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Pattern Recognition of Individual and Combined Fingers Movements Based Prosthesis Control Using Surface EMG Signals

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ABSTRAC- Prosthesis control system is the need for the amputees or disable person for performing their daily household work and interaction with the outside world. It is the fundamental component of modern prostheses, which uses the myoelectric signals from an individual's muscles to control the prosthesis movements. The surface electromyogram signals (SEMG) being noninvasive has been used as a control source for multifunction powered prostheses controllers. In spite of the fact there is wide research on the myoelectric control of movements of forearm and hand movements but a little research has been carried out for control of more dexterous individual and combined fingers. With the current demands of such prostheses a challenge that exists is the ability to precisely control a large number of individual and combined finger movements and that too in a computationally efficient manner. This paper investigates accurate and correct discrimination between individual and combined fingers movements using surface myoelectric signals, in order to control the different finger postures of a prosthetic hand. We have SEMG datasets with eight electrodes located on the human forearm and fifteen classes. Various feature sets are extracted and projected in a manner to ensure that maximum separation exists between the finger movements and then fed to the four different classifiers. Practical results along with the statistical significance tests proved the feasibility of the proposed approach with mean classification accuracy greater than 95% in finger movement classification.

Keywords- Discriminant Locality Preserving Projections (DLPP), Modified k-Nearest neighbor (MkNN), pattern recognition, Sparse Principal Component Analysis (SPCA)

1. INTRODUCTION

Surface electromyogram (SEMG) signal being simple and noninvasive is widely studied and applied in clinics. It is recorded using surface electrodes at an optimum force of muscle contraction. The signal has become an important and effective control input for powered prostheses from last 40 years [1].

After the success of utilizing EMG signals in decoding the intended forearm movements, now the prostheses increasingly integrate humanoid robotic features with many degrees of freedom for which many researchers acknowledge the growing need for controlling these artificial multi-fingered dexterous hands [2]. Previous research on prosthetic fingers control proved the feasibility of classifying individual fingers movements using EMG signals. Peleg *et al.* [3] used two surface EMG electrodes to recognize which individual finger is activated from different features extracted from EMG signals while Tsenov *et al.* [4] used time and frequency domain features and various neural networks classifiers to detect four finger movements including hand close (HC). But, both the group of researchers did not considered combined fingers movements. Tenore *et al.* utilizing thirty two surface electrodes, further extended the idea of EMG based finger control into movements that consisted of flexion and extension of all fingers individually and of the middle, ring and little finger as a group achieving ≥ 98% accuracy for able bodied [5] and ≥ 90% for trans-radial amputees [6]. According to Weir *et al.* [7], it can be difficult to obtain more than three or four stable and sufficiently uncorrelated control signals on a residual limb using surface EMG electrodes. Hence, a reduction in the number of electrodes, without compromising the classification accuracy, would significantly simplify the requirements for controlling a powered prosthetic. Cipriani *et al.* [8] performed real-time experiments on both amputees and able-bodied subjects using eight pairs of electrodes to classify seven fingers movements. These included two classes of combined fingers movements with an average accuracy of 79% on amputees' subjects and 89% on able-bodied subjects using the k-nearest neighbor (kNN) classifier. Moreover, the kNN classifier requires large memory to store all the training patterns to compare each testing sample based on distances. Hence, an effective way to reduce the number of extracted patterns without compromising the classification accuracy is required. Thus, the problem of selecting the most appropriate channels, and consequently the features extracted from these channels, for fingers movement classification requires more investigation. Moreover, the number of important channels is also to be identified because using a large number of channels will only result in a huge set of extracted features which in turn demands dimensionality reduction. On the other hand, not all the extracted features have to be considered when implementing the dimensionality reduction step as the multichannel approach might result in redundant features that may not correlate well with the class label.

Even though there has been a development in a single finger movement classification, but a more focused design of a system that can classify multiple individual and combined movements for the same fingers is required. Practical viability of such a system can be improved if a small number of channels to separate these classes of fingers movements can be developed, leading to low computing cost and minimal interferences. Such a system will enable the design of a more dexterous prosthesis that can follow the human intention of moving different fingers in a more natural manner [9].

Here we will classify both individual and combined finger movements using eight numbers of surface electrodes with fifteen classes.

The paper is constituted as follows: Section 2 describes the dataset, 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.

2. METHODOLOGY

We propose an EMG based forearm prosthesis controller that discriminates between individual and combined fingers movements. The block diagram of the proposed system is shown in Fig.1. Raw surface EMG signal was preprocessed and feature sets extracted. The various dimensionality reduction techniques and suitable classifiers utilized for pattern reorganization of the signals for various individual and combined finger movements. To enhance the accuracy we have incorporated majority voting as post processing.

