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EMG-Controlled Transradial Prostheses - An Investigation into Machine Learning Techniques

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ABSTRACT

The electromyogram (EMG) signals recorded from the surface of skeletal muscles are stochastic in nature and exhibit repeatable patterns for similar muscle activations. Therefore, machine learning algorithms can be used to learn their patterns and identify the movement intent even in the absence of an actual limb. The EMG signals are recorded from the residual muscles/muscle sites after amputation (acquired or congenital) and a representative set of features is extracted. The feature data are passed on to a machine learning algorithm for training and later use in real-time for controlling a prosthetic device. Numerous features of the EMG signal based on its amplitude, spectral contents, and stochastic nature have been proposed. Similarly, various dimensionality reduction techniques, as well as, classification algorithms have also been used. In this study, we provide in-depth analyses of different features of the EMG signals and classification algorithms along with the effect of dimensionality reduction on the classification accuracy. The surface EMG data recorded from the forearm muscles of twelve able-bodied volunteers was used to extract six different feature sets (fourteen individual features). The feature data with/without dimensionality reduction was used to train and test three different classification algorithms, i.e., the linear discriminant analysis (LDA), support vector machines (SVM), and artificial neural networks (ANN). Our extensive study showed that the feature set consisting of the EMG amplitude, spectral, and stochasticity information provided the highest classification accuracy with a linear classifier, i.e., the LDA.

General Terms

EMG-Controlled Prosthetic Devices, Pattern Classification

Keywords

Electromyogram, Prosthesis, Linear Discriminant Analysis, Support Vector Machines, Artificial Neural Networks

1. INTRODUCTION

The electromyogram (EMG) signals are recorded from the surface of skeletal muscles and represent muscle excitation and activation quantitatively [22], [15]. These signals contain important information about the neural processes taking place in the Central Nervous System (CNS) related to the planning and execution of voluntary movements [8], [15]. The EMG signals have been used by researcher and clinicians for decades to investigate muscles in healthy as well as pathological conditions [23], [26], [1]. Recently, owing to the advancements in machine learning and pattern classification techniques, the EMG signals are being used extensively to control prosthetic devices [6], [4], [27], [24], [2]. These prosthetic devices are externally powered and are actuated using the intended movement information produced by these machine learning algorithms [6], [25]. Generally, the surface EMG signals are recorded from leftover muscles of amputees and after the necessary preprocessing representative features are extracted [7], [6]. Using feature data, a supervised or unsupervised machine learning algorithm is trained [16], [7]. Later, the EMG signals from the same set of muscles are fed to the trained machine learning algorithm, which provides information about the movement the user intended to perform [25].

The machine learning approaches exploit the distinguishable and repeatable patterns in muscle activations. A generalized schematic layout for extraction of movement intent using machine learning is provided in Fig. 1. In line with other machine learning applications, the process of movement identification consists of two distinct stages, i.e., algorithm training using a set of training data, and movement identification using EMG data from same muscles in real-time. Later, the movement intent or movement class information is passed on to the actuation mechanism of the prosthetic device to actually perform the movement. After recording the EMG signals from physiologically relevant muscles/muscle sites, the signals may be preprocessed with different filters to improve their quality and reduce noise [15]. The EMG data is first segmented into analysis windows of convenient size and representative features are extracted from each analysis window [28]. The choice of the analysis window size depends upon the type of the classifier and the number and type of features used [33]. A reasonable choice for analysis window size is 150 ms to 250 ms [33]. On the other hand, the raw EMG data are rarely used directly as an input to the classification algorithm due to its stochastic nature and high dimensionality [27].

One of the major challenges in EMG-controlled prosthetic devices is the selection of the most informative and representative feature set. A variety of features has been identified based on the amplitude, spectral contents as well as the stochastic nature of the EMG signals [16]. The time domain (TD) features that are related to the amplitude of the EMG signals may include mean absolute value (MAV) of the EMG signal, integrated mean absolute value (IMAV), mean absolute value slope (MAVS), Willison amplitude (WA), variance (VAR), zero crossings (ZC), slope sign change

