Classification of the Myoelectric Signals of Movement of Forearms for Prosthesis Control

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***Abstract*—Biomedical signals are commonly used as a convenient solution of Human Computer Interface (HCI) for the disabled persons. Myoelectric control system is the fundamental component of modern prostheses, which uses the myoelectric signals from an individual's muscles to control the prosthesis movements. For this purpose, surface electromyogram (SEMG) data collected from thirty participants using eight electrodes located on the human forearm is used. Various feature sets were extracted and projected in a manner that ensured maximum separation between different movements of hand and then fed to the four different classifiers. We have used Sparse Principal component analysis as feature projection which very profoundly discriminated the feature sets. The second contribution is the use of a majority voting algorithm post processing approach to maximize the probability of correct classification of the myoelectric data for different movements of forearms. Practical results and ANOVA tests proved the feasibility of the proposed approach with an average classification accuracy > 98% for different subjects forearm movements. The focus of this work is to optimize the configuration of the classification scheme. The SVM ensemble based limb motion classification system demonstrates exceptional classification accuracy and results in a robust method of motion classification with low computational load.**

***Index Terms*—Discriminant Locality Preserving Projections (DLPP), myoelectric control, Myoelectric Signal (MES), pattern classification, prosthesis, Sparse Principal Component Analysis (SPCA)**

I. Introduction

Surface electromyogram (SEMG) signal is one of the most significant biomedical signals. The use of SEMG signal is simple, fast and convenient, hence widely studied and applied in clinic. It is generated by muscular contraction and can be recorded using surface electrodes. The noninvasive surface electromyogram (SEMG) signal provides information about neuromuscular activity and has become an important and effective control input for powered prostheses from last 40 years [1].

The loss of the human upper-limb, limits the ability of amputees to interact with the real world. The life of the amputees can be enhanced by restoring their ability to interact with the outer world. This can be made possible by using powered upper-limb prostheses. These prostheses derive their control command from myoelectric signals generated by the human muscles [2].

Generated by the human muscles, they muscles are used to derive control commands for powered upper-limb prostheses.

A myoelectric control system has to be accurate, response time is such that delay is not perceivable by the user and intuitive interface relieves the mental burden by the user. Electrically powered prostheses with myoelectric control have many advantages over other types of prostheses. It can be routinely fitted to upper limb deficient clients for clinical evaluations of the functional benefits. The user is freed of straps and mechanical switch control. The muscle activity required to provide control signals is relatively small.

Many myoelectric control systems are available capable of controlling a single device such as a hand, an elbow or a wrist in a prosthetic limb [3]. Many researchers have demonstrated the feasibility of myoelectric control for various feature sets and classification methods [4]-[7]. The surface EMG signals have been successfully utilized in decoding the intended forearm movements.

Myoelectric control has been successfully utilized in rehabilitation and human-computer interfaces [8], [9]. The myoelectric signals acquired from healthy subjects can be considered as an emulation of the amputee's command signals extending from the shoulder and intended for various hand movements. Moreover, the rehabilitation experts have suggested, for initial evaluation purposes, myoelectric signals from the healthy hand should be considered even in the case of the amputees [3], [4], [10], [11]-[13]. Also, the myoelectric signals may differ from one person to another as a result of different physiological and recording conditions. The large sample sizes do not mean that they will be more beneficial [14].

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In the realization of myoelectric control, the key problem is to accurately recognize the user's intent. From the last four decades, researchers have studied the classification of hand motions by sensing the activities of upper arm muscles and have succeeded with recognition rate more than 90 percent.

To classify the acquired surface myoelectric signals into one of a predefined set of forearm movements, pattern recognition of the myoelectric signal is used. It plays a key role in advanced control of powered prostheses for individuals with amputations or congenitally deficient forearms [4]-[5]. The concept of employing pattern recognition for myoelectric signal control schemes was first developed in late 1960s or early 1970s [15], [16]. First successful pattern recognition based approach offering real time performance and high accuracy was developed by Hudgins in 1993. The approach used Time Domain (TD) statistics with multilayer perceptron (MLP) neural network as classifier. Four types of limb motions were classified with an error rate around 10% [4]. This work incited a renewed interest in the pattern recognition based myoelectric control, and a great deal of work was ensued. These efforts have investigated the efficacy of various feature sets [18]-[20] (time-frequency and time-scale representations) and classifiers, Gaussian Mixture Models (GMMs) [17], self-organizing neural networks [21], dynamic artificial neural networks [22], genetic algorithms [23], fuzzy logic [29] and Hidden Markov Model [25].