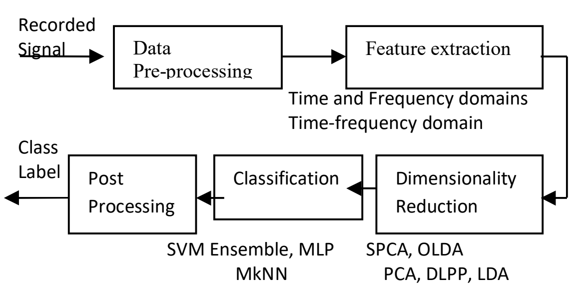
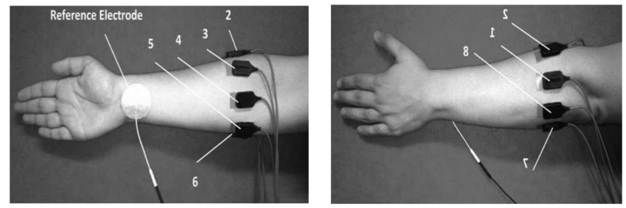


Figure1. Block diagram of the myoelectric signal classification system for prosthesis control.

2.1 Data Collection

The dataset utilized has been collected by Rami N. Khushaba, University of Technology, Sydney. The dataset consists of surface EMG signals recorded from eight channels mounted across the circumference of the forearm and collected from eight subjects, aged between 20 and 35 years. All subjects are normally limbed with no neurological or muscular disorders. A 2-slot adhesive skin interface was applied on each of the sensors to firmly stick the sensors to the skin. The positions of these electrodes are shown in Figure 2.



(a) Anterior electrodes positions (b) Posterior electrodes positions

Figure 2: Positions of the electrodes placed on the circumference of the forearm

The recorded EMG signals were amplified using an amplifier with a gain of 1000. The signal was sampled at 4000 Hz using a 12-bit analog-to-digital converter. The myoelectric signals were filtered using a band pass filter between 20-450 Hz with a 50 Hz notch filter to remove the line interference. Fifteen classes of individual and combined fingers movements were collected as shown in the Figure 3. Each movement is of 5 seconds duration. Each of the fifteen fingers movements has three trials.

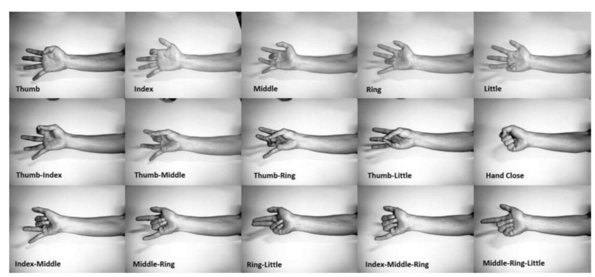


Figure 3: Different movement classes [10]

2.2. Feature Extraction

Features are used to model and analyze raw electromyogram signal, hence success of any pattern recognition 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 [11]. They are usually computed from the preprocessed myoelectric signal in time, frequency and time-frequency domain. Either a disjoint or an overlapped windowing scheme is utilized. Better classification performance is achieved using the overlapped windowing scheme at the cost of more computational complexity in the training and the testing phase for certain classifiers [12]. Therefore, the size of the window and its increment is chosen accordingly.

The feature set selected should be such that it is capable of capturing the characteristics of the MES for different motions. A tradeoff in classification 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.

Overlapping windows of 256msec spaced 128msec and 32msec apart for training data and testing data respectively were analyzed. In addition, the transitional data 256msec before or after a change in limb motion was removed from the training set to improve the classification accuracy.

Three feature sets were extracted. The goal of these feature sets is to increase the size of the extracted feature set by combining various features in time and time-frequency domains. In the first set TFD1, root mean square, mean absolute value, mean and median frequency and a 6^{th} order time varying autoregressive model is used. The second one TFD2 comprises of TFD1 and STFT. The third one WT constitutes DWT and WPT with 5 levels of decomposition using Daubechis and Symmlet wavelet family respectively.

2.3 Feature Reduction

It is fairly certain that the success of a chosen feature set depends upon the proper size of the feature set. In many pattern recognition applications, a large number of features are extracted in order to ensure an accurate classification of each segment of the signal into one of a predefined set of classes. One possible example is the utilization of the time-frequency analysis methods, which proved to be sucessful in the analysis of myoelectric signals. Such methods usually end up with extracting a large number of features. Hence there is need of feature selection and projection technique to have the optimal size of the feature set. Thus Dimensionality reduction plays a vital role in the pattern classification.

In our work we had used four three different feature selection and projection techniques: Orthogonal Linear Discriminant Analysis (OLDA), Discriminant Locality Preserving Projections (DLPP) and Sparse Principal component analysis (SPCA).