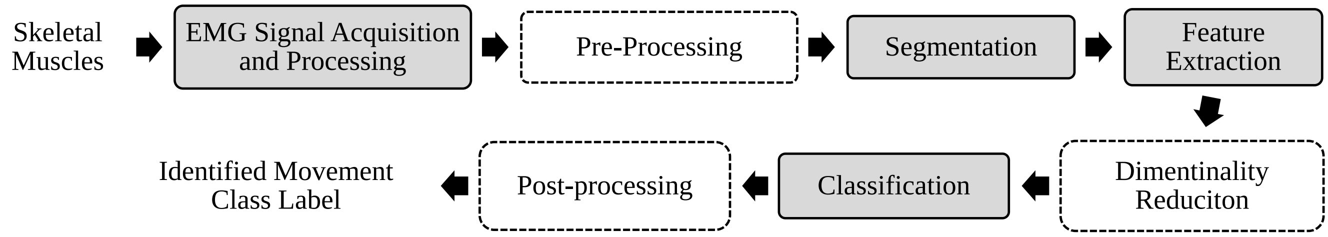

Fig. 1. The schematic layout of a general machine learning algorithm used for the extraction of movement intent from the EMG signals. The gray boxes represent processes considered mandatory, while dotted white boxes represent optional processes. The surface EMG signals from relevant muscles/muscle sites are recorded in the raw form. After preprocessing and segmentation of the EMG data, an informative set of features is extracted from analysis windows. The feature data is then provided to the classification algorithm as an input, referred to as the training of the algorithm. In case, the feature set is reasonably large, the dimensionality of the feature set may also be reduced using techniques such as the principal component analysis (PCA), or the independent component analysis (ICA). Once trained, the classification algorithm can be used to identify movement intent given the EMG signals from the same set of muscles/muscle sites. Sometimes, the post-processing is also performed to improve classification accuracy [31].

(SSC), waveform length (WL), and mean square value (MSV) [36], [27]. The spectral or frequency domain (FD) features may include the mean frequency of the EMG spectrum (MNF), median frequency (MDF), frequency ratio and short-time Fourier transform (STFT) [36]. On the other hand, EMG signals are also modeled as a stochastic process using the autoregressive (AR) processes [28] or Generalized Autoregressive Conditional Heteroscedastic (AR-GARCH) processes [27]. Using the EMG data, the AR/AR-GARCH model coefficients are estimated and used as a feature set [28], [25]. Mathematical definitions of these features are provided in Table 1.

The quantity of the EMG data is generally increased for better training and to improve the classification accuracy of machine learning algorithms [24]. However, as the number of EMG channels, i.e. the selected muscle sites, and the number of features are increased, the dimensionality of the EMG feature data may increase significantly. Numerous algorithms have been proposed in the EMG literature to reduce data dimensionality, including the principal component analysis (PCA) and independent component analysis (ICA) [16], [10], [18].

The selection of an appropriate and efficient classification algorithm is another big challenge in this research [29]. A number of classification algorithms have been proposed, including the linear/quadratic discriminant analysis (LDA/QDA) [30], [35], the support vector machines (SVM) [21], [14], [19], Gaussian mixture model (GMM) [11], [3], K-nearest neighbor (K-NN) with lazy learning [5], and various flavors of the artificial neural networks (ANN) [9], [32] [34], [13].

The classification accuracy of a machine learning scheme for the EMG-controlled prosthetic device may depend upon many factors, including the selected feature set, the classification algorithm, dimensionality reduction technique (if used), the number and nature of movements being classified, the EMG hardware, as well as the user training [17], [25], [12]. In this study, we address a subset of these confounding factors, i.e., we explore various feature sets, a dimensionality reduction scheme (the principal component analysis, PCA), and three classification algorithms, i.e., the LDA, SVM and ANN to find the best combination for the given EMG data from twelve able-bodied subjects performing a finite number of hand and wrist movements.

2. METHODS

2.1 Experimental Methods

The study received approval from the institutional review board (IRB) of the University of Arkansas at Little Rock, USA. All participants provided an informed consent before the start of the experiment. A total of twelve able-bodied male and female volunteers were selected for the study. All participants were healthy, right hand dominant with no neuromuscular disorder history. Our movement set consisted of two hand movements, i.e., hand open (HO) and hand close (HC), and four wrist movements, i.e., forearm pronation (PR), forearm supination (SP), wrist flexion (WF) and wrist extension (WE). We also included 'rest' (RT) in our classification scheme.

