exercise shows combined second and third class), and grasping and activity postures [25].

Differential electrodes were used to examine and record the muscle's electrical activity to obtain preprocessed raw sEMG signal in the rectified form which is sampled at 2 kHz with the help of a base station comprising a set of another 12 electrodes. During the collection of data, a laptop was placed in front of each subject. Subjects were asked to position their hand on the desktop from which they perceive visual stimuli for each movement and the measuring systems continuously recorded their data. Different movements were displayed on the desktop placed in front of the intact subjects to copy by them with their right hand. The amputees tried to use their impaired arm to follow these movements [24].

This study is based on the evaluation of the first exercise of the NinaPro database which shows 12 finger movements (index finger flexion, index finger extension, middle flexion, middle extension, ring flexion, ring extension, little finger flexion, little finger extension, thumb flexion, thumb extension, thumb adduction, and thumb abduction) as shown in Fig. 1a.

Since various noise factors cause a disturbance in raw EMG signals such as extrinsic factors induced due to inappropriate distance between the electrodes or improper electrode placement or intrinsic factors like anatomical and environmental which may be minimized if the signal-to-noise ratio (SNR) of the signals is increased [26]. Similarly, the noise produced by electromagnetic devices may be removed in order to attain a more informative signal if electrodes and other circuitry are correctly installed. The data, after its collection, were set to the highest frequency limit, i.e., 100 Hz to filter at 1 Hz with a low-pass filter. The normalization of sEMG data acquired for each subject was ensured at zero mean with a unit standard deviation [25].

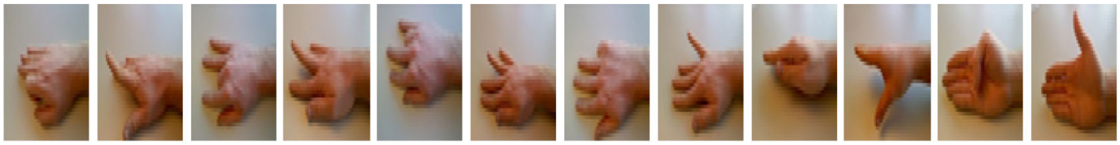
2.2 Dataset 2

Data for this dataset [2, 27] was collected from ten healthy and six trans-radial amputees [9]. The age of healthy subjects varied from 18 to 38 years with an average age of 24.5 years, while the age of disabled subjects varied from 23 to 56 years with an average age of 34.8 years. This dataset was recorded either from the right hand of healthy subjects or from the disabled hand of trans-radial amputees. These experimental procedures were authorized by the RIU Islamabad research ethics committee. Figure 2 represents the different hand movements of dataset 2 investigated in this study.

2.2.1 Data Collection

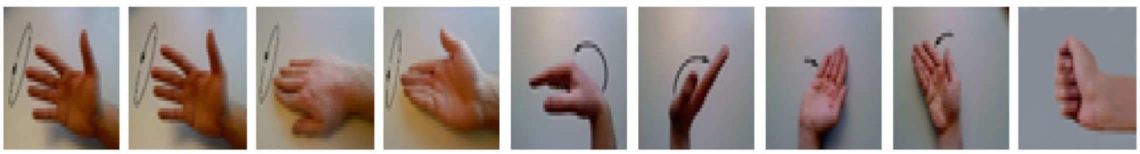
Six surface electrodes were used to record sEMG data and six intramuscular electrodes to collect intramuscular (imEMG) data for eleven movements from each subject. Three of the surface electrodes and three of the intramuscular electrodes were placed on flexor digitorum superficialis and flexor carpi radialis, while three of each EMG electrodes were fixed on extensor digitorum communis and extensor carpi radialis. Only five surface electrodes could be placed on the disabled arm of three of the trans-radial amputee subjects, while two of them could get only five intramuscular electrodes on their hands due to small available space. Data were collected for seven successive days from each subject. Data for each movement were recorded with four repetitions every single day with a contraction and relaxation span of five seconds each. In this way, each trial was completed in a duration of 400 s. Surface EMG data were filtered using an analog bandpass filter of 10–500 Hz while imEMG with a bandpass filter of 0.1–4.4 kHz, each with a sampling frequency of 8 kHz. The eleven movements performed by each subject were in a sequence of hand open, hand close, flex hand, an extended hand, pronation, supination, side grip, fine grip, agree, and pointer.