2.4 Classification

Myoelectric signal classification for prosthetic control is a difficult problem. 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. We have utilized four different classifiers; SVM ensemble [13], MLP, LDA and Modified kNN(MkNN) [14] for the prosthesis control.

2.5 Post Processing

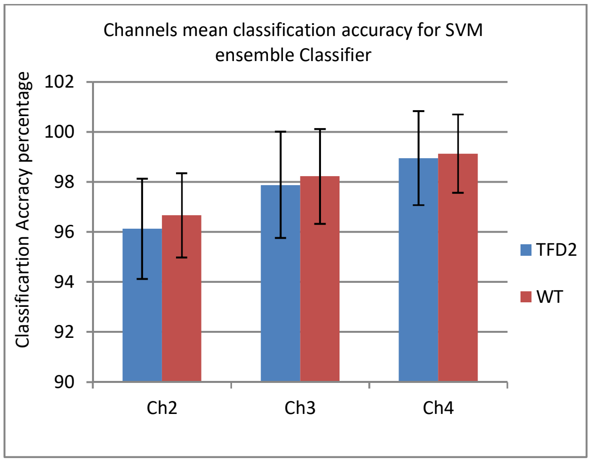
Post processing techniques are usually utilized after classification to prevent overwhelming the prosthetic controller with varying classification decisions. By eliminating spurious misclassification, the classifier performance is enhanced [15]. The EMG classification accuracy results were enhanced using a majority vote (MV) technique. In a MV scheme, an acceptable delay of 256msec 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 [15].

3. RESULTS

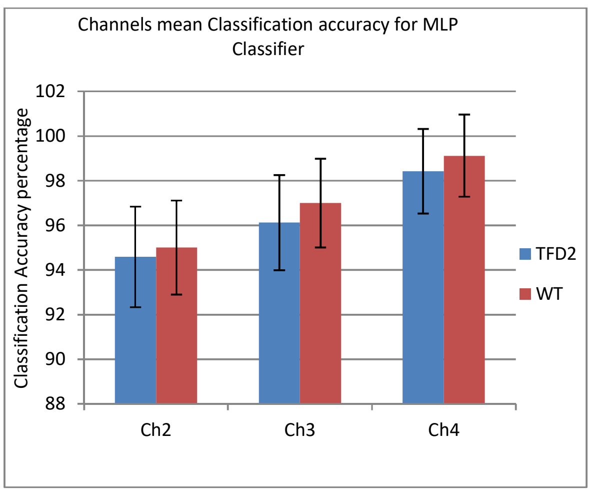
We explored the optimal channel subsets to identify the regions of the forearm where the optimal channels are located. The feature sets TFD2 and WT were utilized. A brute-force method was used to process every possible combination of channels and that combination of channels which provided the highest classification accuracy was selected as the channel subset. The best combination of 2, 3 and 4 channels were searched that best interacted together. The Table 1 shows combination of channels and corresponding accuracies for every subject. The average classification results along with the standard deviations are shown in Figure 4.

Table 1. Channel accuracies with different feature sets and different number of channels

Channels	2	3	4	2	3	4
Feature sets/ Subjects	TFD2			WT		
1	97.5072	98.2644	99.5703	97.8568	98.1906	99.8983
2	98.1945	98.9458	99.2916	98.0651	99.6428	100
3	97.9121	98.4652	100	98.0965	97.9824	99.8715
4	98.2074	99.0911	98.6532	97.9873	98.8256	100
5	97.6358	99.1597	100	98.2464	98.5308	99.2317
6	97.5210	98.0453	99.4048	97.7952	99.6957	100
7	98.2081	99.2476	100	97.8709	98.1906	99.7946
8	97.7953	99.3459	100	98.3056	98.6344	100



(a) Channels mean classification accuracy for SVM ensemble



(b) Channels mean classification accuracy for MLP

Figure 4. Channels mean classification accuracy for feature sets

Two feature subsets DWT and WPT using OWP, LDB and JBB were extracted. The DWT features subset and the WT features subset were formed with four levels of decomposition using Daubechis and the Symmlet wavelet family respectively.

Before starting the process of feature subset selection, the memory required by each of the feature selection algorithm LDB, OWP and JBB was calculated. A maximum of 35 features subsets were used. The memory requirements are recorded in Table 2.