Before the start of the EMG data collection, each participant was sitting comfortably in a chair with the armrest adjusted as per comfort. A graphical user interface (GUI) was used to provide visual and auditory cues to participants for guiding through the data collection process. A single trial consisted of four repetitions of each movement and each repetition was five seconds long. There was a short break of five seconds between consecutive movements. A total of ten trials were recorded for each participant. Participants were instructed to maintain comfortable and repeatable force levels for all movements.

We used a total of eight EMG disposable, self-adhesive silver/silver chloride (Ag/AgCl) snap electrodes. The electrodes had two circular conductive areas of 1 cm each and inter-electrode distance of 2 cm. All electrodes were placed around the circumference of the forearm symmetrically. The electrodes were placed at the proximal end of the forehand at a location of 1/3 of the distance between medial epicondyle of the humerus and styloid process of the ulna. The electrodes used were. We used Noraxon TeleMyo Direct Transmission System (DTS) (Noraxon USA, Inc.) with wireless sensors to record the EMG signals. The amplifier had inbuilt bandpass filter of 10-500 Hz as well as a single differential (SD) spatial filter. EMG data from forearm muscles were recorded using wireless probes with an inbuilt preamplifier. The DTS Analog Module further transmitted analog output to an NI-USB 6009 (National Instrument Corporation, Austin, TX, USA) data acquisition card to acquire and digitize the EMG data at the rate of 2000 samples per second [24]. The BioPatRec software was modified to acquire and process the EMG data [20], [24]. The schematic layout of the experimental setup is given in Fig. 2A. During the experiment, the

