Discrimination Among Hand Motions Using Combination of Features

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Thesis Supervisor:

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MASTER THESIS WORK

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ABSTRACT

Electromyography is commonly used in signal monitoring for the rehabilitation of prosthetic systems. The extraction and selection of the features is equally critical for monitoring and controlling a more precise prosthetic device. We aim to create an invariant feature set which would allow amputees to control their prosthetics intuitively and precisely, no matter at which limb position the movement starts. This study introduces a new different set of feature which is Logarithmic Band Power fused with Spectral Amplitude. LDA classifier was implemented to evaluate the performance of various combinations of feature sets involving both time and frequency domain. Classification performance of some comparable feature sets along with the proposed feature set is evaluated on sEMG data. Data of ten participants performing four different motion classes, at three different limb positions was extracted for training and testing. Results demonstrate that, relative to other feature sets, the proposed feature set achieves a substantial reduction in the classification error rate. Achieving a classification accuracy of 83% when averaged across all subjects and limb positions, the proposed method is comparable to the existing state of the art techniques.

Key Words: Surface EMG, Hand motion, Linear discriminant analysis, Feature extraction, Logarithmic band power, Classification accuracy, Cross validation.

CHAPTER 1

Introduction

CHAPTER 1: Introduction

For decades, Surface Electromyography (sEMG) has played a very significant role in providing an insight into monitoring muscle activities [1][2][3]. The technique pertains to the collection of signals from skeletal muscle tissues that are regulated by the nervous system and emitted during muscle contraction [4][5][6]. People who suffer from upper limb impairment are unable to produce a contraction during movement [7]. Recording these signals is the primary tool for understanding the behavior of the human body under both normal and pathological conditions [8][9]. Many techniques have been introduced to monitor muscle movements and behavior [10][11]. EMG signals are becoming increasingly valuable and have been widely applied in many applications including biomedical, prosthesis and rehabilitation devices [12][13][14].

Recent studies, however, have highlighted one of the advanced approaches to signal processing which is pattern recognition (PR) algorithm [15][16][17]. The PR scheme has demonstrated the ability to control several degrees of freedom and have reported high performance in laboratory conditions [18]. PR unlocks the ability of prosthetic users by enabling them to discriminate multiple degrees of freedom (DOFs) and gain simultaneous control in a manner more similar to the natural upper limb movement, providing the user unprecedented limb control [19]. Because PR offers a full intuitive control system, any changes in skin conditions or discomfort can be treated without the need to remove the prosthesis, thereby reducing the user's mental effort [20].

Despite current advances, the performance of this system in the commercial world remains low owing to the following reasons: lack of class robustness [21], a large number of electrodes requirement at the same time [22], interpretation of EMG signals acquired through surface electrodes alone, is inherently noisy and thus has been found debatable in providing an objective framework to assess the overall performance of prosthetic systems [23,24,25], and the impact of the limb position which implies that a system would probably not generalize well in various arm positions when being trained on single limb position.[26].

The EMG identification, processing and classification framework allows for a more systematic and accurate evaluation of neurophysiological and rehabilitative tools [27][28]. One of the challenges we need to address in order to achieve robust results is to pick a feature vector which must be considered carefully. [12].

Feature extraction plays a key role in analyzing and classifying the signals of EMG as it can speed up and boost the classifiers performance [29][30][31]. Time domain features are calculated as a time function and are by far the most prominent in EMG hand motion recognition, because of their ease of application and measurement [32]. All functions in the time domain could be used in real time. Commonly, features of this group are widely used to detect the onset of muscle contraction and muscle shrinkage activity. [12][33].

In my thesis, I intend to determine the most insightful and compact feature set to be provided to the classifier in order to avoid the use of redundant features and to analyze a good vector function using the classifier and statistical analysis. We have proposed our novel feature set; the Logarithmic Band Power based on time domain derivations, fused with frequency domain Spectral Amplitude within the already available techniques, which improves the classification accuracy. Logarithmic band power creates a visible threshold gap by minimizing and maximizing the values, thus detecting minute changes in signal to noise ratio in dynamic environment [34], which otherwise handicap the architecture because of noise in the signals.

Furthermore, we also benchmark our proposed scheme with other available techniques by extracting features from the EMG signal obtained with only two channels on the whole and that too by using surface electrodes alone, which then has been used as a feature extraction tool for the application of hand gesture differentiation.

Statement of Purpose

The EMG signals obtained using surface electrodes is inherently noisy and not a robust source of input information for prosthetic systems alone [15]. Additionally, one of the problems associated is the limb position effect, which states that a system trained on a single arm position is likely to fail to generalize to different arm positions [16].

One of the challenges we need to address to achieve robust performance, is the careful selection of a feature vector, as selecting the appropriate set of features is one of the important factors for successful classification of EMG signal [8].

Aims and Objectives

The aim of our study is to evaluate the most informative and compact feature set, to examine a good feature vector using statistical analysis and classifier.

The objectives include:

- Data acquisition by using surface electrodes
- Preprocessing and feature extraction of acquired signal
- Analysis of feature combinations using LDA classifier

CHAPTER 2

Literature Review

CHAPTER 2: Literature Review

The literature review is presented in relation to two things, i.e. feature extraction and data acquisition techniques. Both aspects have a direct impact on the outcome of the results (prediction) and are thus consistent with the wider approach set out in this study.

Feature Extraction

Many features are resilient across various forms of noise; thus, intensive approaches for pre-processing of the data shall be avoided as proposed by Phinyomark et al.[12]. Furthermore, appropriate features may achieve high accuracy of classification depicted by Oskoe et al.[35].