Table 2. Memory requirements by each of the features selection for DWT and WPT feature subsets

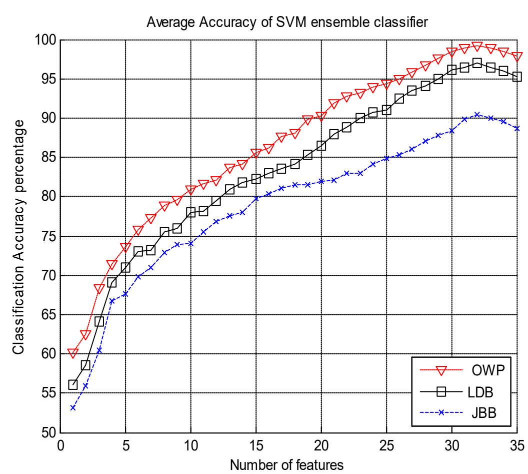
Features	JBB	OWP	LDB
DWT	6121.5	3528.4	2484.6
WPT	3528.4	1698.7	1698.7

From the Table 2 it is very clear that OWP required much lower memory and hence computational time than JBB and LDB. For both the feature subsets size the average classification accuracy was computed for 30 iterations. The Table 3 shows the classification accuracy for WPT features. Similar result was obtained for DWT also.

Table 3. Classification accuracy using WPT features

Features	OWP	LDB	JBB
SVM ensemble	95.6274	94.1596	93.9895
MkNN	95.1234	93.6527	93.4198

The Table 3 shows that the performance of OWP over the other methods regardless of the classifiers employed. The performance of LDB and JBB algorithms is quite similar. The Figure 5 depicts the cclassification accuracy using WPT features for SVM ensemble and MkNN classifiers. The total accuracy achieved by the OWP is higher than that achieved by the JBB and the LDB. Methods like JBB and LDB require much more features to achieve comparable results.



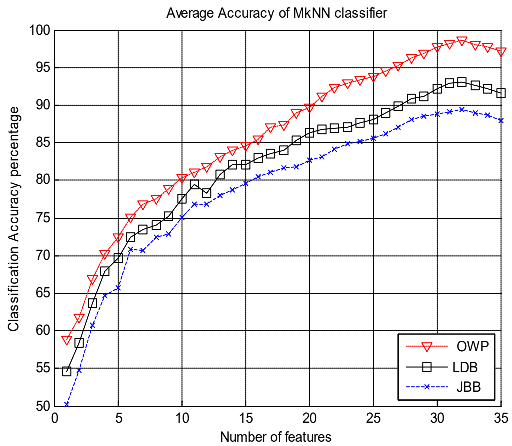


Figure 5. Classification accuracy using WPT features for SVM ensemble and MkNN classifiers

Further, we investigate the significance of the SPCA algorithm. A continuous (overlapping) windowing scheme in which an analysis window of size 200msec (800 samples) was incremented by 50msec. Small value of window causes degradation in the performance. With the window size 200msec an output class decision can be obtained in less than 300msec, a threshold defined in the literature [16].

Features TFD1, TFD2 and WT were extracted from each analysis window. In the dimensionality reduction step, the performance of the SPCA algorithm [17] was compared against traditional PCA, discriminant analysis based feature projection methods (LDA ULDA and OLDA) and the DLPP. During the experiments, it was found that using larger number of principal components provided nearly the same results with no statistical significant difference as using smaller number of principal components. Therefore to minimize the computational cost, only first 50 principal components were utilized.

In the final position of the EMG recognition system, three classifiers: SVM ensemble, Modified k-Nearest neighbor (MkNN) and Multilayer perceptron (MLP) included. The number of neighbors in MkNN was set to 5 (experimentally selected) and the MLP with 30 hidden layer nodes and was trained using back propagation algorithm. The SVM ensemble was used with 10 LSVMs with addaboost. In order to smooth the output of the classifier a majority vote post processing step was utilized in the final step of the system. For a given decision point d_i, the majority vote decision smoothes the classifier output by considering the current decision along with the previous m decisions and future m decisions (m=8 in this experiment).

The classification error rates achieved by the SPCA algorithm in comparison to PCA, DLPP, LDA, ULDA and OLDA are shown in Figure 6 using three different classifiers.