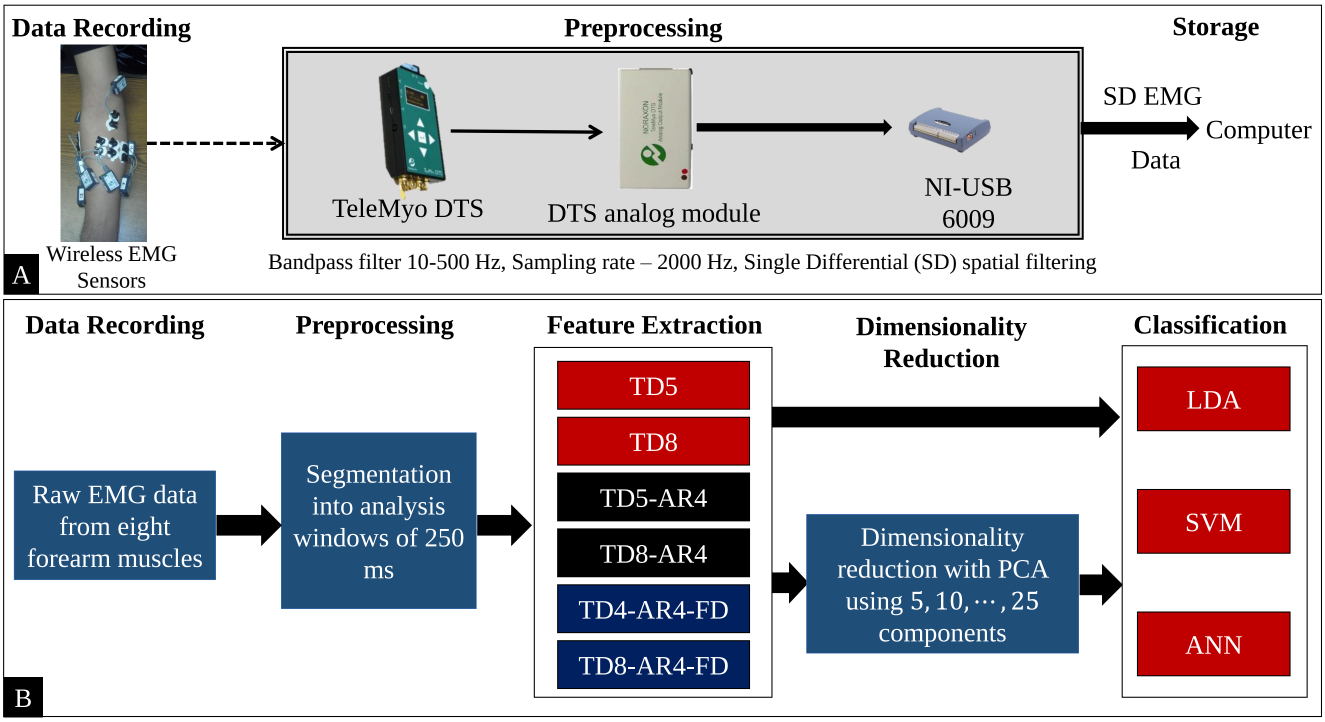

Fig. 2. **A**: Experimental data collection and acquisition of the EMG data from the forearm muscles using TeleMyo DTS, DTS analog module, and a data acquisition module (NI-USB 6009) [24]. The data were recorded using the BioPatRec software at the sampling rate of 2000 Hz [20]. The resulting single differential (SD) EMG data were stored in the computer for later processing. **B**: A schematic layout of the adopted scheme for testing various feature sets, the dimensionality reduction algorithm, and classifiers. The EMG data from eight channels were segmented and various time domain (TD), 4^{th} order autoregressive (AR) coefficients, two frequency domain (FD) features, i.e., the mean frequency (MNF), and median frequency (MDF) were calculated. The feature datasets were passed on to three different classification algorithms, including the linear discriminant (LDA), support vector machine (SVM), and the artificial neural network (ANN) with and without dimensionality reduction using the principal component analysis (PCA).

EMG data were stored in computer disk and were later processed in Matlab (Natick, MA, USA).

We developed a comprehensive scheme to test various sets of EMG features (including TD, AR, and FD), classification algorithms (including the LDA, SVM, and ANN), and the effect of dimensionality reduction on the classification accuracy (using the PCA algorithm). A schematic layout of the adopted scheme is presented in Fig. 2B.

2.2 EMG Feature Sets

After segmentation of the EMG data from all eight channels using analysis windows of size 250 ms, we extracted the TD, AR coefficients, and FD features. In total, we extracted fourteen features, i.e., 8 from TD analysis, 4 from AR, and 2 from FD. These fourteen features were combined to form six different feature sets. Mathematical definitions of all features used in this study are provided in Table 1.

2.3 Dimensionality Reduction using Principal Component Analysis (PCA)

We used the PCA algorithm to reduce the dimensionality of the EMG feature data. We calculated classification accuracies for the EMG feature data without dimensionality reduction and then successively increased the number of principal components from 5 to 25, i.e., $5, 10, \cdots, 25$. The principal components were estimated using Matlab function *pca*.

(1) **TD5**: Our first feature set referred to as the TD5 consisted of five TD features, i.e., RMS, MAV, the number of ZC, WL, and the number of SSC of the EMG signal during the whole length of the analysis window.
(2) **TD8**: The TD8 feature set consisted of all features of TD5 and three additional features, i.e., VAR, WA, and MAVS of the EMG signal in an analysis window.
(3) **TD5-AR4**: This feature set consisted of TD5 and coefficients of the 4^{th} order AR (AR4).
(4) **TD5-AR4-FD**: This feature set consisted of TD5, AR4, MNF and MDF of the EMG spectrum.
(5) **TD8-AR4**: This feature set consisted of TD8 and AR4.
(6) **TD8-AR4-FD**: This feature set consisted of TD8, AR4, MNF, and MDF of the EMG spectrum.

2.4 Machine Learning Algorithms

We used three different machine learning algorithms in our testing scheme, i.e., the linear discriminant analysis (LDA), support vector machines (SVM), and the artificial neural networks (ANN). All three algorithms were tested using the same feature sets and the EMG training data. The classification algorithms were implemented using Matlab's inbuilt functions. The LDA was imple-

Table 1. Definitions of various features of the EMG signal [16], [25]. Time domain (TD), Autoregressive (AR), and frequency domain (FD). $x_i(k)$ is the k^{th} signal sample of the i^{th} segment, N is the number of samples in the segment i, x_{th} is a predefined threshold.

