Pattern Recognition Based Prosthesis Control for Movement of Forearms Using Surface and Intramuscular EMG Signals

Anjana Goen, D. C. Tiwari

Abstract**—**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. The surface electromyogram signal (sEMG) being noninvasive has been used as an input to prostheses controllers for many years. Recent technological advances has led to the development of implantable myoelectric sensors which enable the internal myoelectric signal (MES) to be used as input to these prostheses controllers. The intramuscular measurement can provide focal recordings from deep muscles of the forearm and independent signals relatively free of crosstalk thus allowing for more independent control sites. However, little work has been done to compare the two inputs. In this paper we have compared the classification accuracy of six pattern recognition based myoelectric controllers which use surface myoelectric signals recorded using untargeted (symmetric) surface electrode arrays to the same controllers with multichannel intramuscular myolectric signals from targeted intramuscular electrodes as inputs. There was no significant enhancement in the classification accuracy as a result of using the intramuscular EMG measurement technique when compared to the results acquired using the surface EMG measurement technique. Impressive classification accuracy (99%) could be achieved by optimally selecting only five channels of surface EMG.

Keywords**—**Discriminant Locality Preserving Projections (DLPP), myoelectric signal (MES), Sparse Principal Component Analysis (SPCA), Time Frequency Representations (TFRs).

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, these muscles are used to derive control commands for powered upper-limb prostheses.

Myoelectric control has been successfully utilized in rehabilitation and human-computer interfaces [3], [4]. 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 [5]-[10]. 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 [11].

The paper is organized as: Section II describes the surface and intramuscular datasets, the feature extraction, feature set reduction, classification and post processing. Section III and Section IV presents the experimental results and discussion respectively and finally, conclusions are drawn in Section V.

II. Methodology

We propose a comparison between an EMG based forearm prosthesis controller that employs an array of surface electrodes placed on the human forearm to the system with intramuscular electrodes. The goal is to investigate whether the intramuscular myoelectric signal based prostheses controllers outweighs the loss of the more global information contained in the surface myoelectric signal. The classification accuracy for identification of ten classes of forearm movements is compared using various feature sets and classifiers.

The block diagram of the proposed system is shown in Fig. 1. Raw surface EMG signals were preprocessed and feature sets were extracted. Because of the large number of channels dimensionality of the features being very high hence, the dimensionality reduction techniques were employed to reduce the feature size and transform into new feature subsets. Suitable classifiers SVM ensemble, LDA, MLP and MkNN (Modified kNN) were utilized for pattern recognition of the signals from different classes of the forearm movements. To enhance the accuracy we have incorporated majority voting as post processing.

Anjana Goen is in the department of Electronics and Communication Engineering at Rustamji Institute of Technology, Tekanpur and Research Scholar in Jiwaji University, Gwalior, India (phone: +919425755052, e-mail: anjana_1999@yahoo.co.in).

D. C. Tiwari is, Professor in School of Studies in Electronics at Jiwaji University, Gwalior, India (e-mail:dctiwari_1999@yahoo.co.in).

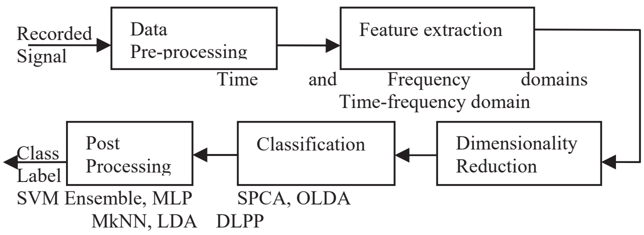

Fig. 1 Block diagram of the Myoelectric signal classification system for prosthesis control