Three parameters have been recommended by Bostani et al.[36] to be used for quantitative analysis namely; maximum class separability, robustness, and complexity. A number of research works were primarily concerned with exploring the appropriate feature vector for various EMG signal classification applications. [36],[35],[12],[37]. Du et al.[38] proposed there are several works which allow a profound comparison of efficiency of features, especially from the point of view of redundancy . Usually the features required for analysis of EMG signal can typically be divided into three main broad groups: time domain, frequency domain (FD) and time frequency.

In our study, we have considered only the first two feature groups, since features in the last group cannot be used directly on their own as shown by Engelhart et al.[39]. Time domain features are simple and easy to implement as they have no raw EMG time-series based transformation. Spectral or frequency domain features are frequently used for the interpretation of motor unit (MU) recruitment and muscle fatigue analysis [12].

Data Acquisition Techniques

Literature explains some important techniques used for acquiring EMG signals. Angkoon Phinyomark et al.[12] summarizes the impact on the hand and finger movements classification performance, at a sampling rate (low: 200Hzvs. high: 1000Hz) , for twenty-six different features as well as on eight sets of multiple features, that too by using a range of datasets of both capable and amputee subjects [40]. Mad jochumsom et al.[23] study the influence of arm position on classification of hand gestures by integrating the signals acquired through surface and intramuscular EMG, thus gained a classification accuracy of 98% for Mean Absolute Value (MAV) and Waveform Length (WL) compared to Zero Crossing (ZC) and Slope Sign Change (SSC) features.

J.Too et al.[41] chose flexor carpi radialis, and flexor pollicis longus muscles selected to evaluate multiple hand movement with two reference electrodes at the elbow. 6 motions of fingers were performed, followed by flint rehab exercise guideline using LDA classifier. Time domain features (RMS, MAV) and Frequency Domain features were evaluated (mean frequency (MNF), median frequency (MDF) and frequency ratio). The present study showed that the FD features achieved the highest accuracy of 91.34% in LDA. Nizam Uddin Ahamed et al.[42] summarizes specifically the erector spinae and trapezium muscles, which make up upper back and lower musculature, while offering the Islamic prayer (Salat). Multiple frequency as well as time domain features of the EMG signal have been studied in order to detect major differences in muscle activity. Both time and frequency domain features were evaluated. The experiments indicated that both these muscles strike the right balance in terms of relaxation and contraction while bowing during Salat. Furthermore, frequency domain features suggest that the lower spinal muscle contracts at every alternate position during prayer. Findings of this research helped to set up a recovery treatment plan for elderly people with back pain, which helps them to not skip performing their compulsory Salats.

CHAPTER 3

Methodology

CHAPTER 3: Methodology

Methodology

The block diagram of proposed methodology has been presented in Figure 1.

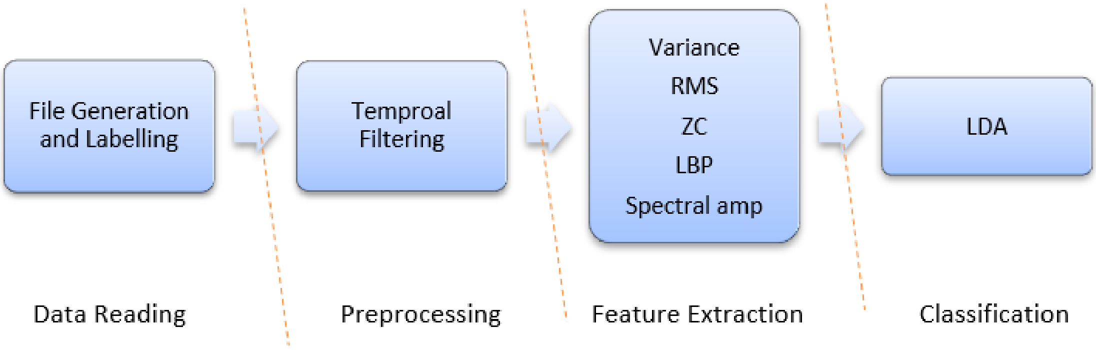


Figure 1. Block diagram representing proposed method.

Data Acquisition

Dataset

The data used for the experimentation was taken from [44]. From this datatset, we extracted the data of ten participants for two channels, at three degrees (0°, 45° and 90° respectively), for the following four hand motions: close hand, open hand, extend hand, flex hand, for three trials each. The targeted muscles were extensor carpi radialis and flexor carpi ulnaris where the electrodes were mounted on the right forearm. A reference electrode was placed on the left forearm near the subject's wrist. Signal was sampled at a sampling frequency of 4000 Hz, converted by a 12bit analog- to- digital converter. A visual representation of the set-up depicting the four motions specifically extracted from the above dataset for the three angles is shown in Figure 2.