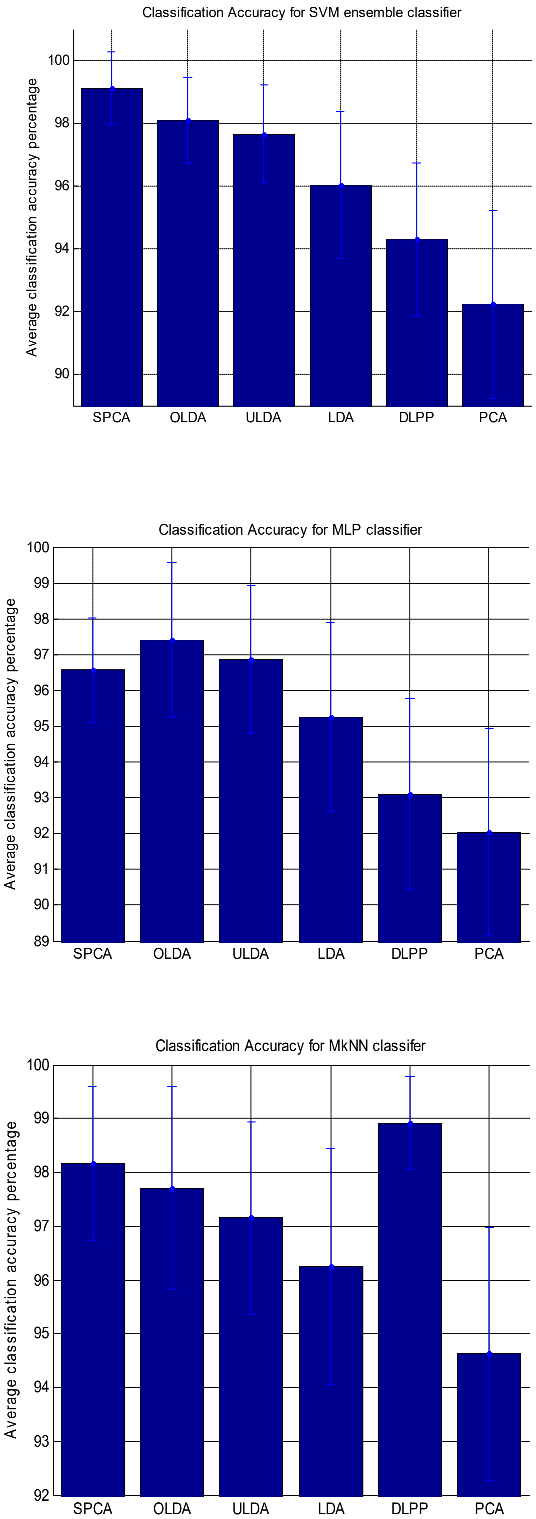


Figure 6. Classification accuracy using different feature projection techniques

After done with the dimensionality reduction methods, the second part of the experiment is performed to check the significance of utilizing a nonlinear classifier MLP for separating the different classes in comparison to linear SVM ensemble classifier. The classification accuracy results for different classes i.e. 7, 8, 9, 10, 11, 12, 13, 14 and 15 were computed using both the classifiers. The different classes of movements (less than the total number of classes) considered for classification are shown in Table 4. The selection of classes is based on a sequential manner, i.e. removing one class at a time (but different strategy for selecting classes can also be made). The plot shown in Figure 7 shows the classification accuracy of both SVM ensemble and MLP employing SPCA as dimensionality reduction tool. The given results are the actual accuracy rates achieved by the classifier as no post processing steps were performed.

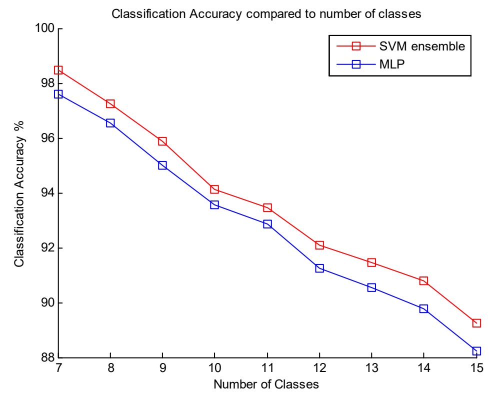


Figure 7. Classification accuracy for different number of classes

Table 4. Different classes of movements

Classes of movements	T	I	M	R	L	TI	TM	TR	TL	IM	MR	RL	IMR	MRL	HC
7	√	√	√	√	√	√	√	*	*	*	*	*	*	*	*
8	√	√	√	√	√	√	√	√	*	*	*	*	*	*	*
9	√	√	√	√	√	√	√	√	√	*	*	*	*	*	*
10	√	√	√	√	√	√	√	√	√	√	*	*	*	*	*
11	√	√	√	√	√	√	√	√	√	√	√	*	*	*	*
12	√	√	√	√	√	√	√	√	√	√	√	√	*	*	*
13	√	√	√	√	√	√	√	√	√	√	√	√	√	*	*
14	√	√	√	√	√	√	√	√	√	√	√	√	√	√	*
15	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√

In addition to the above experiments, in order to check the significance of using MLP and to test the hypothesis that the classification accuracy results for features projected with SPCA and classified with the two classifiers: MLP and SVM ensemble are not to different from each other, a two-way analysis of variance (ANOVA) test was utilized with the significance level set to α= 0.05. The p-value being less than 1 indicated that there was not much difference in the classification accuracies achieved by the two classifiers. The results achieved by linear SVM ensemble and nonlinear MLP classifiers are same. Since, both the classifiers require iterative processes hence the possibility of over-fitting is nullified.