These systems exhibit high accuracy and are capable of being tuned to an individual user thus learning the characteristics of the MES activity accompanying their contraction efforts.

The paper is constituted as follows: Section 2 describes the data collection procedure, the feature extraction, feature set reduction, classification and post processing. Section 3 and section 4 presents the experimental results and discussion respectively and finally, conclusions are drawn in Section 5.

II. Methodology

We propose an EMG based forearm movement system that employs eight EMG electrodes placed on the surface of the human forearm. The goal is to employ effective feature reduction techniques and classifiers to increase the classification accuracy for identification of seven classes of forearm movements.

The block diagram of the proposed system is shown in Fig. 1. Raw surface EMG signals were preprocessed and feature sets were extracted. From the extracted features sets SPCA and other feature reduction techniques OLDA, DLPP, LDB were used to project extracted features into a new feature set with enhanced discrimination ability. Suitable classifiers SVM ensemble, LDA, MLP and KNN were utilized to recognize the signals from different classes of the forearm movements. To eliminate spurious misclassification and minimizing the number of training patterns, majority voting was used that increased the classification accuracy.

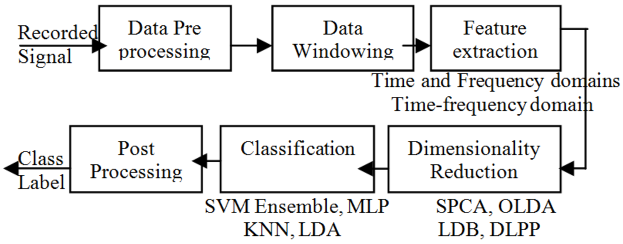

Figure1. Block diagram of the myoelectric signal classification system for prosthesis control.

A. Data Collection

The data utilized in this paper is same that is used in [26]. The surface electromyogram signals were collected from thirty subjects consisting of eighteen females and twelve males. Duo-trode Ag-AgCl eight electrodes were placed on seven sites of the forearm and on the bicep for collecting eight channels of myoelectric data. An Ag-AgCl Red-Dot electrode was placed on the wrist as common ground reference. The signals were amplified with a gain of 1000 and bandwidth of 1 Hz to 1 KHz to be sampled at 3 KHz.

Seven distinct forearm movements: hand open (HO), hand close (HC), supination (S), pronation (P), wrist flexion (WF), wrist extension (WE) and rest (R) were recorded. Within each trial, the subject repeated each forearm movements four times, holding each movement for duration of three seconds. The order of these movements was randomized. A five-second rest period was introduced at the start and end of each trial. Each session comprised of six trials and four such sessions were recorded.

In the original research paper [26], data from only the fourth session was used. For the same reason, we have used data from the fourth session. The data from the first four trials were used for training data and the remaining two trials for testing. The Fig. 2 shows the placement of electrodes on the forearm.