A. Data Collection

The two datasets, first one represents a steady state Surface EMG and the second one steady state Intramuscular EMG, was acquired from the University of New Brunswick, Canada. The original research group of these datasets is [12]. The SEMG datasets were acquired using 16 surface electrodes linear array with inter-electrode spacing of 2cm connected to PRIMA EMG 16 amplifier configured to make differential measurements between adjacent electrodes mounted around the upper forearm as shown in Fig. 2. The IEMG datasets were acquired, using 6 intramuscular electrodes consisted of 10cm of insulated 44guage nickel alloy wires in a paired configuration which had an inter-electrode spacing of 1mm and were housed in a 27guage cannula. Each session of the datasets consisted of two trials of each motion. Six normally limbed, healthy male subjects (abbreviated as 'AW', 'KS', 'LH', 'MW', 'SM' and 'WM') between the ages of 23 and 30were prompted to complete medium force isometric contractions of 5 seconds duration followed by a brief rest period. Each channel was pre-filtered between 10-500 Hz using a 4^{th} order Bessel band pass filter with a gain of 2000 and a CMRR greater than 96dB/channel. The capabilities of feature sets, dimensionality reduction techniques, and classifiers will be explored in detail for the generalization of the prosthetic control problem. Each record is of 256msec in duration (256 points sampled at 1024 Hz).There are ten motions associated with three degree of freedom (DOF's) of the wrist, two different hand grips and a rest state. Fig. 2 shows the placement of electrodes on the forearm.

The IEMG datasets were acquired, using 6 intramuscular electrodes consisted of 10cm of insulated 44guage nickel alloy wires in a paired configuration which had an inter-electrode spacing of 1mm and were housed in a 27guage cannula. Each session of the datasets consisted of two trials of each motion. Six normally limbed, healthy male subjects between the ages of 23 and 30were prompted to complete medium force isometric contractions of 5 seconds duration followed by a brief rest period. Each channel was pre-filtered between 10-3000 Hz using a 4^{th} order Bessel band pass filter with a gain of 2000 and a CMRR greater than 100 dB. Each record is of 256msec in duration (256 points sampled at 1024 Hz).There are ten motions associated with three degree of freedom (DOF's) of the wrist, two different hand grips and a rest state. Fig. 3 shows the ten classes of movement of the forearm. The classes are same for both the datasets i.e. SEMG and IEMG.

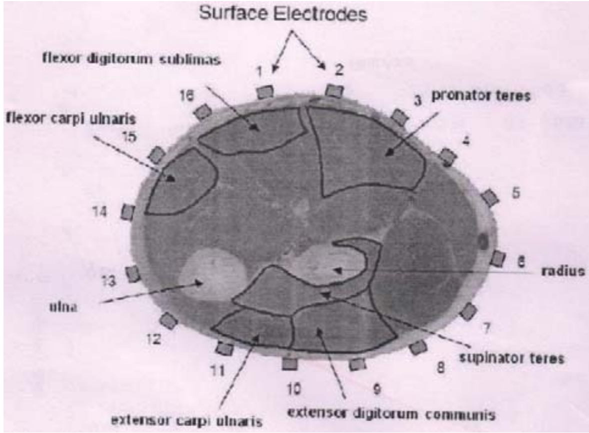

Fig. 2 A cross-section of the upper forearm showing the surface electrodes location and internal control sites on upper forearm [12]

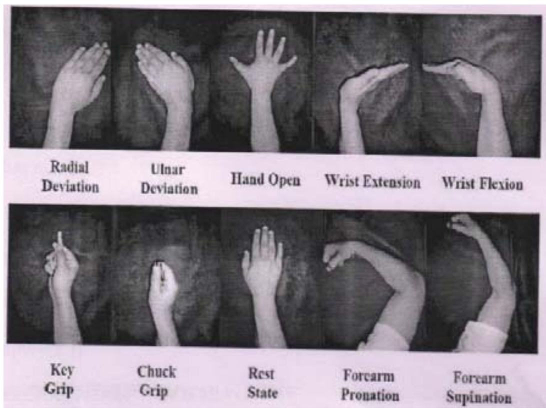

Fig. 3 Different movement classes considered in this paper [12]

B. 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. The classification performance is more profoundly affected by the choice of feature set [13]. Features are usually computed from the preprocessed myoelectric signal in time, frequency and time-frequency domain. Either a disjoint or an overlapped windowing scheme can be utilized. Better classification performance can be achieved using the overlapped windowing scheme at the cost of more computational complexity in the training and the testing phase for certain classifiers [14]. Therefore, the size of the window and its increment matters most.