During the offline analysis of data after its collection, the onset and offset span of individual segments showed time drifting. Therefore, the semiautomatic approach was applied in MATLAB 2016a for labeling each segment. The manual selection of onset duration with the help of a cursor placed on the data was performed to store the corresponding segment automatically. The data at first and last second were eliminated to overcome noise effects, thus reducing each segment to three seconds.

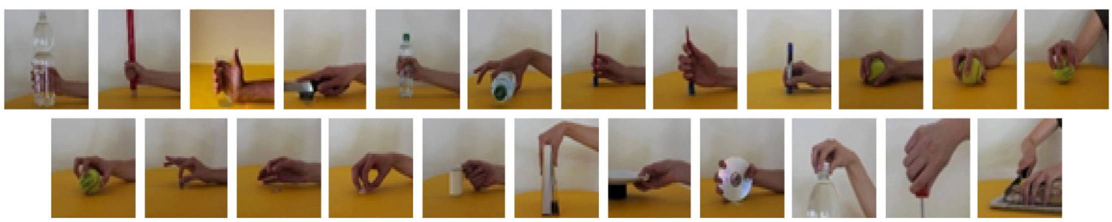


(a) 12 basic flexions and extensions of the fingers

(b) 8 isometric and isotonic hand configurations



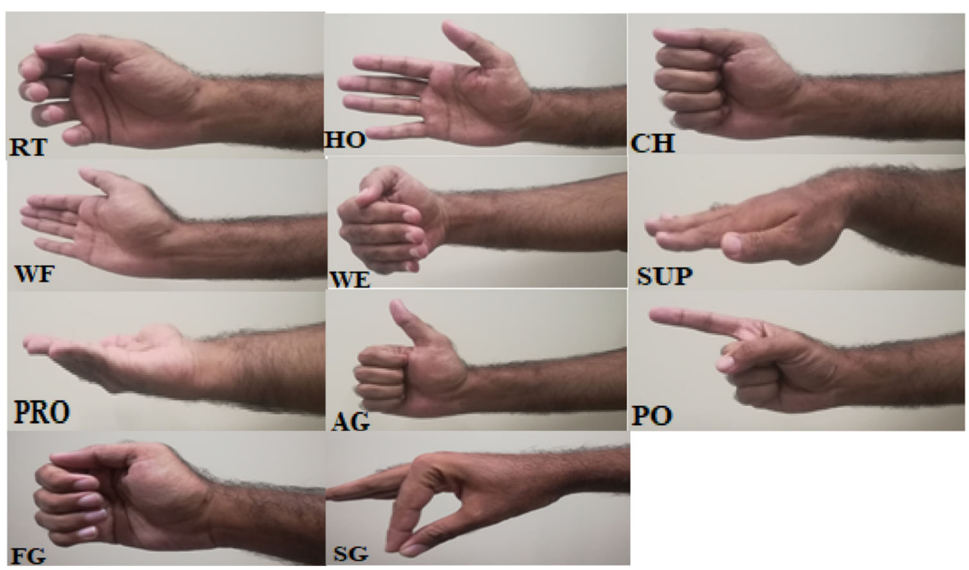
(c) 9 basic wrist movements



(d) 23 grasp and activity movements

Fig. 1 Fifty-two movements executed in the NinaPro dataset [25]

Fig. 2 Eleven hand movements of dataset 2 including rest (RT), hand open (HO), close hand (CH). Wrist flexion (WF), wrist extension (WE), supination (SUP), pronation (PRO), agree (AG), pointer (PO), fine grip (FG), and side grip (SG)



2.2.2 Data Processing

The sEMG and imEMG data were independently processed and digitally filtered with a third-order Butterworth bandpass filter using a bandwidth of 20–500 Hz for surface channels and 0.6–1.5 kHz for intramuscular channels. The selection of lower cutoff frequency ensured to overcome the movement artifacts. Then, 2.2 power spectral density was analyzed for the data of each subject for each day which showed the distribution of 50 Hz noise and its harmonics in most of the data for different subjects. To eliminate this noise, a third-order configurable Butterworth filter was explicitly used.

2.3 Features Extraction

Features are extracted from the preprocessed data in order to attain a feature vector that contains desired information and eliminates the superfluous noisy data from EMG signals. The feature vector determined should propose a set of best suitable features to extract the most appropriate information from the data. This step is of great significance for the classification of data because if proper features extraction is not performed before using data as input to the classifier, satisfactory classification performance and computational efficiency cannot be achieved [28–31].