In the next experiment, the classifier type was fixed to SVM ensemble being much faster than MLP. The performance of feature projection techniques SPCA, PCA OLDA, ULDA and DLPP were tested on the extracted TFD2 feature set with the SVM ensemble classifier. To have an idea about the capability of eight channel system in separating different forearm movements, the system performance was tested on different number of classes of movements. The classification accuracy results along with the standard error for the system performance with different feature projection techniques of the classes 7, 8, 9, 10, 11, 12, 13 and 14 individually out of the total 15 classes is shown in the Figure 5.34. The number of features This was done in order to check if the generalization of the classifier is achieved by dimensionality reduction or better projection that leads to good clustering or a mixture of both.

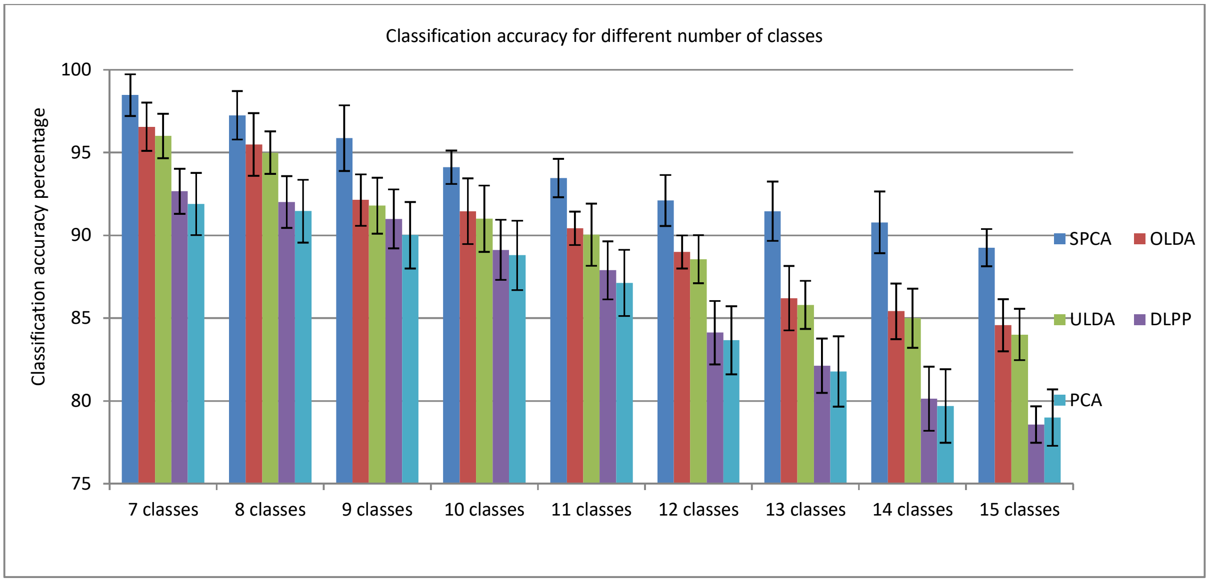


Figure 8. Average classification accuracy achieved across eight subjects using different methods and number of classes.

According to the classification accuracy results given in Figure 8 one can clearly categorize the performance of the different feature projection techniques. The SPCA offered the best performance in terms of classification accuracy across different number of classes. The performance of OLDA and ULDA is very close to each other but achieving slightly lower accuracy than SPCA The performance of DLPP is less than that of OLDA and ULDA. The SPCA aims at preserving the global Euclidean structure but the DLPP aims at preserving the local neighborhood structure of the high dimensional data that lies on a low dimensional manifold embedded in the ambient space [18]. Also DLPP shares many of the data representation properties of nonlinear techniques such as Laplacian Eigen-maps or Locally Linear embedding thus offering better performance than PCA.

Inspite of the above facts about DLPP, the classification results obtained using the features projected by DLPP is low because it projects the original feature sets into a new domain with the same number of features as the original feature set. Thus, the use of smaller number of features i.e. c-1 features, (c being the number of classes) does not requires providing good classification accuracies, as the information in the transformed domain may be dispersed along some of the remaining dimensions. Since it is difficult to decide the optimal number of features, it results in losing some useful information required for classification. Conversely, OLDA and ULDA project the original feature set into a new domain with only c-1 dimensions, where c is equal to number of classes, thus in this method dimensionality reduction is embedded in the projection process. In the last step of implementation of OLDA, QR decomposition is utilized to transform the set of uncorrelated features into orthogonal features thus both ULDA and OLDA show competent results. Hence, the reduced feature sets produced by SPCA, ULDA and OLDA proved to present better classification results than DLPP. The SPCA first applies PCA to remove redundancies, then it operates to preserve the within class structure of the data. Therefore SPCA was capable of achieving the highest classification accuracy across different number of classes.