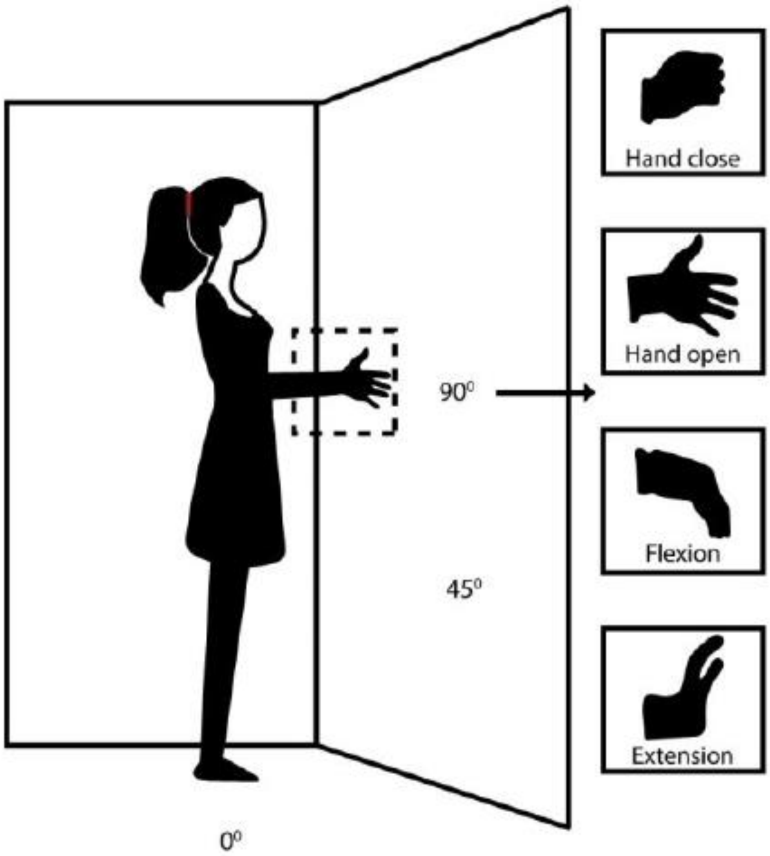


Figure 2. Visual Representation of extracted data (from the dataset) of only four motion classes (close, open, flex, and extend) for three different arm positions (0°, 45° and 90°).

Preprocessing

In each trial, sEMG data was acquired at a sampling frequency of 4000 samples/second (5 seconds for each trial). The sEMG was band pass filtered between 50 to 150 HZ for each motion. Following this, temporal filtering was performed, after which five best features were extracted for each of the motion at each of the respective three degrees (0°, 45° and 90°), from 1 second data window with 0.0625 seconds (62.5ms) increment.

Feature Extraction

Feature Screening

Forward Feature Selection technique has been applied in order to reduce the dimensionality of feature sets. Features were selected such that if the classification accuracy improved by adding a certain feature to the feature set, that feature is to be kept in the feature set. However, if the added feature negatively affects classification accuracy, then it is to be removed. Similarly, features were removed from the feature set one by one in an inverted order, so long as their subtraction did not negatively impact the classification accuracy. Whichever feature reduced the accuracy considerably, that feature was not removed from the feature set [45].

Feature Combinations

The features extracted were variance, root mean square, zero crossing, logarithmic band power, spectral amplitude (mentioned in Table 1). Features were classified with LDA classifier using 5-folds.

Table 1. Description of Features.

FEATURE	DESCRIPTION
ROOT MEAN SQUARE (RMS)	This is the square root of the arithmetic mean of the squares of a set of numbers [12]. $RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$ (1)
VARIANCE (VAR)	It is described as an average of the variable's square deviation values. [23] $VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2$ (2)
ZERO CROSSING (ZC)	It is the number of times the amplitude values of EMG signal crosses zero amplitude level [23].
LOGARITHMIC BAND POWER (LBP)	The logarithmic quantity known as power or field level. On a logarithmic scale could be used to describe a change in value or an absolute value respectively. [24]. LBP=$log(1+x)^2$ (3)
SPECTRAL AMPLITUDE (SA)	Spectral analysis highlights the amplitude of signal at discrete frequencies. [12]
VARIANCE (VAR)	It is described as an average of the variable's square deviation values. [23] $VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2$ (2)

The cross-validation accuracies of various combinations of features, from the previously shortlisted features (as represented in Table 1), have been calculated to finalize the feature sets that we have used later in this study. Following were the combinations, shown in Figure 3, which had the best cross validation accuracies when tested on each of the positions separately.

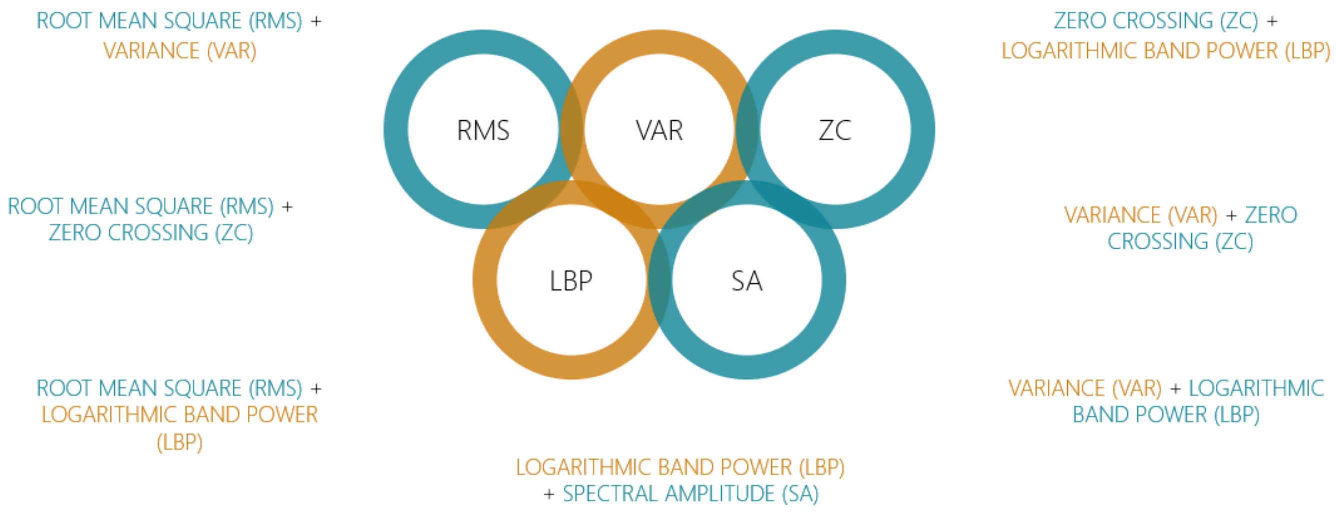


Figure 3. Selected features and their respective combinations.