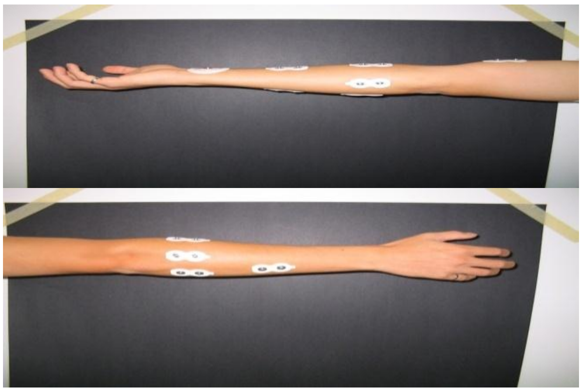

Figure 2. Electrodes placement on the right forearm

B. Feature Extraction

Due to the stochastic nature of the EMG, an instantaneous sample contains relatively little information about the overall muscle activity, hence features should be chosen very cautiously. They are used to model and analyze raw electromyogram signals, so success of any classification problem depends almost entirely on the selection and extraction of features. Instead of focusing upon the classifier, the authors have demonstrated in previous work that the classification performance is more profoundly affected by the choice of feature set [19]. They are usually computed from the preprocessed myoelectric signal in time, frequency and time-frequency domain using a sliding window approach. Either a disjoint or an overlapped windowing scheme is utilized. The overlapped windowing scheme produces better classification performance but it leads to higher computational costs in the training and the testing phase for certain classifiers [27]. Hence the selected window size and its increments, is chosen accordingly.

Specifically, a wavelet-based approach exhibits superior performance in comparison to Hudgins' time domain approach. The performance of Hudgins' time domain feature set (TD), and the feature set based upon the Time Varying Auto Regressive model (TVAR), the short-time Fourier transform (STFT), the discrete wavelet transform (DWT), and the wavelet packet transform (WPT) were compared with the work of few previous researchers.

For the STFT, a Hamming window of length 128 points with an overlap of 50% gave the best performance. The DWT and WPT experienced the best performance when using a daubechis mother wavelet and a symmlet mother wavelet, of order four and five respectively.

The feature set should be capable to capture the characteristics or properties of the MES for different limb motions. Consideration of the feature set must involve the computational load required; a tradeoff in accuracy and computational complexity does exist. In our work, features in the time, frequency and time -frequency domains have been extracted using sliding window techniques. In time domain, mean absolute value, root mean square of the EMG signal was calculated to extract basic amplitude information and AR modeling is performed. Features in the time domain are limited successful, myoelectric signal being non stationary. Some characteristic variables in power spectral density say mean and median frequency and small time Fourier transform is computed in the frequency domain but it is also not useful in multifunction myoelectric control [4]. Current advances in time-frequency analysis are crucial to understand the complexity of myoelectric signal. Discrete Wavelet Transform (DWT) and Wavelet Packet Transform (WPT) has been extracted which contains useful information in time and frequency domain. According to a basis function called wavelet function, DWT decomposes the original myoelectric signal into some multi-resolution components. The wavelet function is both translated and extended in time, undertaking a two-dimensional cross correlation with the time domain myoelectric signal. Also, there is no universal wavelet function, suitable to all types of signal. Hence, the selection of a wavelet function becomes an important factor to achieve optimal performance in the signal processing. WPT offers more range of possibilities for signal analysis than DWT [28].

Overlapping window of 256 ms was analyzed, which were spaced 128ms and 32 ms apart for training data and testing data respectively. To improve the accuracy, the transitional data 256ms before or after a change in limb motion was removed from the training set.

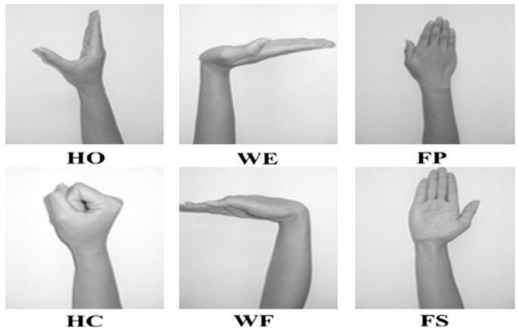

Figure 3. Different movement classes considered in this paper

C. Feature Reduction

Dimensionality reduction is an important process before classification is performed. LDA is a supervised, nonlinear dimensionality reduction technique. Unlike other nonlinear reduction methods, it provides a powerful mapping with less computational effort. The maximum class discrimination is achieved by maximizing the ratio of the between-class distance to the within-class distance. The classical LDA fails for under sampled problems where the data dimensionality is much larger than the size of the sample and all the scatter matrices are singular. Therefore we have employed orthogonal LDA (OLDA), which computes a set of orthogonal discriminant vectors via the simultaneous diagonalization of the scatter matrices.

Orthogonal LDA (OLDA): All the extracted features formed one large feature set which were then reduced in dimensionality with the Orthogonal Linear Discrinminant Analysis (OLDA) feature projection. With c being the number of problem classes, maximum of c -1 feature can be produced here 7 numbers of features were produced [27]. The orthogonal transformation in OLDA can be solved by the following optimization problem.