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 (overlapped) window techniques.

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

Four different feature sets were extracted from the dataset to perform the experiments for classification of forearm movements. The first feature set consisted of the short time frequency transform (STFT) here the signal was divided into short segments and Fourier transform applied. 10 numbers of segments with an overlap rate of 12% were utilized. In combination with STFT feature, autoregressive (TVAR) model parameters of 6^{th} order were used in the same feature set termed as TD2. The second one consisted of discrete wavelet transform (DWT). The EMG records were decomposed using a Symmlet family of wavelets with four levels of decomposition. This feature set is termed as the DWT feature set. The third one, WPT feature set is of wavelet packet transform (WPT). Four levels of decomposition using a Symmlet family of wavelets were used to decompose the signal. The fourth and the last one TD1 feature set is a combination of time Domain and frequency domain features. The same four feature sets were also extracted from IEMG, except that it has lower dimensions as the number of channel is reduced from 16 to 6 only.

C. 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 successful 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.

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

D. 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, MLP, LDA and Modified kNN (MkNN) for the prosthesis control.

SVM Ensemble

In 1995, Krogh [15] pointed out that the generalization error of collection is equal to average generalization error of individual minus the average differences of individual.

In this paper, we have used an ensemble algorithm based on bagging [16] and culture algorithm [17]. The base learners of high difference are generated by bagging method which is a re-sampling training data technology. 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. 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. 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:

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, 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 [18].

Modified kNN

Modified kNN or weighted kNN is the modified version of kNN method which uses the k nearest neighbors, regardless of their classes. It uses weighted votes from each sample rather than a simple majority or plurality voting rule. Each of the k samples is given a weighted vote that is usually equal to some decreasing function of its distance from the unknown sample. These weighted votes are then summed for each class, and the class with the largest total vote is chosen. In this algorithm [19], firstly every training sample is validated. The validity of every point in training set is computed using (1):

$$Validity(x) = \frac{1}{H}\sum_{i=1}^{H} S(lbl(x)lbl(N_i(x))) \tag{1}$$

where H is the number of considered neighbors and lbl(x) returns the true class label of the sample x. $N_i(x)$ stands for the i^{th} nearest neighbor of the point x. The function S in (2) defines the similarity between the point x and the i^{th} nearest neighbor.

$$S(a,b) = \begin{Bmatrix} 1 & a = b \\ 0 & a \neq b \end{Bmatrix} \tag{2}$$

In the last, the weight of each neighbor sample is derived according to (3):

$$W(i) = Validity(i) \times \frac{1}{d_e+\alpha} \tag{3}$$

where W(i) and Validity(i) stand for the weight and the validity of the i^{th} nearest sample in the train set. In addition, d_e is Euclidean distance and α is a smoothing regulator and here it is selected as α = 0.5. This technique has the effect of giving greater importance to the reference samples that have greater validity and closeness to the test samples. This distance weighted kNN technique is very similar to the window technique for estimating density functions.

E. 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 [5]. 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 [5].

III. Results

To have a fair comparison with the original research work of this dataset [15], the same testing schemes is utilized here. The trial one dataset was used to train each of the four classifiers and trial two dataset to test and hence to determine the classification accuracy of the control scheme. Similar to the original research Majority voting was used after classification. The decisions comprised of the current window, the previous eight windows, and the next eight windows. Thus, 17 decisions were used in a majority vote while keeping the user perceived delay less than 300 msec. In additions to this, the decisions for periods between class transitions were removed.

Feature subsets were selected using JBB, LDB, and OWP, for the above analysis windows length and increment. Each of the trials one and two have more than 2000 patterns separately. Four different classifiers: the SVM ensemble classifier with 10 linear SVMs, Modified kNN (MkNN) classifier simple and computationally effective, MLP classifier using back propagation with two hidden layers having 8 nodes in each layer and LDA classifier (used in the original research [12]) which is a little bit computationally expensive but provides a deterministic solution. The classification accuracies of the features extracted by the different methods using SVM ensemble, MLP, MkNN and LDA were computed. Fig. 4 shows the average classification accuracy achieved across six subjects using SVM ensemble. Similar results were achieved for the other three classifiers.