Analysis

Offline analysis was performed using various combinations of the features mentioned in above table. A variety of combination of various feature sets will be debated in order to explain the uses of existing feature sets and to provide the solution for the search of an appropriate set of feature. Cross-validation accuracies of different feature set combinations were computed to handpick the best feature set which are then tested on later.

Cross-validation accuracies depict that logarithmic band power when combined with the certain other features (variance, RMS, and spectral amplitude) gave the best cross-validation accuracies at all the three positions when given to a classifier. We further move on with the testing of these feature sets (LBPSA, LBPR, LBPV, RV).

Classification

Two types of classification analyses were carried out: 1). Between position classification (BPC), 2). Across position classification (APC).

1. For BPC, classification accuracy was calculated using a 5-fold cross-validation procedure in the case where data to train and test pertained to different positions. The impact of classifier performance on being trained with the knowledge of data from one position and then tested on another position was checked in the BPC scenario (e.g. trained on 0° and tested on 45°). All pairwise comparisons were tested here. 4-class classification accuracy was calculated for each comparison.

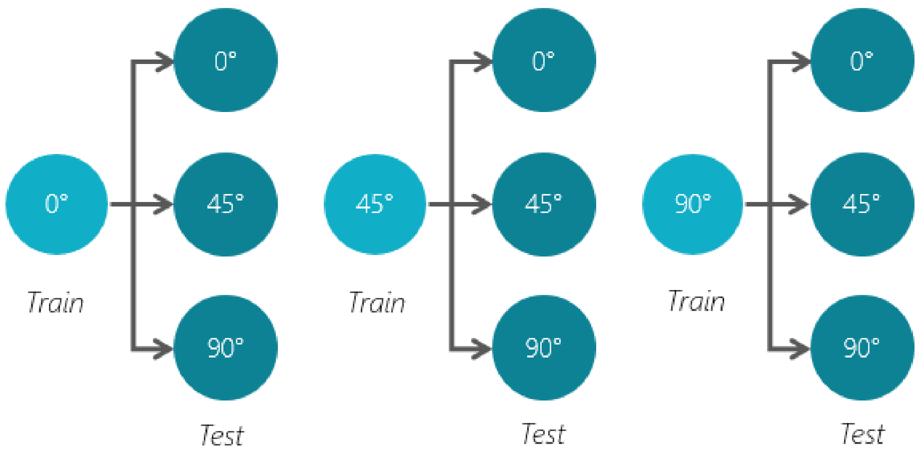


Figure 4. Representation of Between Position Classification (BPC), when testing at single positions.

2. For APC, classification accuracy was determined on the basis of the same 5-fold cross validation technique as used for BPC, and this scenario involved the training of the classifier on data that included information from all three arm positions, with testing being carried out at single as well as at multiple positions. Again, the performance of the classifier is checked by reporting the average classification accuracies (4 class problems) across the test folds.

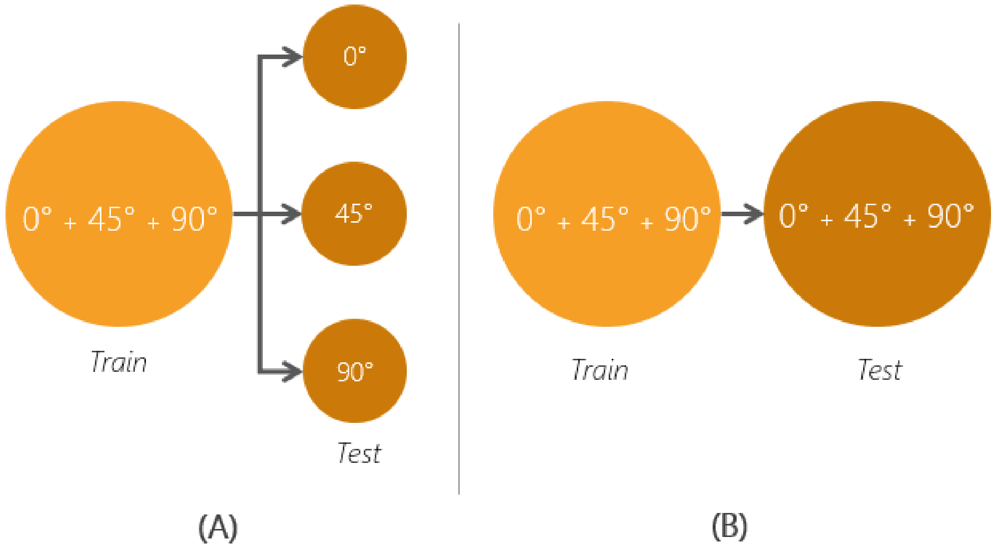


Figure 5. Representation of Across Position Classification (APC). (A) Single position testing, (B) Multiple position testing.

Statistics

One-way ANOVA was applied for the calibration of training and testing at single limb position (BPC). The effect of "Arm position" (0°,45°,90°) has been taken out using statistics, for the best feature set ,LBPSA.

One-way ANOVA was applied for the calibration of training at multiple positions and testing at single position only (APC). The effect of "Feature Type" (LBPV, RLBP, LBPSA, and LBPR) on classification error rate has been investigated using the statistical analysis. To analyze the impact of the APC framework on the training role, the mean was reported across the test participants (e.g. train on subject 1-9 and test on subject 10). Following this, a 1-way ANOVA test was used, with 'Arm Position' as the predictor for sEMG (three levels: 0°, 45° and 90°).