$G = \mathrm{argmax}_{G \varepsilon IR^{m \times l}: GTG} = I_l^{trace}((S_t^L)^+ S_b^L)$ where $(S_t^L)^+$ denotes pseudo-inverse [29] of (S_t^L). The orthogonality condition is imposed in the constraint. The computation of the optimal transformation of OLDA is based on the simultaneous diagonalization of the three scatter matrices [30], [31], [32].

The application of OLDA is justified by the high variance nature of the myoelectric signal which causes the information to be liberally dispersed amongst the original feature set extracted from the EMG signals. Feature projection methods can consolidate such information more effectively than feature selection based methods in EMG signals classification problems [18]. Further, in [29], [33] the performance of OLDA against that of nonlinear projection methods was compared. Also OLDA has low computational cost compared to nonlinear projection methods.

Sparse PCA (SPCA): Principal component analysis (PCA) is commonly used in data processing and dimensionality reduction. In PCA, it is difficult to interpret the results as each principal component is formed by linearly combining all the original variables. The fact that PCA does not consider the class label in the projection process limits the performance of PCA when compared to other projection methods. Sparse Permanent component analysis (SPCA) is considered as a combination of feature selection and projection. SPCA provides a means of unsupervised dimensionality reduction, as no class membership qualifies the data when specifying the eigenvectors of maximum variance [13].

Sparse Principal Component Analysis (SPCA) uses the *lasso* (*elastic net*) to produce modified principal components with sparse loadings. It allows flexible control on the sparse structure of the resulting loadings. As a principled procedure, it is computationally efficient, has high explained variance and ability in identifying important variables. It maximizes the variance explained by a linear combination of the input variables, but simultaneously constrains the number of nonzero coefficients. We have used it to find a subspace whose basis vectors correspond to the maximum-variance directions in the original space [34].

In addition to SPCA we have also used Discriminant Locality Preserving Projections (DLPP), Orthogonal Linear Discriminant analysis (OLDA) and Local Discriminant Bases (LDB) as feature reduction or projection techniques. The performance of DLPP and OLDA were almost similar. Fig. 4 shows the classification accuracy for different classifiers.

D. Classification

Myoelectric signal classification for prosthetic control is a difficult problem, as the myoelectric signal is random in nature due to the complex strategies of motor unit firing and recruitment inherent in neuromuscular control strategies. Several factors must be considered for choosing a classifier for the myoelectric signal classification applications. A suitable classifier must be accurate enough to generalize well the novel data and capable of being optimized to suit the unique patterns generated by individual users. It is essential that it should be computationally efficient in the act of classifying novel patterns, as it must satisfy the real-time constraints of myoelectric control. It is not necessary that it should be capable of being trained in a reasonable amount of time [25].

The LDA and the MLP are easily implemented and well understood representatives of statistical and neural classifiers respectively. Although some classifiers demonstrate obvious advantages over others but is the feature set that most dramatically affects the classification performance, and this is our main focus in this work.

SVM Ensemble: A SVM is an intelligent learning method and is the core of classification in myoelectric control. It has high accuracy, robust performance, and low computational load but suitable for two-class classification. In Ensemble learning multiple learners are trained to solve the same problem. It tries to construct a set of hypotheses and combine them to use. Since an ensemble contains a number of base learners, its generalization ability is much stronger than that of base learners.

In 1995, Krogh indicated that the generalization error of ensemble is equal to average generalization error of individual SVMs minus the average differences of individual SVMs. Therefore, to enhance the generalization performance, we should not only maximize the generalization ability of individuals, but to also increase the differences between the various individuals.

In this paper, we have used an ensemble algorithm based on bagging [35] and culture algorithm [36]. The base learners of high difference are generated by bagging method which is a re-sampling the training data technology. The generalization performance of some selected base learner ensemble is better than all of the base learners [37]. Some base learners with high accuracy and large differences are selected by CA to ensemble. The method uses multiple versions of a training set by using the bootstrap, i.e. sampling with replacement. Each of these datasets is used to train a different model. The outputs of the models are combined by voting to create a single output.