The total accuracy across all subjects 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.

Table I shows the mean classification accuracy results along with the standard error for all four classifiers. The results in Table I clearly indicate the significant performance of the OWP method; this is because it extracts the energy of wavelet coefficients as features in comparison to the other techniques. We also investigated that if by adding more number of features will improve the classification performance or not. The feature sets TD1, TD2, DWT and WPT were utilised. Because of the large number (16) of channels, the resultant feature vector dimensionality was very large. Thus, feature sets of lower dimensions were selected using feature projection techniques SPCA, OLDA and DLPP.

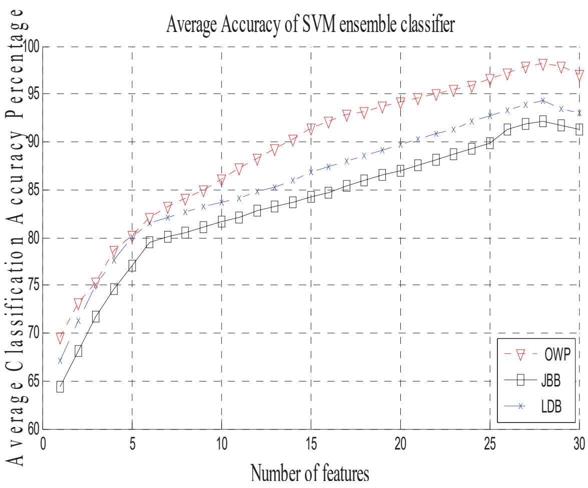

Fig. 4 Tradeoff between the number of features retained and classification accuracy

TABLE I
CLASSIFICATION ACCURACY WITH STANDARD ERROR

Classifiers	OWP	LDB	JBB
SVM ensemble	98.2312±2.0435	94.2654±4.3478	92.1247±3.6232
LDA	97.1694±3.2155	92.2983±5.7971	85.0235±4.1592
MkNN	92.9658±3.2344	89.0259±6.5217	83.1239±7.2464
MLP	93.8784±3.3676	90.3691±4.1682	84.2657±2.6957

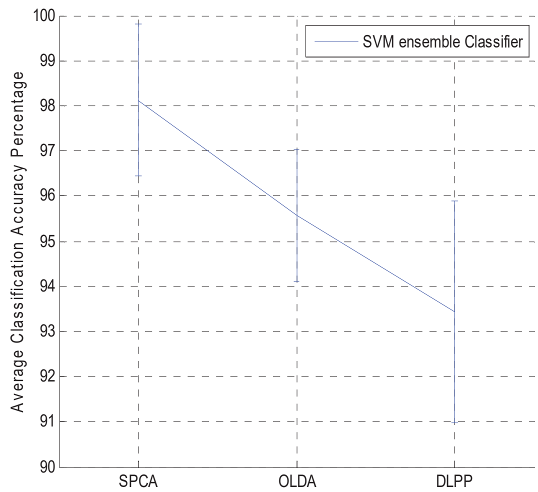

Fig. 5 Classification accuracies achieved across six subjects

We had used the same four classifiers mentioned above. The results obtained with all the four features sets were iterated for 10 times each and the average accuracy across all the feature sets was computed. The average classification accuracies with standard deviation as error bars for the SVM ensemble classifier is shown in Fig. 5.

In the original research for this dataset collected by [12], the optimal channel subsets were investigated to recognize the regions of the forearm where the channels were located. A Brute-force method was employed and in this method each and every possible combination of channels was processed and the channels which provided the highest classification accuracy were selected as the channel subset. Two features sets TD (TD1 and TD2 feature sets combined) and WT (DWT and WPT feature sets combined) were utilized. The brute-force method was used to search for the best combinations of 2, 3, 4 and 5 channels that best interact together. Table II shows the subject and its corresponding classification accuracy. The results show that with the use of only five channels, very high classification accuracy is achieved, for the TD feature set it is 99.40% and for WT feature set it is 99.72%. The result suggests that surface electrodes placed over the extensors/supinator, flexor carpi ulnaris, and flexor digitorum subliminus are essential in providing good classification accuracy and five channels are sufficient. With different feature sets and classifiers, we could achieve results similar to the results of the original research with different feature sets and classifiers.

