TOOLBOX FOR MYOELECTRIC CONTROL

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***Abstract*:**

Surface myoelectric signals (MES) are used as effective input for the control of upper arm prostheses (artificial limbs). Initially, measurements using amplitudes were widely used to classify the parameters of MES, but a very simple approach used for the three-state system for each MES control site imposed a practical limit (e.g., hand open, rest and hand close). Therefore, in this paper we demonstrate that by using a very simple pattern classification system we can achieve high accuracy of classification. One can increase the classification accuracy by making little changes like changing the pattern recognition components used in the system. For example, different features, reduction of feature methods, and classifiers that yield a system which is improved.

Keywords: Surface myoelectric signals, pattern classification, classification accuracy, feature reduction methods, classifiers, pattern recognition.
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1. Introduction

Myoelectric signals are the electrical manifestation of the contraction muscles and neuro and muscular activities. Surface myoelectric signals are the signals recorded on surface of our skin. These signals can be used artificial limbs such as upper arms. Many external devices are used to identify the characteristics of the surface myoelectric signals. One of them are the amplitude measures but this is a simple approach which has many limitations like it cannot parameterize the movements when hands are closed, opened etc., So there is a need to parameterize the myoelectric signals. After many tries moving autoregressive average model was used instead of measurement using amplitudes, and has high accuracy in identifying the limb movements from a single myoelectric signal control site.

Later pattern recognition techniques were implemented which give 90% accuracy for normal limbed persons and 80% accuracy for amputee persons. However, the subjects were restricted to a certain position preventing them from motion. In recent years, pattern recognition techniques were developed where the user is not restricted to a certain position.

The pattern recognition process can be divided into three steps i.e., extraction of features, reduction of features and classification. Apart from these stages we can do pre-processing methods like filtering, amplification and post processing methods like smoothing can be used. The first stage feature extraction means the extraction or transformation of signal into certain features that represent the signal. The common features that can be extracted from the signals are root mean square value, median frequency, auto regressive coefficients, zero crossings, integrated absolute value etc., other features like wavelets and wavelet transforms can also be extracted.

After the feature extraction process may the feature vectors may have high dimensionality or more values as the signals may be samples to extract the features. We need to reduce the feature vector dimensionality in order to simplify the work for classifiers, feature reduction stage is used. Ideally, feature reduction reduces the intra class variations. Feature reduction improves the signal quality, reduces noise and it also reduces redundancies in the feature vector data. Some of the feature reduction methods are linear discriminant analysis (LDA), generalized discriminant analysis (GDA), principal component analysis (PCA) etc., and selection of features is calculated using Euclidean distance class separability technique.

The third stage classification maps the specific features into classes with the help of mapping function determined from the training data. There are many classification techniques. Some of them are linear discriminant classifiers, multi-layer perceptron (MLP), hidden Markov models, fuzzy systems and Gaussian mixture models.

Pattern recognition for myoelectric signals has many techniques. The need for the methods with greater accuracy are needed. The data and the implementation details play a major role in the result. In this paper, we compared two reduction of feature methods like principal component analysis (PCA) and uncorrelated linear discriminant analysis (ULDA) and generated a simplistic recognition of pattern system. In the result or output, we can see that the ULDA outperforms the PCA technique.

2. Methods

As discussed earlier we have three phases in pattern recognition. For the development of toolbox for myoelectric control we used Matlab software from MathWorks.

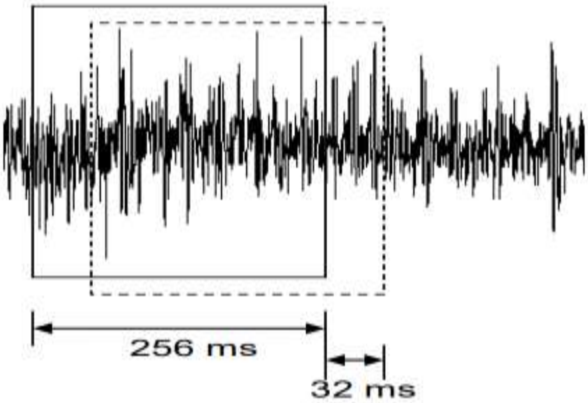

Fig 1: Sliding window analysis

In the above figure, an example for sliding analysis window is given. In which the window is sized 256ms and spaced by 32ms.