Type	Name	Mathematical definition
TD-1	Root mean square (RMS)	$\sqrt{\frac{1}{N}\sum\limits_{k=1}^{N}[x_i(k)]^2}$
TD-2	Mean absolute value (MAV)	$\frac{1}{N}\sum\limits_{k=1}^{N}\lvert x_i(k)\rvert$
TD-3	Zero Crossing (ZC)	$\sum\limits_{k=1}^{N} f(k)$ with $f(k) = 1$ if $x_i(k) * x_i(k+1) < 0$ and $\lvert x_i(k) - x_i(k+1)\rvert > x_{th}$
TD-4	Waveform Length (WL)	$\sum\limits_{k=1}^{N}(\lvert x_i(k) - x_i(k+1\rvert)$
TD-5	Slope Sign Change (SSC)	$\sum\limits_{k=1}^{N-1} f[\{x_i(k) - x_i(k+1)\}\{x_i(k) + x_i(k+1)\}]$
		$f(x) = \begin{cases} 1 & \text{if } x > x_{th} \\ 0 & \text{otherwise} \end{cases}$
TD-6	Variance (Var)	$\frac{1}{N}\sum\limits_{k=1}^{N}(x_i - \bar{x_i})^2$, where $\bar{x}_i = \frac{1}{N}\sum\limits_{i=1}^{N} x_i$
TD-7	Willison Amplitude (WA)	$\sum\limits_{k=1}^{N} f(\lvert x_i(k) - x_i(k+1)\rvert)$ with $f(x) = \begin{cases} 1 & \text{if } x > x_{th} \\ 0 & \text{otherwise} \end{cases}$
TD-8	Mean Absolute Value Slope (MAVS)	$MAV_{i+1} - MAV_i$
AR1-4	Autoregressive 4$^{\text{th}}$ order (AR4)	$x_i(k) = \sum\limits_{j=1}^{4} a_j x_i(k-j)$
FD-1	Mean Frequency EMG Spectrum (MNF)	$\frac{\sum_{j=1}^{M} f_j P_j}{\sum_{j=1}^{M} P_j}$
FD-2	Median Frequency EMG Spectrum (MDF)	$\sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j$

mented using Matlab command *fitcdiscr* with the 'DiscrimType' set to 'linear'. We used a 10-fold cross-validation scheme for the LDA testing and reported the same classification accuracies in the Results section. For the SVM, we used Matlab's *fitcecoc* function with a 10-fold cross-validation and a one-vs-one scheme. For the ANN classification, we used two hidden layers and divided the data randomly into three bins, i.e., 70% of the data for training, 15% for validation, and 15% for testing. The network was trained using the Levenberg-Marquardt backpropagation algorithm. The classification accuracy data represent average values over all cross-validation runs.

3. RESULTS

3.1 Dimensionality Reduction Using the Principal Component Analysis (PCA)

We start by presenting our results for the dimensionality reduction using the PCA algorithm. In Fig. 3, we present percentage variability explained by an increasing number of principal components of the PCA. It is evident that ten principal components explained more than 98% variability in the EMG feature data.

The classification accuracies from all three algorithms, i.e., LDA, SVM, and ANN using two different TD feature sets, i.e., TD5 and TD8 for a range of principal components are presented in Fig. 4A and B respectively. The classification accuracies presented in these figures are average values calculated across all twelve tested participants. We observed that the classification accuracies for all algorithms were a function of the number of principal components of the PCA and increased significantly with the increasing number of principal components. However, we observed the highest classification accuracies for the case when no dimensionality reduction was performed. It is also evident that the classification accuracy of the LDA was significantly higher than the SVM and ANN for both feature sets.

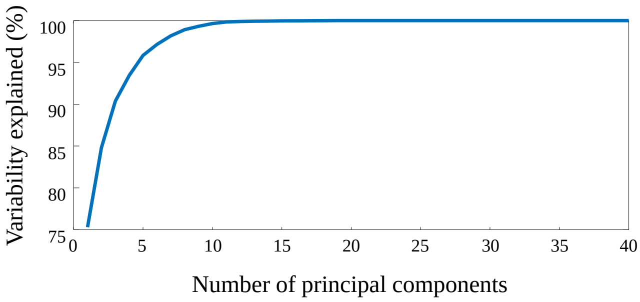

Fig. 3. The variability explained (in %) by an increasing number of principal components of the EMG feature data. It is evident that first 10 components explained more than 98% variability in the feature data.

In Fig. 4C, we present classification accuracies for the LDA using four different feature sets, i.e., TD5-AR4, TD5-AR4-FD, TD8-AR4, TD8-AR4-FD with and without dimensionality reduction using the PCA. It is evident that the PCA did not improve classification accuracy, rather a decrease in the classification accuracy is noted for all cases. An increase in the number of principal components increased the classification accuracy for all tested feature sets.