TABLE II
CHANNEL ACCURACIES FOR DIFFERENT FEATURE SETS AND DIFFERENT NUMBER OF CHANNELS FOR SVM ENSEMBLE CLASSIFIER

Feature sets	TD				WT			
	Number of channels				Number of channels			
Subjects	2	3	4	5	2	3	4	5
AW	96.4857	97.9710	98.2373	99.2671	97.7763	97.8729	98.1906	99.8986
LH	96.8623	97.6232	98.6957	100	97.2419	98.3333	98.6344	99.3478
KS	95.6232	98.1867	97.9894	100	96.4214	98.3963	100	99.0725
MW	95.6646	98.6232	99.0725	99.0911	98.6562	97.6874	98.9258	100
SM	95. 7489	98.1449	100	100	96.4866	97.2464	98.5308	100
WM	96.2155	98.4884	99.5217	98.0435	97.4048	96.7971	98.6957	100

Fig. 6 shows the classification accuracy for each of the channels with TD feature sets using SVM ensemble classifier. Similar results were obtained for TD and WT feature sets and other classifiers. The accuracy increases as the number of channels is increased but after channel eight, there is gradual decrease in the classification accuracy irrespective of the classifiers. Thus, we can say that eight numbers of channels are sufficient, in fact is difficult to place more number of channels on the amputees forearm.

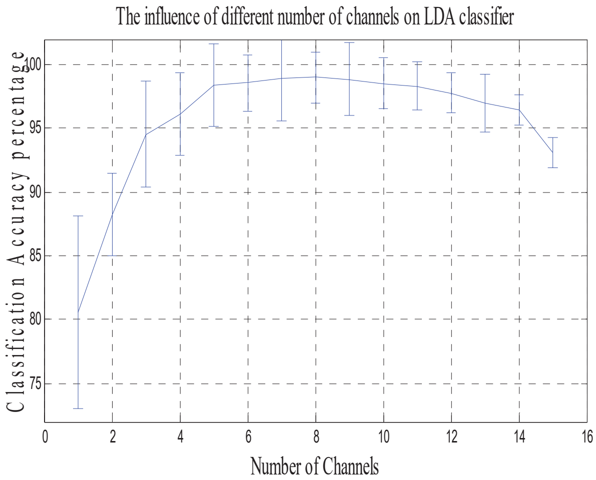

Fig. 6 Classification accuracy for SVM ensemble classifier as channels is added into channel subsets

Seven different feature sets: TD, TD plus a sixth order AR model (TDAR), a sixth order AR model (AR) alone, STFT, FD, DWT and WPT feature sets were used. The same classifiers were investigated. Fig. 7 depicts the result of a direct comparison of seven feature sets; WPT has been shown to provide the highest classification accuracy. Although the result shown in Fig. 7 was created specifically by considering SVM ensemble classifier, the results hold true for all the other three classifiers: MLP, LDA, and MkNN.

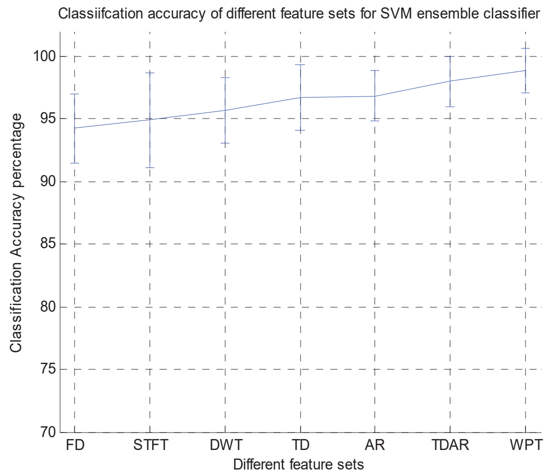

Fig. 7 The classification performance of a ten-class control problem averaged over six normally limbed subjects