Three types of features are used which include time domain, frequency domain, and combination of both. Englehart et al. [32] used combined time and frequency domain features and suggested that they are more informative for the pattern recognition of data but are not very efficient computationally. On the other hand, time domain features are more viable due to their computational efficiency and less complexity in comparison with frequency domain features [33]. These features are workable for dimensionality reduction purpose and are useful for pattern classification of EMG.

This study utilizes four-time domain features which are mean absolute value (MAV), slope sign change (SSC), zero crossing (ZC), and waveform length feature (WL) [34] known as Hudgins features. These features were derived from each data channel using a window length of 200 ms with a window gap of 28.5 ms. All the six surface EMG channels were utilized for extraction while for combined sEMG and imEMG, principal component analysis (PCA) was used for feature vector reduction for all the channels to make them equal to surface features.

2.4 Methods Used for Classification

The accurate classification performance requires the selection of well-suited classifiers. In this study, LDA and ANN were used for classification purposes. LDA is an extensively used classifier because it is simple and can be easily trained and implemented. It is a linear classifier and is feasible to use as a dimensionality reduction technique. It can perform both binary and multi-class classification to generate the desired output. Artificial neural networks resemble the structure of biological NNs and can be used as both linear and nonlinear classifiers. Therefore, researchers suggested the use of ANNs for the precise recognition of myoelectric signals as they are capable of the real-time analysis of EMG data [35]. ANNs can work as a nonlinear unsupervised learning technique for statistical analysis and modeling of EMG data.

In this study, the classification accuracy of LDA and ANN was compared for both datasets separately.

2.4.1 Artificial Neural Networks

An ANN is made up of three or more interconnected layers of neurons [9, 10]. The first layer of the network consists of the input neurons which send data (labeled or unlabeled) through the deeper hidden neural layers to the output layer. Each neuron has a set of connecting weighted links characterized by weight W. The weighted sum of the inputs X is computed by the function u as:

$$u = \sum_{j=1}^{m} W_j X_j$$

The amplitude of the output 'y' is limited by using activation function (usually nonlinear)φ

$$y = \varphi(u + b)$$

where b is a bias term.

2.4.2 Linear Discriminant Analysis

It is a supervised dimensionality reduction technique that separates two or more classes [36]. It is widely used as a data classification technique which gives decision regions for the required set of classes as output. Reducing the number of features helps improve the performance of a classifier. This technique leads to generating an optimal subspace with minimized within-class variance and maximized between-class distance.

Mathematically,

$$y = W^T * x$$

while Fisher's criterion is given by

$$J(w) = \frac{|\mu_1 - \mu_2|^2}{s_1^2 + s_2^2}$$

where μ_1, μ_2 are the projected means of the classes while s_1,s_2 show scatter of the projection.

Table 1 Percent classification accuracies obtained with both ANN and LDA classifiers for each subject of dataset 1

Subject no.	ANN (%)	LDA (%)
01	89.31	81.67
02	94.22	79.01
03	92.10	83.11
04	94.03	85.24
05	95.01	90.32
06	87.43	86.01
07	90.67	81.21
08	93.89	84.76
09	88.47	87.44
10	92.42	91.09
11	91.05	82.72
12	90.11	89.34
13	87.83	87.67
14	94.06	89.89
15	88.35	84.37
16	90.48	83.40
17	93.58	87.05
18	91.69	88.92
19	85.33	81.67
20	92.09	89.98
21	87.49	84.00
22	94.43	86.85
23	91.74	82.34
24	95.01	83.52
25	94.67	86.31
26	86.46	84.76
27	88.92	83.45
Mean ± SD	91.14 ± 2.88	85.41 ± 3.19

3 Discussion of the Results

The dataset 1 was acquired from NinaPro database 1 which contains sEMG data of 12 finger movements collected from 27 subjects. The subject-wise mean accuracies for each classifier are demonstrated in Table 1, and the overall mean with standard deviation (SD) is shown in Fig. 3. The percent classification accuracies obtained using ANN are 91.14% which is higher than that achieved by LDA which is 85.41%.

The dataset 2 contains sEMG and combined EMG data collected from ten healthy and six amputee subjects over seven consecutive days. The classification was performed for healthy and amputee subjects separately with fivefold cross-validation using onefold as testing data and the rest of the fourfold data as training data. This training and testing of data were conducted five times in the same way, every time using a new data fold as a testing set. The results were evaluated by taking the mean of all these five repetitions.