Statistical significance was determined with Bonferroni's post hoc test, where significance was surmised when $P < 0.05$ and the proportion of variance and effect size is given by r^2. All the analysis was conducted using GraphPad Prism.

CHAPTER 4

Results

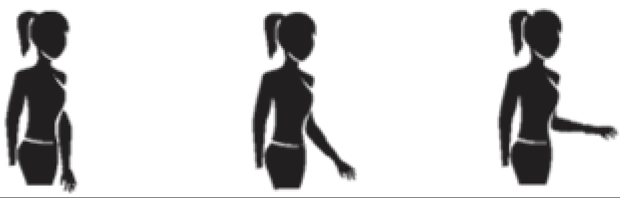
CHAPTER 4: Results

Training at Single Limb Position (BPC)

In the first part, classifier is trained at one of the limb positions, namely, P1 (0°), P2 (45°) and P3 (90°), while we check the ability of the trained classifier to generalize upon unknown data from some other position. The first row of Table 2 displays the classification performance when LDA classifier is equipped with EMG features only from position one and then checking out with the new data from position 2.

Table 2. Classification error rates averaged across all ten subjects while training and testing at single limb position, for the feature set LBPSA. The results are reported as mean ± standard deviation (across the subjects) for surface EMG (sEMG).

TESTING



TRAINING

	0°	45°	90°
0°	-	37.55 ± 15	48.82 ± 12
45°	46.3 ± 11	-	49.95 ± 11
90°	48.62 ±16	49.8 ± 11	-

These findings reflect the average throughout all the problem classes (motions) during the training of classifier and then testing the classifier with data of each of the applicable limb position one after the other stated in columns. For the purpose of avoiding complexity by mentioning the testing results of all the feature set combinations, we have reported here the combination logarithmic band power fused with spectral amp (LBPSA), with the best training and testing results.

Each entry in the Table 2 reflects the average performance for the defined train and test sets of all movement classes for all the subjects for log spectral feature set combination.

The mean inter-position classification accuracies (an average of 10 subjects performing four motion classes at three different positions) were 62.45%, 51.18%, 53.7%, 50.5%, 51.38%, 50.2% respectively, when training and testing at various positions.

Statistics for BPC

The statistics results in no significant difference ($F_{(2,6)}$ = 0.01; P = 0.9; r^2 = 0.006) between 'Arm position' for sEMG for 0°, 45° and 90° for the feature set of LBPSA (as represented in Figure 6, 7 and 8, respectively).

As predicted, influence of the various limb positions can be clearly demonstrated from the accuracy of myoelectric PR system . In this sort of situation, the classifier can properly generalize on data, at which the classifier has initially been trained on, i.e. the classification error performance of EMG is largely dependent on the limb location. As a consequence, developing a prosthetic control system trained at one limb position could not be sufficient to build a system which is good for multi-position usage. Therefore, it is necessary to train data in many EMG recording positions, as suggested by Chen [33].

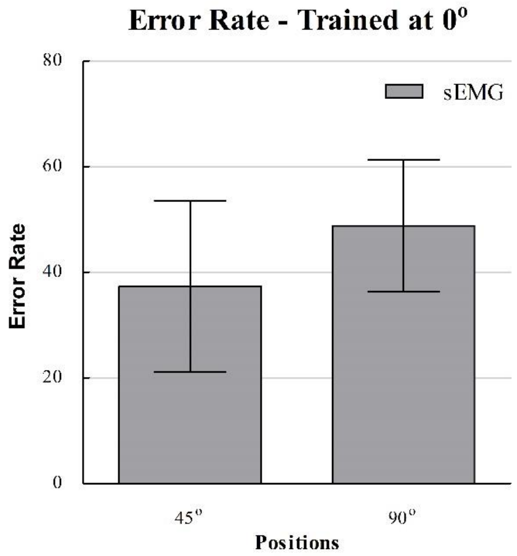


Figure 7. Graphs representing the error rates in percentage when classifier is trained at 0° and tested individually at all positions individually, for the feature LBPSA.

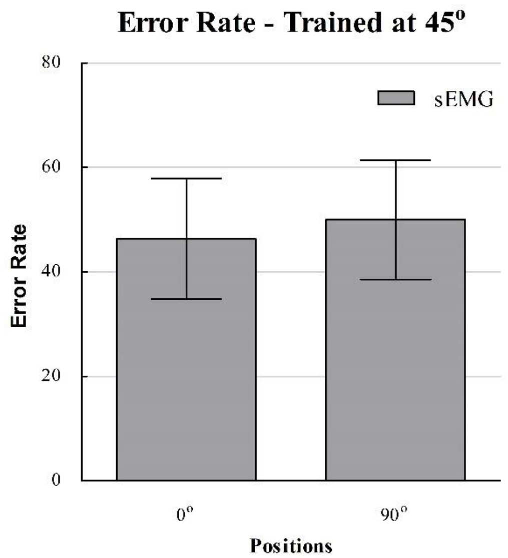


Figure 6. Graphs representing the error rates in percentage when classifier is trained at 45° and tested individually at all positions individually, for the feature LBPSA.

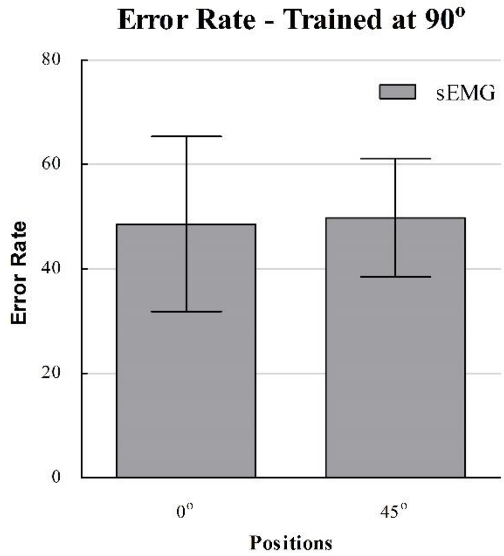


Figure 8. Graphs representing the error rates in percentage when classifier is trained at 90° and tested individually at all positions individually, for the feature LBPSA.