A. Comparison between SEMG and IEMG Signals Classification Accuracy

Four feature set combinations were used to make the comparison between the surface and intramuscular EMG signals as inputs. The TD, TD plus a sixth order AR model

(TDAR), a sixth order AR model (AR) alone, STFT feature sets were used. The classifiers investigated were a SVM ensemble, LDA and MLP with 12 hidden layer nodes (similar to [12]) which was trained using the back propagation algorithm. LDA and MLP classifiers were also used in the original research by [12]. For each combination, data windows of 256msec were used to extract features. The 256msec window was incremented by 32msec, producing a decision at 32msec intervals. These decisions were smoothed by determining the *majority vote* of the 17decisions: the current window, the next eight windows, and the previous eight windows, maintaining the user perceived delay less than 300 msec. We have used the same techniques as the original researcher [12] to have a fair comparison. The SPCA was used for feature projection which involves PCA as the initial step. The first 40 principal components of the feature sets were used in processing similar to [12]. The trial one of the data set was used to train the classifiers and the trial two was tested to evaluate the classification accuracy of the control scheme.

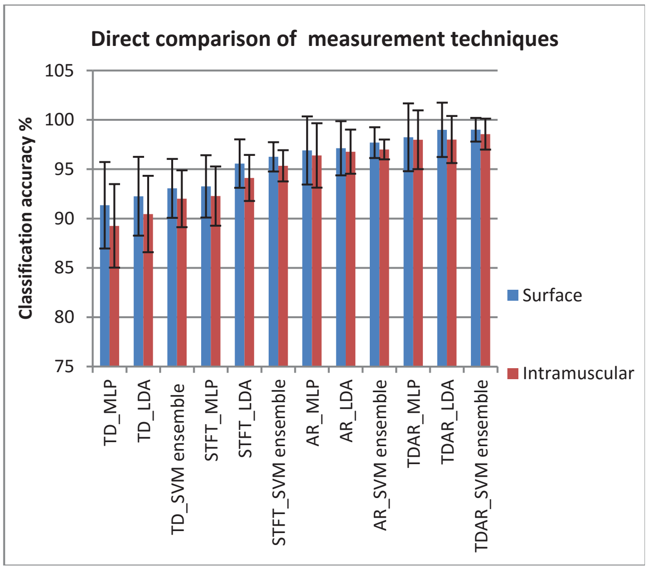

Fig. 8 The average classification accuracy and standard deviation for the twelve different control schemes

Fig. 8 displays the average classification accuracy and standard deviation across twelve different feature set/classifier combinations of six subjects. The classification accuracy is almost same for both the signals, SEMG and IEMG. We applied a paired T-test to test whether there is any significant difference in classification accuracy resulting from the different measurement techniques for each of the control schemes mentioned in the paper. It was found that there was no significant difference between the measurement techniques; each control scheme yields very high classification accuracy irrespective of the classifiers and the different feature sets also mattered a little. We achieved the accuracy greater than 99% with the TDAR feature set and SVM ensemble classifier whereas the highest accuracy achieved in the original research [12] is equal to 98% with TDAR and LDA. Thus, the surface EMG (SEMG) signals are as much accurate as the intramuscular EMG (IEMG) signals except more number of electrodes was utilized in case of SEMG to carry out the same processes accuracy. In an amputated arm, it is difficult to place large number of electrodes, but we have seen that in our experiments with SEMG dataset only 5 numbers of electrodes out of 15 were sufficient to achieve the highest classification accuracy and as the number of channel combinations was increased the classification accuracy decreased. Similar was the observation with the IEMG signals here we could achieve the highest classification accuracy with only four number of electrodes. There is not any significant difference in the classification accuracy attained using the two signals i.e. SEMG and IEMG implemented with the same techniques of feature projection and classification.