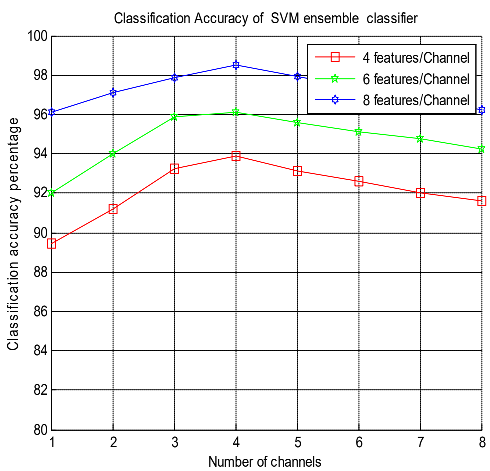
To establish the statistical significance of the SPCA, a two-way analysis of variance (ANOVA) test was applied on the results achieved by OLDA, ULDA, PCA and DLPP in comparison to SPCA. The ANOVA test was applied to the results achieved on all eight subjects for seven, eleven and fifteen classes problem i.e. for the best, moderate and worst case scenario. The significance level was set to α= 0.05. The ANOVA test results are given in Table 5.

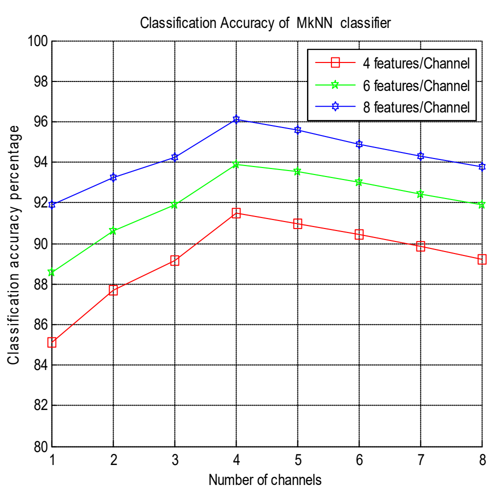
Table 5. Two-way analysis of variance test results

SPCA vs →	PCA	DLPP	ULDA	OLDA
7 classes	0.0050	0.0057	0.0070	0.0078
11 classes	0.0008	0.0013	0.0049	0.0055
15 classes	0.0001	0.0003	0.0028	0.0034

All of the above results of the experiments show that the SPCA is capable of showing a powerful performance across different classifiers and varying number of classes.

In the last we calculated the effect of number of features per channel to get an idea if there is requirement of large number of channels while recording myoelectric signals with surface electrodes placed on the forearm. For amputees it is difficult to have a large surface where more number of electrodes can be placed. At the most three to four surface electrodes can be placed comfortably while recording the myoelectric signals. The classifiers SVM ensemble with 10 numbers of Linear SVMs, MkNN with number of nearest neighbours equal to five (k = 5) and MLP with one hidden layer having eight nodes were used to classify the WPT features extracted using OWP. It is clear observed from the Figure 9 that as the channels are added, the classification accuracy increases; but the increase is not linear, it quickly reaches to a high value as the first few channels are added and then gradually approaches to a maximum value. Thus the inclusion of more channels did not achieve any significant enhancement in the classification accuracy instead the accuracy slightly decreases with addition of more number of channels. This is true for all the three classifiers.





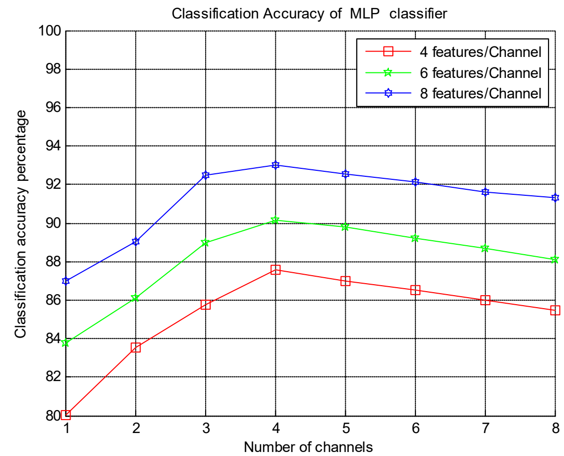


Figure 9. Tradeoff between number of channels and features

In an amputated arm it is difficult to place large number of surface electrodes, we proved in our experiment that only four numbers of electrodes out of eight were sufficient to achieve the highest classification accuracy and as the number of channels increased the classification accuracy decreased.

4. DISCUSSION

In an amputated arm it is difficult to place large number of surface electrodes. We proved in our experiment that only four numbers of electrodes out of eight were sufficient to achieve the highest classification accuracy of 99.12% irrespective of the feature sets and the classifiers. There is a need of optimal location of electrodes so that maximum information can be captured. Also as the number of channels increased the classification accuracy decreased. The performance of the OWP was proved in an experiment with WPT feature sets for SVM ensemble and MkNN classifiers. OWP outperformed LDB and JBB for both the classifiers. The representation of the signal and the way it is extracted matters most. The significance of SPCA in dimensionality reduction was shown against OLDA, ULDA, PCA and DLPP techniques irrespective of the classifiers. Efficacy of DLPP proved good with the MkNN classifier. We also showed that the performance of the nonlinear classifier MLP is as good as linear SVM ensemble except it is computationally more complex. The statistical test proved the experimental results.