On the other hand, it has been proposed that, accelerometer has indicated that classification error rate could be reduced during the multi position data training [43]. In our next segment, we check the hypothesis whether or not the inclusion of training statistics from more than one limb positions will enhance the output of the classifier. It is supported by the assumption that the classifier is aware of the given data distribution at various positions of limb such that the unknown data can be generalized more effectively.

Training at Multiple Limb Positions (APC)

Trained at Multiple, Tested at Single Position

Here three different take a look at situations are suggested, each referring to one position. Unknown data from one position will be kept for testing, which means that the information from each of the three positions P1 (0°), P2 (45°), P3 (90°) will be used to train the classifier on all positions. For instance, when data of P1 is used for testing of classifier, all other data from P2 and P3 will be kept for training, and so on shown in Figure 9.

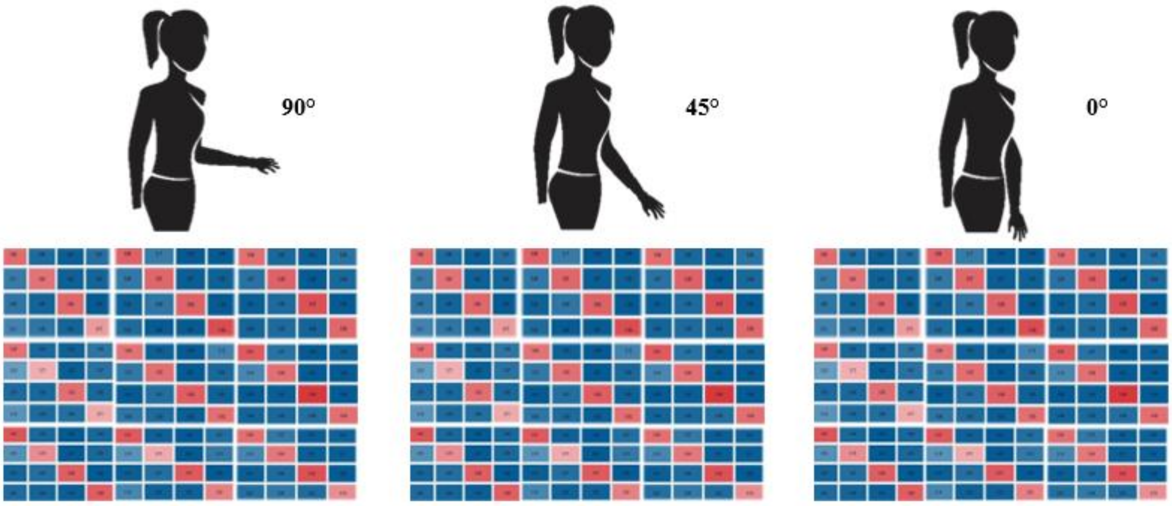


Figure 9. Confusion matrix plots while training at multiple limb positions and testing on individual unseen limb position data.

The error rate of classification for this experiment is shown as in Table 3 in relation to three test positions at which the classifier was tested. 'All' represents the combination of individual features(LBP,VAR,RMS,SA) taken together. LDA result demonstrated that LBPSA feature set obtained the highest classification accuracy of 82.2%, 82.18%, 81.33%, shown in Table 3, as compared to other features set. In addition, the result indicated that this features in discriminating the hand movements was more accurate compared to other feature sets. Results also indicate an overall improvement when training on EMG records from multiple positions. A classification average of 81.99% over various limb positions is obtained.

Table 3. Error Rate when training at all positions and testing at single positions. The results are reported as mean ± standard deviation (across the subjects) for surface EMG [s]. 'LV': Log and Variance, 'RV': RMS and Variance, 'LS': Log and Spectral, and 'LR': Log and RMS.

Position **Feature Type**	**All (%) [s]**	**LV (%) [s]**	**RV (%) [s]**	**LS (%) [s]**	**LR (%) [s]**
0°	20.25 ± 5	24.925 ± 9	56.25 ± 10	17.8 ± 4	23.575 ± 12
45°	27.95 ± 6	23.55 ± 8	58.6 ± 10	17.825 ± 5	27.2 ± 8
90°	29.775 ± 6	22.525 ± 15	54.9 ± 10	18.675 ± 4	24.675 ± 9

These results represent that EMG classification performance is depending on the chosen feature set. This dependency can be associated with the shift patterns of Musculo-tendon lever arm and muscle composition differences. Since the classifier now is being trained at various samples, representing the above-mentioned variants, classification error rates were generally reduced by the error rates caused by training at individual limb position. Table 3 further supports the statement of how significant data obtained from multiple limb positions is for training. Moreover, it should be noted here that Logarithmic band power and Spectral Amplitude feature combination exhibits the least error rate compared to other set of features. Even if we combine all the features together, LBPSA gave the least classification error. The graph below (Figure 10) shows feature wise error rates. The difference can be easily compared from the above Table 3.