IV. Discussion

The results of the direct comparison between the surface and intramuscular measurement techniques suggest that the benefits: localized signal, very little muscle crosstalk associated with the intramuscular myoelectric signal do not outweigh the more global information contained in the surface myoelectric signal for pattern recognition-based myoelectric control. From Fig. 6, it is remarkable that there is a slight drop in classification accuracy when increasing from 8-channel optimal subset to 15 channels. This could be because of some loss of useful information after adding 14 or 15 channels. This loss of information could be because of PCA and thereafter SPCA, as we had chosen only 40 components. Using more principal components increases the complexity of the feature set. In addition, the increased dimensionality of the input space would require more training data to provide a thick decision boundary to overcome the curse of dimensionality and may yield high classification accuracy. Addition of more channels to the data changes the feature cluster to a complex shape hence the performance of the PCA or SPCA will be degraded. It is necessitated that more research needs to be conducted to determine the cause of classification degradation when using a higher number of channels. Fig. 8 shows that the classification accuracy remains high and almost same for various control schemes for both the signals. The inference is that pattern recognition-based myoelectric control systems can ease muscle crosstalk and that they probably take advantage of spatial-temporal information between channels contained in the crosstalk for classification purposes. Therefore, for pattern recognition-based myoelectric control, strictly independent control sites are not essential. Though we had utilized information from the 15 channels of surface MES data, only five channels were sufficient to have an excellent pattern recognition-based myoelectric control systems but the channels must be chosen carefully Deep muscles are not clearly available through the surface EMG hence from control perspective, it may be one advantage of intramuscular electrodes where they are accessible.

V. Conclusion

The primary goal of this paper is to compare the pattern recognition classification accuracies using different measurement techniques. From both of the measurement techniques we achieved almost same classification accuracy, a little bit higher with surface MES with different control schemes; hence Surface MES can be successfully used to drive the prosthesis controller. 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 more accurate with five channels with SEMG signals and four channels with IEMG signals and it started deteriorating as more number of channels was introduced. 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 highest accuracy was obtained with WPT feature sets and then TDAR feature set, but the performance of other features sets was close to the TDAR and WPT feature sets. With MkNN also, we achieved results comparable to the other classifiers which has an added advantage of less computational cost and simplicity.

Acknowledgment

The authors are thankful to Sh. K. Englehart, UNB, Canada for providing myoelectric signal database.