3.2 Classification Algorithms

The classification accuracy data from all three algorithms, i.e., the LDA, SVM, and ANN using TD5 feature set is presented in Fig. 5 for all twelve participants. The average values calculated across all tested participants are also shown. We observed good classification

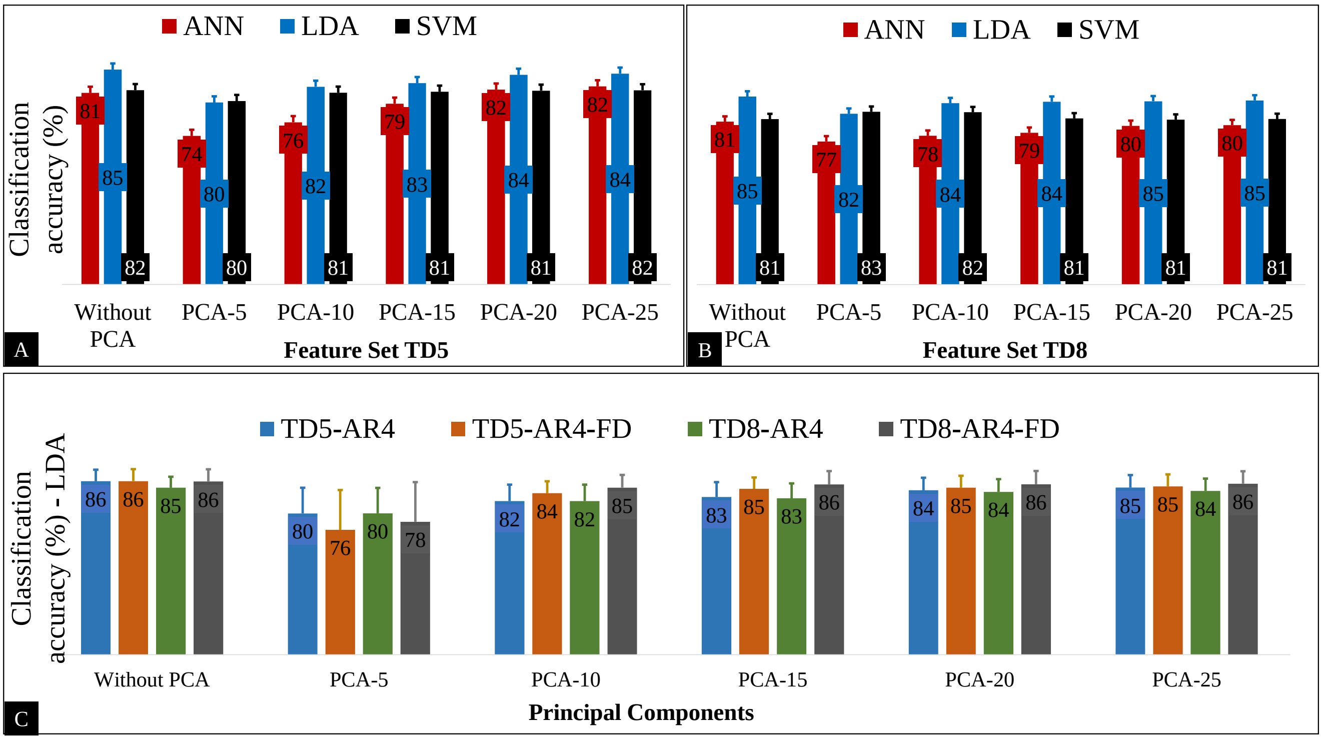

Fig. 4. The effect of dimensionality reduction on the classification accuracy using different feature sets and classification algorithms. **A**:The classification accuracy of three different classification algorithms, i.e., linear discriminant analysis (LDA), support vector machines (SVM), and artificial neural networks (ANN) is presented. The dimensionality reduction was performed using the principal component analysis (PCA). The classification accuracy data presented here are the averaged values calculated across all tested subjects. The small capped lines on the bars represent single standard deviation. We used the TD5 feature set that consisted of 5 TD features calculated for each analysis window, i.e., root mean square (RMS), mean absolute value (MAV), the number of zero crossings (ZC), waveform length (WL), and the number of slope sign changes (SSC). For the dimensionality reduction, PCA-5 indicates that first five components of the PCA were used as the new feature set and so on. It is evident that the dimensionality reduction decreased the classification accuracy for all algorithms. We also note that the LDA performed better than all other classification algorithms. **B**: The classification accuracy of LDA, SVM, and ANN for the feature set TD8. The feature set TD8 included all features of the TD5 as well as the variance (VAR) of the EMG signal, Willison amplitude (WA), and mean absolute value slope (MAVS). **C**: The classification accuracy values for the LDA classifier using four different feature sets without and with increasing number of principal components of the PCA. Please refer to Table 1 for the definition of different features.