Using a base learning algorithm, bagging trains a number of base learners each from a different bootstrap sample. The size of a sample is same as that of the training data set and it is obtained by sub sampling the training data set with replacement. For a bootstrap sample, the probability that an example appears at least once is 0.632. After obtaining the base learners, bagging combines them by majority voting and the most-voted class is predicted. The pseudo-code of Bagging is as follows.

Data set D = {(x1, y1), (x2, y2), … (xn, yn),};
Base learning algorithm L;
Number of learning rounds T
Process: for t=1,…,T
Dt = Bootstrap (D); % Generate a bootstrap sample from D
Ft = L (Dt) % Train a base learner ht from the bootstrap sample
end
Output: $f(x) = argmax_y \in Y \sum_{t=1}^{T} 1\ (y = f_t(x))$ *% the value* of 1(a) is 1 if a is true and 0 otherwise

In a cultural algorithm, there are two main spaces: the normal population adopted with evolutionary programming and the belief space. The shared acquired knowledge is stored in the belief space during the evolution of the population. The acceptance function accepts those individuals that can contribute with their knowledge to the belief space. The update function creates the new belief space with the beliefs of the accepted individuals. The idea is to add to the current knowledge the new knowledge acquired by the accepted individuals. The function to generate offspring used in evolutionary programming is modified so that it includes the influence of the belief space in the generation of offspring [38].

E. Post Processing

With the overlapped windowing scheme very dense decision stream is produced and decisions are made more frequently than the required response time of prosthesis. Post processing techniques are usually utilized after classification to prevent overwhelming the prosthetic controller with varying classification decisions. By eliminating spurious misclassification, the classifier performance is enhanced [3]. The EMG classification accuracies are usually smoothed using a majority vote (MV) technique. In a MV scheme, an acceptable delay of 256 ms and an overlapped windowing increment in the test session is used. The number of decisions used in the majority vote is determined by the processing time $T_{process}$ (time consumed during feature extraction, projection and classification) and the acceptable delay T_{delay} (the response time of the control system). We can use the previous decisions, the current decision and the future decisions to form the MV. For a given decision point d_i, the majority vote decision d_{mv} includes the previous m decisions and may also include the future m decisions (with m satisfying the inequality of $m \times T_{process} \leq T_{delay}$ [3]. The value of d_{mv} is simply the class label with the greatest number of occurrences in the 2m+1 decisions.

If the queue does not have m decisions then the system can just implement the voting between the current and the available number of votes in the queue without having to wait for more decisions to be generated. In such a case, the system might show some errors, especially at the transitions, unless the subject is well trained to exhibit the same patterns for the specific hand movement [27].

III. Results

The classification accuracy was computed using three feature reduction techniques before and after post processing i.e. using majority voting. The performance of SPCA was comparable to OLDA hence there was minor difference in the classification accuracies.

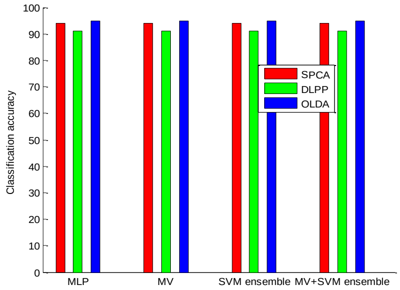

Figure 4a. Using the validation set with extracted features

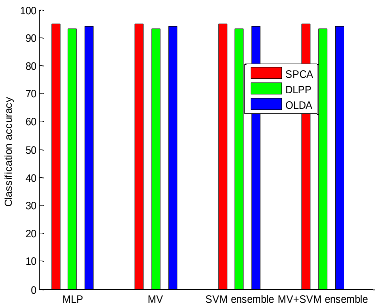

Figure 4b. Using the Testing set with extracted features

The system has been shown to be very accurate in discriminating seven classes of movements. The response was computed averaged across all subjects for different classes using each classifier individually. Fig. 5 shows the validation and testing sets using WPT feature and SVM ensemble as the classifier. It also depicts the performance of OLDA is comparable to DLPP.