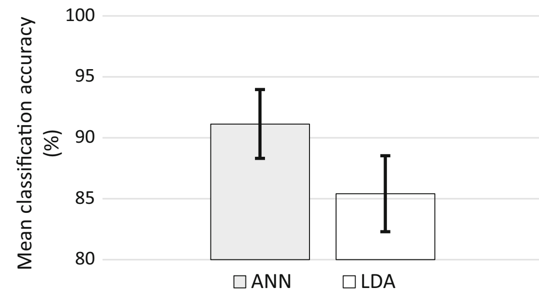


Fig. 3 Mean classification accuracies along with standard deviation for ANN and LDA classifiers using Dataset 1

Table 2 Statistical Friedman test for *p* value calculation OF dataset 1

Total healthy subjects (sEMG)	Mean ± SD		*p* value
	ANN	LDA	
27	91.14 ± 2.82	85.41 ± 3.12	1.2132e−07

Table 3 Statistical Friedman test for *p* value calculation of dataset 2

Data	Mean ± SD		*p* value
	ANN	LDA	
Healthy surface	98.40 ± 0.51	95.92 ± 2.30	3.1447e−15
Healthy combined	98.88 ± 0.07	96.35 ± 1.01	5.5578e−19
Amputee surface	96.24 ± 2.18	89.25 ± 5.62	8.5094e−14
Amputee combined	97.27 ± 0.56	92.64 ± 3.34	1.2121e−13

The percent classification accuracies of LDA and ANN computed for healthy and amputee subjects individually showed the better performance of ANN over LDA as shown in Fig. 4.

ANN achieved a classification accuracy of 98.40% for surface EMG of healthy subjects and 98.88% for combined EMG, whereas LDA shows 95.92% for surface EMG and 96.35% for combined EMG of healthy subjects. Similarly, for amputee subjects, ANN achieved 96.24% classification accuracy for sEMG and 97.27% for combined EMG while LDA shows comparatively low accuracies of 89.25% for sEMG and 92.64% for combined EMG. The above results also conclude that combined EMG gives better classification accuracy as compared to sEMG for both healthy and disabled subjects. Tables 2 and 3 demonstrate these results.

3.1 Statistical Test for Performance Evaluation of Classifiers

The results were analyzed statistically by conducting a Friedman test [37] for datasets 1 and 2 separately. This nonparametric test is performed to examine the divergence between groups when the dependent variable to be measured is arithmetic. For dataset 1, the results of this test for differ-