Deep muscles are not clearly available through the surface EMG hence from control perspective, it may be a disadvantage of surface electrodes.

5. CONCLUSION

The primary goal of this paper is to compare the pattern recognition accuracies using different control schemes. 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 depends on the representation of the signals. The classifier exhibited very good accuracy with TFRs features but the way in which feature sets were projected mattered most. The performance was highest with only four channels and it started deteriorating as more number of channels was added. In our work, the individual SVMs were aggregated to make a collective decision which outperformed the other classifiers and the use of majority voting enhanced the result. The sparsity in the PCA proved boon in the dimensionality reduction. The highest accuracy was obtained with WPT feature sets but the performance of other features sets was close to the WPT feature sets.

6. ACKNOWLEDGMENT

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REFERENCES

[1] P. Parker, K. Englehart and B. Hudgins, "Myoelectric signal processing for control of powered prosthesis", *J. Electromyogram. Kinesiology.* vol. 16, no. 6, pp. 541–548, 2006.
[2] S. Adee, "The revolution will be prosthetized", *IEEE Spectrum*, pp.37-40, 2009.
[3] D. Peleg, E. Braiman, E. Yom-Tov, and G. F. Inbar, "Classification of Finger Activation for Use in a Robotic Prostheses Arm", *IEEE Transactions on Biomedical Engineering*, vol. 10, no. 4, pp. 290-293, 2002.
[4] G. Tsenov, A. H. Zeghbib, F. Palis, N. Shoylev, V. Mladenov, "Neural Networks for Online Classification of Hand and Finger Movements Using Surface EMG signals", *Proceedings of the 8th Seminar on Neural Network Applications in Electrical Engineering*, pp. 167-171, 2006.
[5] F. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings and N. V. Thakor, "Toward the Control of Individual Fingers of a Prosthetic Hand Using Surface EMG Signals", *Proceedings of the 29th Annual International Conference of the IEEE EMBS*, pp.6146-6149, 2007.
[6] F. V. G. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, N. V. Thakor, "Decoding of Individual Finger Movements Using Surface Electrmyography", *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 5, pp. 1427-1434, 2009.
[7] R. Weir, P. R. Troyk, G. DeMichele, D. A. Kerns, J. F. Schorsch, and H. Maas, "Implantable myoelectric sensors (IMESs) for intramuscular electromyogram recording", *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 1, pp. 159-171, 2009.
[8] C. Cipriani, C. Antfolk, M. Controzzi, G. Lundborg, B. Rosen, M.C. Carrozza, and F. Sebelius, "Online Myoelectric Control of a Dexterous Hand Prosthesis by Transradial Amputees", *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. PP, no. 99, 2108667, 2011.
[9] R. N. Khushaba, S. Kodagoda, M.Takruri and G. Dissanayake, "Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals", *An Int. Journal of Expert System with Application*, vol.39, no. 12, pp. 10731-38, 2012.
[10] www.rami-khushaba.com/EMG Repository
[11] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Med. Eng. Phys.*, vol. 21, no. 6-7, pp. 431–438, 1999.
[12] R. N. Khushaba, S. Kodagoda, M.Takruri and G. Dissanayake, "Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals", *An Int. Journal of Expert System with Application*, vol.39, no. 12, pp. 10731-38, 2012.
[13] Y. Freund, R. Schapire, A decision theoretic generalization of online learning and an application to boosting, J. Computer System Sci. vol. 55, no.1, pp. 119–139, 1997.
[14] MKNN: Modified K-Nearest Neighbor Hamid Parvin, Hosein Alizadeh and Behrouz Minaei-Bidgoli.
[15] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control", *IEEE Transaction Biomedical Engineering.*, vol. 50, pp. 848–854, 2003.
[16] T. Farrell, "Multifunction prosthesis control: The effect of targeting surface vs intramuscular electrodes on classification accuracy and the effect of controller delay on prosthesis performance, PhD Thesis, Biomedical Engineering, Northwestern University, 2007.
[17] H. Zou, T. Hastie and R. Tibshirani, "Sparse Principal Component Analysis", *Journal of Computational and Graphical Statistics*, vol. 15, no. 2, pp. 265-286, 2006.
[18] X. He and P. Niyogi, "Locality preserving projections", *In proceedings of the Advances in Neural Information Processing Systems 1 (NIPS),* Vancouver, Canada, 2003.