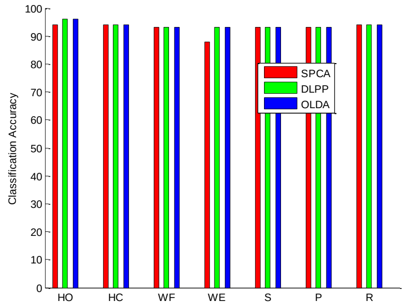

Figure 5a. Using validation set with WPT feature

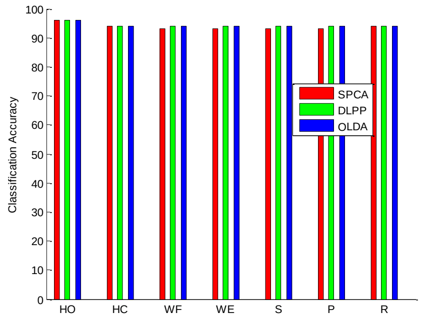

Figure 5b. Using the testing set with WPT feature

We also find out the performance of classifiers for each of the feature reduction projection techniques separately for time and frequency domain features combined (TD+FD), time varying Autoregressive (TVAR) model of 4th order, STFT, DWT and WPT.

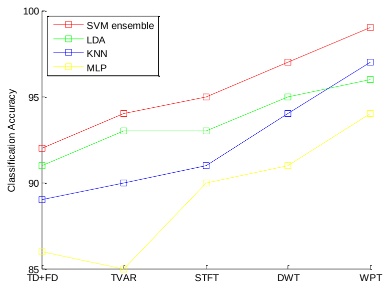

Figure 6a. Classification accuracy averaged across different features using SPCA

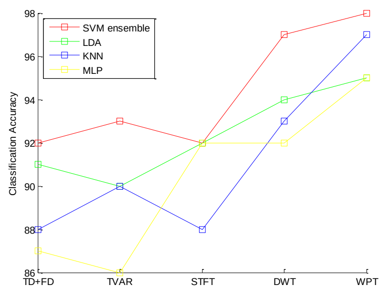

Figure 6b. Classification accuracy averaged across different features using OLDA

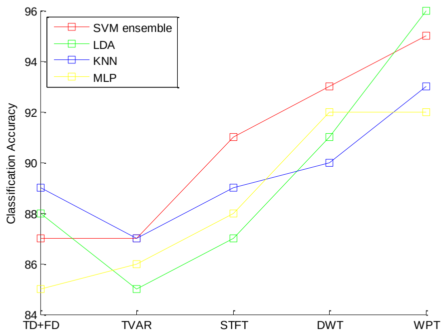

Figure 6c. Classification accuracy averaged across different features using LDB

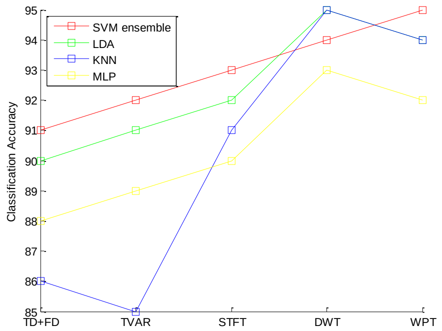

Figure 6d. Classification accuracy averaged across different features using DLPP

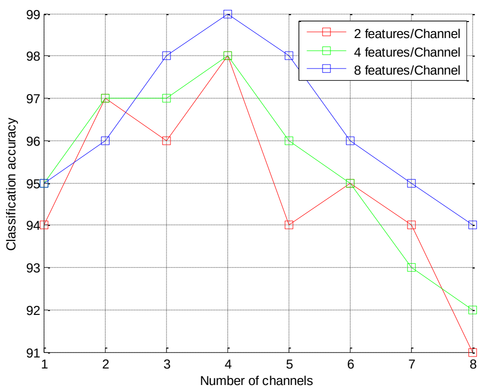

Figure 7. Classification accuracy with number of features per channel

As the number of features per channel increased irrespective of the type of features, more number of features per channel gave more accurate results. The SVM ensemble gave the best result with an accuracy of 99%. To which extent classification performance can be improved with additional channels of myoelectric activity. The response was averaged across all subjects, by empirical analysis and it was observed that more numbers of channels do not profoundly affect the classifier performance. Fig. 7 shows four number of channels are sufficient, after that the performance starts decreasing.