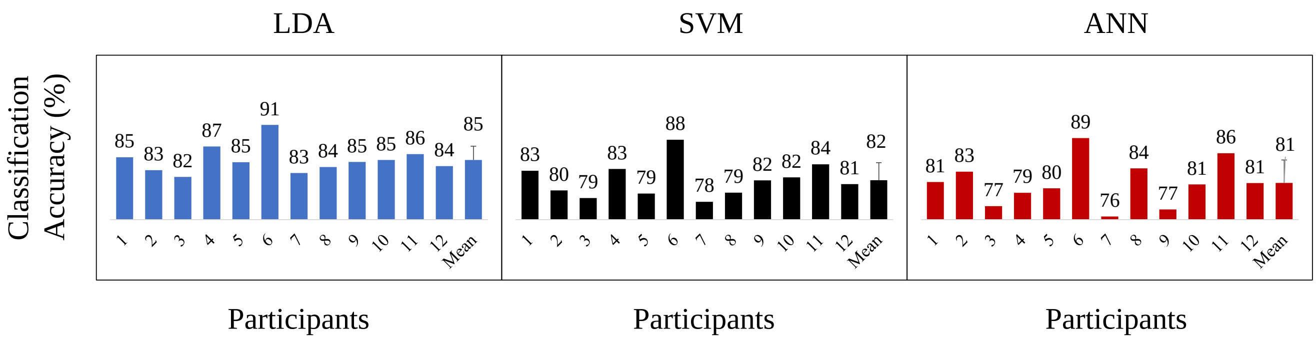

Fig. 5. The classification accuracy for three different classification algorithms, i.e., LDA, SVM, and ANN for all twelve participants using TD5 feature set. The last bars in all three subfigures represent the average data calculated using classification accuracies of all participants. The small caped lines over the bars present single standard deviation. It is evident that the LDA provided the highest classification accuracy for all individuals as well as in the averaged data.

accuracies; however, it is evident that the LDA outperformed other two algorithms, i.e., the SVM and ANN in classification accuracy.

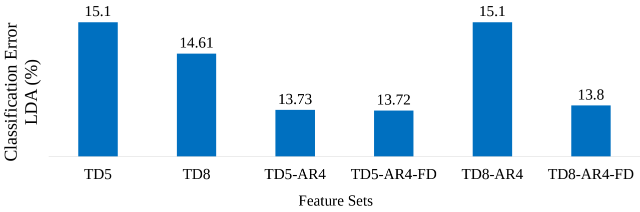

Fig. 6. Classification error in percentage for the LDA classifier using six different feature sets. The TD5-AR4, TD5-AR4-FD, and TD8-AR4-FD showed comparable performance.

3.3 Feature Set

The classification error values of the LDA classifier for six different feature sets calculated using EMG data from all twelve subjects are presented in Fig. 6. We observed that three feature sets, i.e., TD5-AR4, TD5-AR4-FD, and TD8-AR4-FD provide the comparable performance across all tested participants.

3.4 Confusion Matrix

We present the confusion matrix for the LDA classifier with the TD5 feature set in Table 2 for six movements and a rest class. The percentage values presented in the confusion matrix were averaged across all participants.

Table 2. Confusion matrix (%) for the LDA classifier using TD5 feature set. HO - hand open; HC - hand close; WF - wrist flexion; WE - wrist extension; PR - pronation; SP - supination; RT - rest.

	HO	**HC**	**WF**	**WE**	**PR**	**SP**	**RT**
HO	83.14	0.11	0.22	0.32	0.59	0.18	15.44
HC	1.51	82.52	0.01	0.00	0.23	0.19	15.54
WF	1.10	0.10	83.02	0.00	0.71	0.11	14.95
WE	1.42	0.00	0.00	82.30	0.28	0.00	16.00
PR	0.04	0.17	0.21	0.20	83.34	0.30	15.74
SP	0.74	0.24	0.09	0.14	0.20	81.22	17.38
RT	0.04	0.09	0.02	0.09	0.35	0.65	98.75