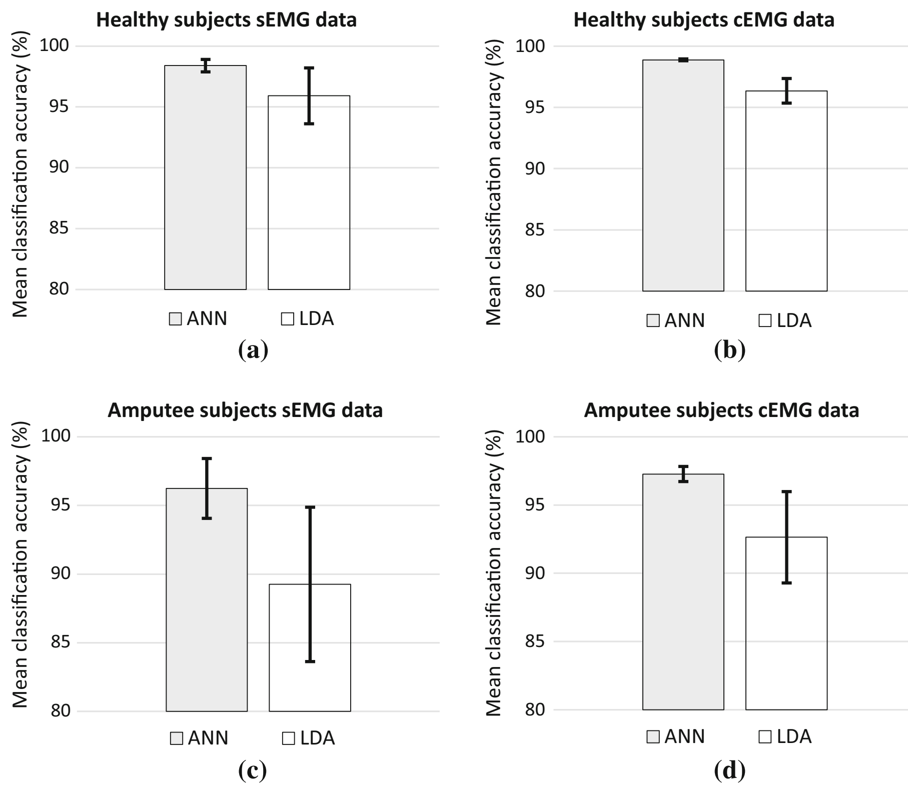


Fig. 4 Classification accuracies of ANN and LDA for Dataset 2. **a** sEMG data of healthy subjects, **b** cEMG data of amputee subjects, (**c**) sEMG data of amputee subjects, and **d** cEMG data of amputee subjects

ences among repeated analysis generated a Chi-squared value of 18.2 which shows the significance of ANN ($p < 0.05$) as compared to LDA. The test results for dataset 1 are shown in Table 2.

The statistical test results for all four cases of dataset 2 are shown in Table 3 which implies that ANN performed significantly better ($p < 0.05$) than LDA.

4 Conclusions

This study is aimed to investigate techniques used for the analysis of EMG signals to improve pattern recognition of hand movements. These techniques are compared to predict better percent classification accuracy which will be helpful for the researchers in EMG signal processing, arm prosthetics, and clinical and biomedical methods. The purpose of this study was to compare the performance of ANN and LDA and to evaluate the results for improved EMG control. It was also investigated if combined sEMG and imEMG could result in better performance for both healthy and disabled subjects.

In this study, two different datasets were used for EMG signal analysis. The dataset 1 was acquired from the publicly accessible NinaPro database which provides sEMG data of 27 subjects for 52 distinct hand movements. We used this dataset for the recognition of twelve finger- and hand movements. The dataset 2 was recorded with the help of six surfaces and six intramuscular electrodes placed in supinator and pronator muscles from ten healthy and six disabled subjects. The processing of data was offline. PCA was used for the feature reduction in combined EMG to compare it with sEMG.

Four widely used time domain features were extracted for each dataset. LDA and ANN were used to classify the hand movements for each individual dataset, and their classification performance was determined separately. For dataset 1, ANN indicated overall better performance as compared to LDA in terms of percent classification accuracy. For dataset 2, ANN outperformed LDA for both surface EMG and combined data of intact and disabled subjects. It was also concluded in this study that combined EMG data surpassed the performance of surface EMG with both LDA and ANN for healthy as well as disabled subjects. Previous research studies proposed the improved results of imEMG which were examined only for healthy subjects.

The ANN and LDA achieved average classification accuracies of 99.27% and 93.64%, respectively, for combined EMG data whereas for sEMG data, ANN and LDA attained 98.24% and 89.25%, respectively. These results verify that combined EMG shows higher accuracy as compared to sEMG. It was also proved statistically that for both intact and amputee subjects, combined sEMG and imEMG data provided better results. This is because the imEMG data collected through a needle or fine wire from deep muscles are less susceptible to crosstalk whereas sEMG may easily be affected by artifacts and crosstalk of electrodes and surrounding muscles.

The datasets used in this study are very helpful and more promising and obvious results may be achieved if data for more dynamic movements are added. Similarly, an increase in the number of EMG channels and the number of features results in the increase in control commands count of classification technique. LDA is more useful in case of using a large number of features as it is capable of reducing the dimensions by converting data into a space vector with no loss of useful information.

Two different datasets were used to evaluate the classification accuracy of machine learning techniques and to investigate the performance of combined EMG data. Data of both healthy and disabled subjects were used for dataset 2 to compute offline classification error. Six electrodes were used each for sEMG and imEMG data collection. The results achieved were verified through a statistical test which confirmed that ANN remarkably performed better than LDA and combined EMG surpassed the performance of sEMG. Similarly, the classification ability of other linear and nonlinear classifiers may be investigated to ensure improved pattern recognition and myoelectric control. Although the findings of this study offer important insights regarding the processing of EMG signals which are critical to evaluate the accurate performance of sequential movements of prosthetic human organs, however, better classification methods for simultaneous limb movements should also be introduced which are suggested for future work. This study may further be improved by considering the effect of nonlinear feature transformation on linear classification methods. Future research could investigate the opportunities of employing pattern recognition methods that duly account for the possibility of unobserved heterogeneity (for more on heterogeneity, please see 38–52).

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