The classification accuracies with random combinations of three, four, five, six- and seven class subsets were obtained. Fig. 8 depicts one set of combination with all the classifiers. SVM ensemble outperformed all other classifiers. Accuracy increased with increase in number of classes but depending upon the type of classifier used.

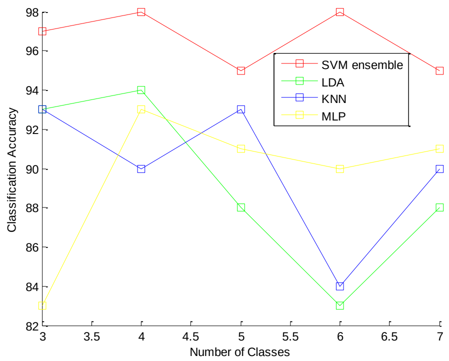

Figure 8. Number of classes verses classification accuracy

The effect of different length of windows of myoelectric signals was computed against the achieved classification accuracies. The window lengths taken into consideration were 128, 256, 384 and 512ms. Four different classifiers were utilized to demonstrate the effectiveness of the projected features that are mutually uncorrelated. The classification accuracy was greater than 98% for 256 ms window length with SPCA as feature projection and SVM ensemble as the classifier. Larger length of window was not effective. The performance of LDB was comparable to SVM. With no majority voting 128ms analysis window provided the best combinations of computational efficiency and classification accuracy. Fig. 10 shows that error percentage with and without majority voting with 256 ms window.

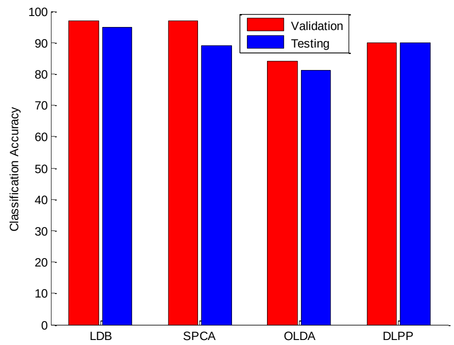

Figure 9. Classification accuracy for 256 ms window for different feature reduction techniques

The geometric mean error ratio measures the relative performance of one method to another. In Table I all the values are less than 1, indicating that WPT outperforms all the other method in terms of error reduction. The result was computed over 30 iterations.

TABLE I. GEOMETRIC MEAN ERROR RATIO

WPT vs	MAV	RMS	Mean frequency	Median frequency	TVAR	STFT	DWT
SVM ensemble	.26	.41	.35	.23	.48	.28	.35
LDA	.49	.62	.57	.91	.42	.16	.72
KNN	.62	.76	.8	15	.67	.72	.15
MLP	.65	.67	.81	.42	.32	.89	.46

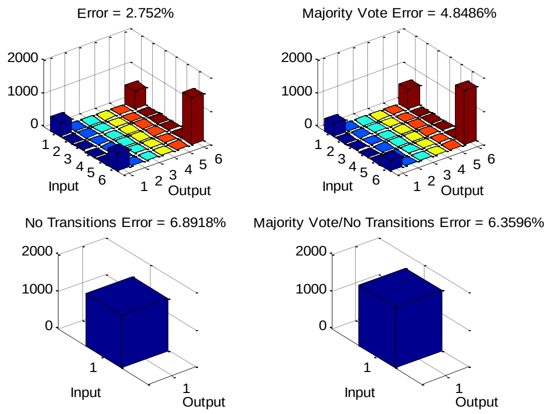

Figure 10. Error percentage with 256 ms window

A one-way analysis of variance (ANOVA) was used to help us to decide if the differences in the achieved error rates among various methods are attributed to the advantages and disadvantages of each method. The significance level was set to value $\alpha = 0.05$ and the corresponding results are shown in Table II. It is clearly indicated in the table that performance of LDB is superior to all other techniques.