4. DISCUSSION

We aimed to investigate the movement classification problem, i.e., the estimation of the movement intent, for the EMG-controlled transradial prosthesis using the surface EMG data from forearm muscles. The identified movement intent by the machine learning algorithm is passed on as the control information to the actuation mechanism of the prosthetic device. The performance of these prosthetic devices significantly depends on the classification accuracy of the employed machine learning algorithms [4], [16], [24], [27]. The accuracy of these machine learning algorithms, in turn, may significantly be affected by the choice of the type and the number of features, the dimensionality reduction technique, as well as, the type of the classification algorithm used. Therefore, using the EMG data from twelve healthy participants, we set out to find a combination of feature set with/without dimensionality reduction, and classification algorithm, that provided highest classification accuracy. Our investigation included three different classification algorithms, i.e., LDA, SVM, and ANN, dimensionality reduction using the PCA, and various combinations of time domain (TD), autoregressive (AR), and frequency domain (FD) features (Fig. 2B).

We used the PCA algorithm to reduce the dimensionality of a range of feature sets before performing classification using the LDA, SVM and ANN algorithms. We found that, for our EMG data, 10 principal components were able to explain more than 98% of the data variability (Fig. 3); however, we still used a range of principal components for our analyses, i.e., $5, 10, \cdots, 25$. We observed that using the PCA algorithm, the classification accuracy for all algorithms, i.e., LDA, SVM, and ANN (Fig. 4A and B) and for different feature sets (Fig. 4C) significantly decreased. The classification accuracy only improved if the number of principal components was increased. We speculate that due to the linear nature of the PCA projections, the nonlinear information in the EMG features was not adequately represented in the PCA reduced data. Therefore, we conclude that it is essential to provide the whole feature sets to the classification algorithms rather than their principal components estimated using the PCA algorithm.

In our analysis, we tested three representative classification algorithms from linear as well as nonlinear domain, i.e., the LDA, SVM, and ANN. We observed that out of all tested algorithms, the LDA outperformed other two, i.e., SVM and ANN in the classification accuracy for all different feature sets (Fig. 5). The LDA also produced highest classification accuracies for all individuals, i.e., compare each participant's classification accuracy across all three classifiers [28]. We believe that the superior performance of the LDA resulted due to its linear structure, i.e., once we have a representative feature set that captured adequate information from the EMG data, a simple linear classifier, such as the LDA, was adequate to achieve good classification accuracies.

Keeping in view the complex nature of the EMG signal, we used features from the EMG amplitude (referred to as the time domain or TD), spectrum (referred to as the frequency domain or FD), as well as, EMG stochastic modeling coefficients (referred to as the autoregressive modeling, AR). We calculated fourteen different features and then combined these into six feature sets, i.e., TD5, TD8, TD5-AR4, TD5-AR4-FD, TD8-AR4, and TD8-AR4-FD (Table 1). We observed that increasing the number of features in a feature set increased the classification accuracy (Fig. 6), i.e., TD5 to TD8 and then to TD5-AR4. However, in the case of TD8-AR4, we observed a reduction in the classification accuracy. Furthermore, adding the spectral information, i.e., FD features increased the classification accuracy for both TD5-AR4 and TD8-AR4 feature sets. Overall, we found the highest classification accuracy was achieved with features that used information from the EMG amplitude, spectrum as well as stochastic modeling, i.e., feature sets TD5-AR4-FD and TD8-AR4-FD. On the other hand, the TD5-AR4 also performed equally good and also entailed the minimum number of computations. Therefore, we consider that the TD5-AR4 was the most efficient feature set for our data.

We also investigated the confusion matrix, i.e., how different movements were confused with each other by the LDA algorithm for the given EMG data. We observed the 'rest' (RT) was highly confused with all movements (i.e., HO, HC, WF, WE, PR, SP). All other confusions of movements with each other were significantly lower.

5. CONCLUSION

We performed detailed investigated into machine learning schemes used for the EMG-controlled prosthetic devices. Specifically, we focused on different features of the EMG signal based on its amplitude, spectral contents, and stochastic modeling. We also investigated the effect of dimensionality reduction as well as used various classification algorithms including the LDA, SVM, and ANN. The highest classification accuracies were recorded for a feature set that employed EMG amplitude, spectral, as well as stochastic modeling information with any form of dimensionality reduction. Further, the simple linear classifier, i.e., LDA outperformed SVM and ANN algorithms in classification accuracy.

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