References

[1] P. Parker, K. Englehart and B. Hudgins, "Myoelectric signal processing for control of powered prosthesis", J. Electromyogr. Kinesiol., vol. 16, no. 6, pp. 541–548, 2006.
[2] R. N. Khushaba, S. Kodagoda, D. Liu and G. Dissanayake, "Electromyogram based fingers movement recognition using neighborhood preserving analysis with QR-decomposition", Seventh Int. Conf. on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), pp. 1-6, 2011.
[3] V. I. Pavlovic, R. Sharma and T. S. Huang, "Visual interpretation of hand gestures for human-computer interaction", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 677-695, 1997.
[4] T. R. Farrell and R. F. ff. Weir, "A Comparison of the Effects of Electrode Implantation and Targeting on Pattern Classification Accuracy for Prosthesis Control", IEEE Trans Biomed Eng., vol.55, no.9, pp. 2198–2211, 2008.
[5] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control", IEEE Trans Biomed Eng., vol. 50, pp. 848–854, 2003.
[6] B. Hudgins, P. Parker and R. N. Scott, "A new strategy for multifunction myoelectric control", IEEE Transaction on Biomedical Engineering, vol. 40, no.1, pp. 82-94, 1993.
[7] K. Englehart, B. Hudgins and A. Philip, "A Wavelet-based continuous classification scheme for Multifunction Myoelectric Control", IEEE Transactions on Biomedical Engineering, vol. 48, no.3, pp. 302-311, 2001.
[8] A. B. Ajiboye and R. F. ff. Weir, "A Heuristic Fuzzy Logic Approach to EMG Pattern Recognition for Multifunctional Prosthesis Control", IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 13, no. 3, pp. 280-291, 2005.
[9] D. Graupe, J. Salahi, and K. H. Kohn, "Multifunction prosthesis and orthosis control via micro-computer identification of temporal pattern differences in single-site myoelectric signals," J. Biomed. Eng., vol. 4, pp. 17–22, 1982.
[10] R. N. Khushaba, S. Kodagoda, D. Liu and G. Dissanayake, "Electromyogram (EMG) Feature Reduction Using Mutual Components Analysis for Multifunction Prosthetic Fingers Control" , in Proc. Int. Conf. on Control, Automation, Robotics & Vision, Guangzhou, pp. 1534-1539, 2012.
[11] M. Khezri and M. Jahed, "A Neuro-Fuzzy Inference System for SEMG-Based Identification of Hand Motion Commands", IEEE Transactions on Industrial Electronics, vol. 58, no. 5, pp 1952-1960, 2011.
[12] L. J. Hargrove, K. Englehart and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification", IEEE Transactions on Biomedical Engineering, vol. 54 no. 5, pp. 847-853, 2007.
[13] 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.
[14] 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.
[15] A. Krogh A and J. Vedelsby, "Neural network ensembles, cross validation, and active learning", *In Advances in Neural Information Processing Systems 7*, pages 231-238, MIT Press, 1995.
[16] B. Leo. "Bagging Predictors", Journal of Machine Learning, vol. 24, no. 2, pp.123–140, 1996.
[17] C. A. C. Coello and R. L. Becerra, "Adding knowledge and efficient data structures to evolutionary programming: A cultural algorithm for constrained optimization", Genetic and Evolutionary Computer Conerence, pp. 201-209, 2002.
[18] C. Tao, "SVM Ensemble Algorithm based on Bagging and CA" Int. Conf. on Mechanical Engineering and Automation, Advances in Biomedical Engineering, vol.10, pp. 389-393, 2012.
[19] H. Parvin, H. Alizadeh and B. Minaei, "A Modification on K-Nearest Neighbor Classifier", Global Journal of Computer Science and Technology, vol.10 no. 14, pp.37, 2010.

Anjana Goen was born in India completed her graduation B.E. (Electronics & Telecommunication) in 1991 from Ranchi University, India and her master's degree M.Tech. (Telecom Technology) in 2008 from RGPV, India. Presently she is pursuing her PhD in biomedical signal processing from Jiwaji University, Gwalior, India.

She had 20 years of teaching experience. She served as lecturer in BIT, Dhanbad and MITS, Gwalior. Since 2000, she worked as an Assistant Professor and from 2014 she is working as an Associate Professor at RJIT, Tekanpur, Madhya Pradesh, India. She had published more than 5 papers in International Journals & Conferences. She had presented more than 10 papers in International & National Conferences. Her interest lies in Digital Signal and Image processing and especially in biomedical signal and image processing.

Ms Goen is life member of IETE and IEI, India. She had been also associated with CSI and ISTE, India.

D. C. Tiwari was born on March 8, 1952 at Gwalior, did B.Sc. (1970) and M.Sc. (1972) from Jiwaji University, Gwalior. He received CSIR (JRF) in Dec. 1972 and completed his PhD in 1976 from BITS Pilani, India. He received CSIR (SRF) and PDF in 1977. He has also carried his research work at Chelsea College London and at ERA Technology, Leatherhead, Surrey, England in1986.

Since 1983 he is in teaching profession and from last 15 years he is Professor in School of Studies in Physics & Electronics. He has also served as Director Institute of Engineering and Vice Chancellor of Jiwaji University, Gwalior. He had published/presented more than 80 papers in International & National Journal and International and National Conferences. He has special interest in plasma and microwave engineering. His interest also lies in embedded electronics and signal processing. He had completed several government projects.

Dr. Tiwari is a fellow member of IETE and life member of ISTE, CSI India. He had received German Academic Exchange Fellowship in 1984. He had also received best participant's lecture medal at Kolhapur in 1993. He had been awarded with best researcher's award at Bhopal in 2009 and teacher's award by Madhya Pradesh Government, 2013.