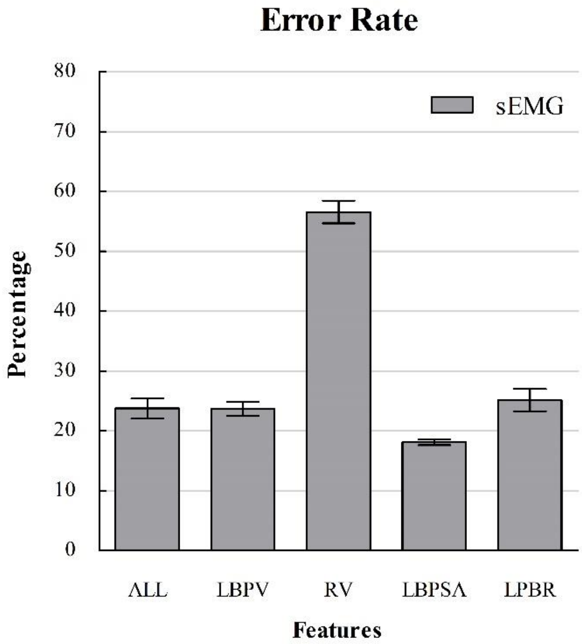


Figure 10. Error rates across the subjects using LDA classifier. The results are displayed as mean (across the subjects) for surface EMG [s] for feature type. 'LBPV': Logarithmic band power and Variance, 'RV': RMS and Variance, 'LBPSA': Logarithmic band power and Spectral Amplitude, and 'LBPR': Log and RMS, 'All' ,combination of individual features.

Statistics for APC

The statistics indicate a significant effect of 'feature type' for sEMG. ($F_{(3,36)}$ = 45.39; $P < 0.05$, $r^2 = 0.79$). Classification accuracies were higher for LBPSA as compared to RV, LBPV, LBPR and ALL (when all four individual features are taken together) combination shown in fig.7. However, the statistics showed no significant difference ($F_{(2,27)}$ = 0.18; $P = 0.8$; $r^2 = 0.01$) between 'Arm position' for sEMG for 0°, 45° and 90° (as represented in Figure 11).

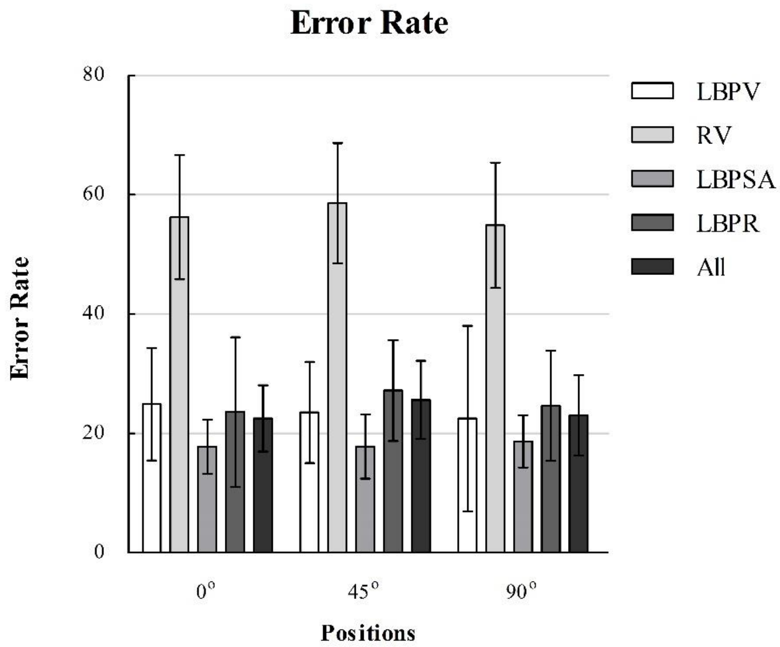


Figure 11. Error rates across the subjects when training at all positions (0°, 45° and 90°) and testing at individual positions. The results are displayed as mean (across the subjects) for surface EMG [s] for feature type. `LBPV': Logarithmic band power and Variance, `RV': RMS and Variance, `LBPSA': Logarithmic band power and Spectral Amplitude, and `LBPR': Log and RMS, `All': combination of individual features.

Trained at Multiple, Tested at Multiple Positions

Our findings also show that the classification system is capable of successfully performing the testing on unknown EMG data from all three P1, P2, P3 positions, while being trained on all three positions. For example, for testing on subject 1 and subject 2 (combined at the three angles), classifier was trained on combined dataset from subject 2 to subject 10 (from all the three positions combined) as shown in Figure 12.

The classifier has been able to better generalize unknown test data from either position in a particular way. Mean cross validation accuracies for LBPSA were **85.86%** (when trained on subject 1-8), which further supports the evidence that LBPSA combination seem to be an efficient feature combination.

The results depict an overall average of **83.07%** classification test accuracy for LBPSA feature set (when tested on subject 9 and 10).