TABLE II. RESULT OF ONE WAY ANOVA TEST

LDB vs	ρ value
SPCA	.0085
OLDA	.0286
DLPP	.0278

Here different wavelet families the Symmlet, Coiflet and Daubechis of order 5, 5 and 4 respectively were employed. The decomposition level was made 6 for both the methods and SVM ensemble was used as classifier. Leave-one-out cross validation was employed for testing, as the number of samples being small. Table III shows the corresponding error rates achieved by classifier.

TABLE III. NUMERICAL VALUES OF THE ACHIEVED ERROR RATES

Features	Sym5	Db4	Coif5
DWT	11.18	5.23	21.16
WPT	1.54	8.63	11.52

IV. DISCUSSION

The covariance structure is removed, by projecting the feature sets onto the orthonormal axes of maximum variance. If the original feature space possesses significant linear dependencies then lesser principal components can be discarded with little loss of information. In the original feature sets, the information is liberally dispersed; therefore, a SPCA will consolidate this information much effectively than other feature selection methods. There is significant degree of linear dependency amongst coefficients of the STFT, the DWT and the WPT, in the high-dimensional space. The loose structure of the transient myoelectric signal subtends a substantial degree of within-class dispersion in the time-frequency domain. SPCA appears to effectively accommodate these effects. The improvement that SPCA offers to TD features is not as pronounced as to the TFR sets, as the original dimensionality is relatively low. For TFR feature sets subject to SPCA, the LDA classifier occasionally shows better generalization performance compared to the MLP classifier. Despite of the fact that the MLP is being capable of prescribing nonlinear class boundaries, thus encompasses the capabilities of the LDA.

With the increase in dimensionality of the feature set, the degree of nonlinearity between class boundaries must diminish. In the high dimensional feature space of TFRs, a significant degree of linear dependency exists. The SPCA preserves the linearity that exists between classes while projecting the TFR coefficients onto a relatively low dimensional space. The fact that the SPCA-projected TFR features have reasonably linear class boundaries and that they have relatively low dimension diminishes the advantage that a MLP may have over a LDA.

The performance of MLP can be made comparable to LDA with appropriate number of hidden layer nodes and properly trained. For a given subject if the size of the MLP is inappropriate, the network may be over trained or undertrained and will reduce the generalization performance of the MLP. The LDA does not learn from its architecture or training algorithm being unsupervised, even then it consistently performs very well. The added advantage of SPCA over MLP classifiers is lesser training time. The added advantage of SPCA is that the back propagation algorithm is speedup as the Hessian matrix of the cost function is more diagonalized than usual. Along each weight axis, is independently generated an appropriate scaling of the learning rate [20].

TABLE IV. COMPARISON BETWEEN PROPOSED SYSTEM AND THE WORK OF OTHER RESEARCHERS

Researchers	Classifiers	Features	Classification accuracy	Reference
Hudgins et al	ANN	Time domain	70-98 %	[4]
Engle hart et al	ANN & LDA	Time frequency	87-94%	[3], [10]
Lee et al	Baye's Classifier	ZC variance	91%	[39]
Graupe et al	Nonlinear discriminants	AR model coefficients	99%	[12]
Khezri et al	ANFIS	TFRs & TD	86-100%	[14]
This work	ANN & LDA	TFRs, AR & TD	95-98%	

Table IV presents the results of the comparison of our work with the other researchers. The results indicate that the combinations of the eight features and using SVM ensemble as a classifier provide a suitable SEMG pattern identifier in recognizing the forearm movement. Based on the level of complexity and rate of correctness, the proposed analytical system proves to be superior. Table IV depicts our overall results for the seven classes of forearm movements show a marked improvement over the previous studies.

V. CONCLUSION

The primary goal of this paper was to compare the pattern recognition classification accuracies and to explore the pattern recognition algorithms which can be utilized within the prosthesis device controllers. These intelligent pattern recognition models will enhance the life of amputees and help them to restore their ability of interacting with the outer world.

The classification of myoelectric signal depended on the domains from which features were extracted. The classifier exhibited very good accuracy with TFRs features but the way in which feature sets were projected mattered most. The performance was more accurate with four channels and it started deteriorating as more number of channels was introduced. In our work, the individual SVMs were aggregated to make a collective decision using majority voting which outperformed the other classifiers. The highest accuracy was obtained with feature sets utilizing all signal features, but WPT outperformed all other features.

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