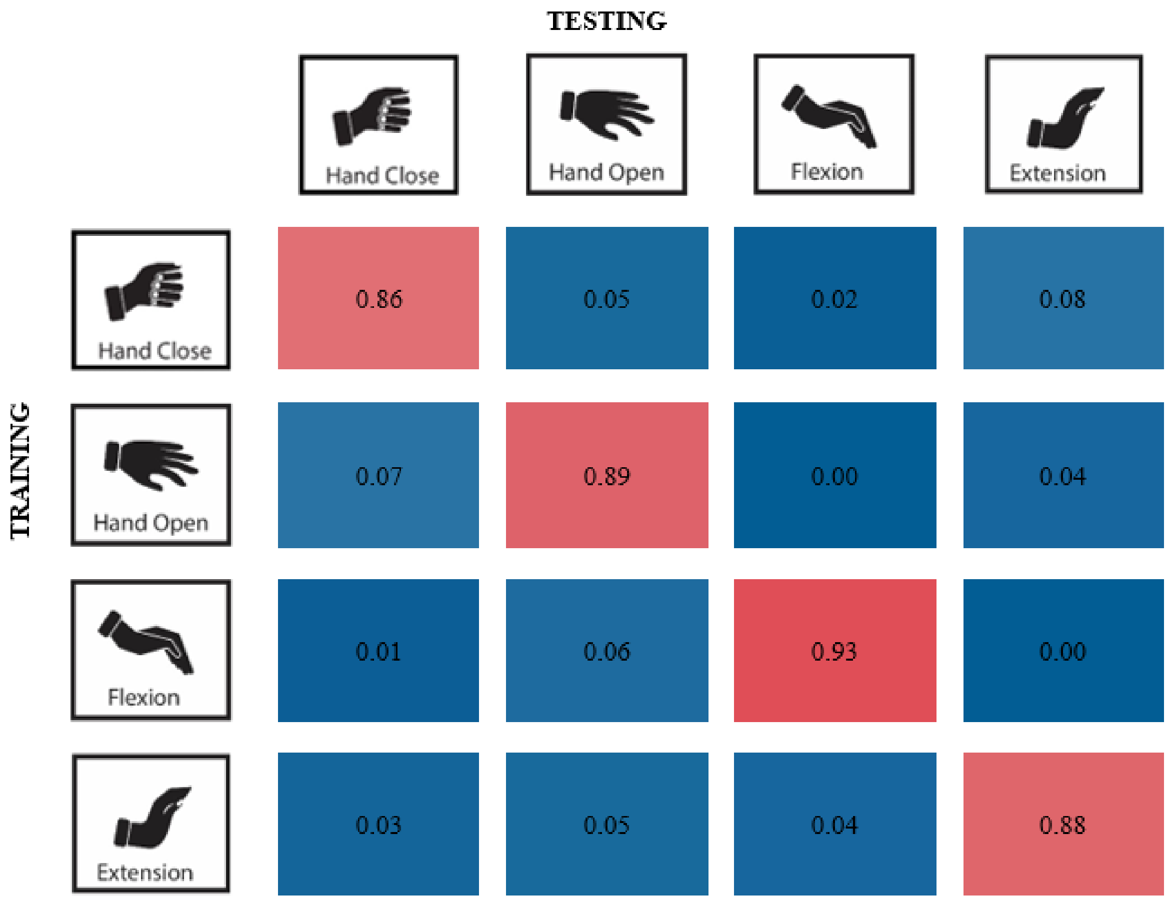


Figure 12. Training and testing at multiple positions (angles) for all motions.

CHAPTER 5

Discussion

CHAPTER 5: Discussion

Although the changes in arm position had some influence on all of the feature type combinations, however, LBPSA group was least affected by the position changes. Among the various combination of features, the best set of features were RV, LBPV and LBPR. The combination of LBPSA was the best feature type which resulted in much higher classification accuracies than those obtained for the other feature sets, when using sEMG alone.

One of the causes is shift in muscle due to motion artifact. It is in accordance with the approach that the four-class motion demonstrates a lowest accuracy of classification, where training is carried out on data from all the three positions whereas testing at a single position i.e. 90 degree.

In addition, motor variation may also affect the classification accuracy because of a shift of ar m position during active motions [44]. With adjustments in position, we believe the ability of subjects to render movements with identical characteristics in terms of kinetics is somehow diminished. Our study showed that two factors influence the effectiveness of the EMG system at various limb positions. The first factor shows to be linked to the best of extracted features and their potential to distinguish hand movements at numerous limb positions. Changes in the properties of EMG signal may lead to changes in signal intensity, structure, frequency and time spectrum interpretation.

The second factor is use of the feature set. We proposed a new feature set (LBPSA) based on time domain derivative fused with spectral analysis to deal with the effects of the above listed factors. However, various methods have been used to resolve the impact of limb position, such as the use of accelerometers for identifying the arm location or simply calibrate the device at several positions [43].

Findings indicate that it is possible to generalize well on unknown positions by using the proposed feature set by acquiring data of EMG from multiple limb positions. For example, LBPSA yielded an overall testing classification accuracy of 83.07% while feature set consisting of RV, LBPR, LBPV, LBPSA yielded an overall classification performance of 76.20% for the same subjects which supports our research fact that recruitment of more(or even all features) is unable to make up for the loss of signal information in case of surface EMG, which in turn indicates that our current feature set has been effective in tackling the impact of the limb position to a large extent.

Our analysis has also compared with some of the already available feature extraction methods, from the literature suggesting that our newly proposed feature set in the present study was more efficient than many of the already available features and seem to be far less sensitive to outliers and yields good classification performance. Hence this novel feature set is recommended to be used instead of other common features ,as it may help to reduce data collection costs ,since we have focused on the signals obtained from surface EMG alone, which are thought to be relatively unreliable because of their sensitivity to environmental conditions.

CHAPTER 6

Conclusion

CHAPTER 6: Conclusion

Conclusion

In this study, it has been determined that the classification accuracy improved as more arm positions were taken up for training and testing i.e. training and testing the classifier at all limb positions. Similarly, the lowest classification accuracy was obtained by training the classification system on data from one position and testing on another position (BPC). Among all the feature set combinations, the proposed feature set - Logarithmic Band Power with Spectral Amplitude (LBPSA) - was the best feature type.

Future Aspects

It would be important to undertake a detailed function investigation study in future by involving more useful techniques to obtain data. Also, testing the model on less noisy intramuscular EMG data to evaluate the performance between surface and intramuscular EMG is also required. Clinical trials of real-time EMG classifications on subjects with upper limb amputation to test versatility of our model also needs to be conducted.

CHAPTER 7

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