A. Feature Extraction Methods

Features of the signal are extracted from the myoelectric signals using analysis window sliding technique. In sliding analysis window, the statistics are calculated with a sliding window of certain length or sequence. The window is moved over the signal and the values are calculated

Feature extraction methods that are used here are mean square root value, absolute mean value, zero crossings, integrated absolute value, slope changes and auto regression coefficients

1. Mean square root value

It is the arithmetic mean of the set of values or the square root of the squares of the values. It is also called as quadratic mean.

2. Zero crossings

It is a point where the signal value changes i.e., from positive to negative or vice versa. It is commonly used in electronics, image processing

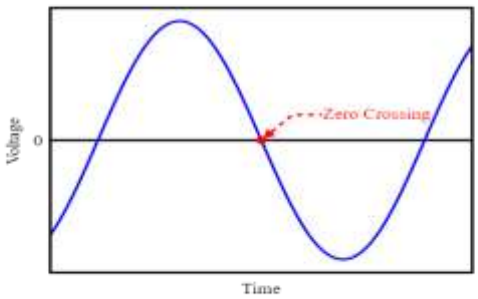

Fig 2: zero crossings

3. Auto regression

It is used for predicting the future values when there is a correlation between the time series and based on the past values.

B. Feature Reduction Methods

Feature reduction methods that are used here are uncorrelated linear discriminant analysis (ULDA) and principal component analysis (PCA).

1. Principal Component Analysis

In this method the principal components are calculated and these components are used to perform changes to the basics of the data. Sometimes we use the principal components that are calculated first and ignoring the rest.

It is mostly used for reduction of vector dimension by projecting every data point onto only the few principal components that are calculated first in order to obtain lower-dimensional data while preserving data variations as much as possible.

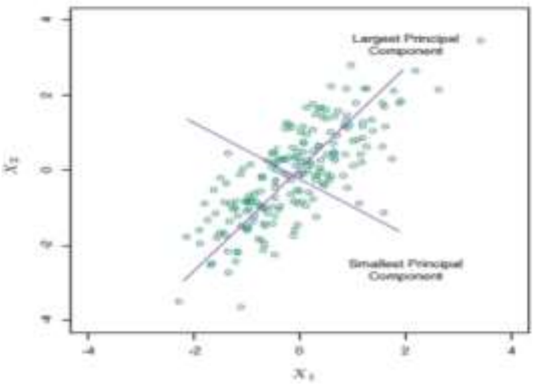

Fig 3: Principal component analysis

2. Uncorrelated LDA

It is mainly used to find linear combination of features that separates two or more classes or objects. It tries to express one dependant variable as a function of other features or measurements. This is similar to PCA process.

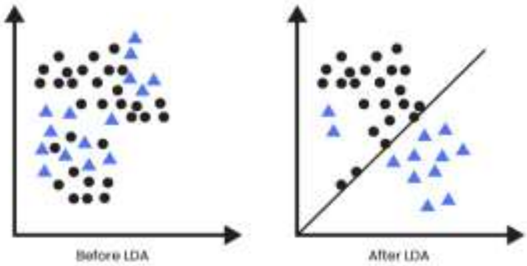

Fig 4: Linear discriminant analysis

PCA method is unsupervised one i.e., it does not depend on class labels for feature reduction. It corresponds to the linear variations of the projected principal components. LDA is a supervised method. It depends on the class labels for feature reduction. It maximizes the between the class distance to the with in the class distance. But LDA has few drawbacks like singularity. It can be overcome by using ULDA method, where ULDA removes the uncorrelated points. Thus, reducing the redundancies and singularity problem

C. Classification

In classification, we simply used linear discriminant classifier which do not need iterative training. The main advantage of this classifier is that its potential for avoiding the under trained samples and over trained samples. When feature reduction stage is done properly then the high dimensionality problem can be removed. So, the need for non-linear classifiers like MLP's, fuzzy vectors which achieve higher accuracy are not needed.

3. Data

The data used in this pattern recognition system is collected from 30 subjects in 7 positions. The MES signals are recorded using electrodes, in which one electrode is place on wrist and another on ground as reference. The recorded signals are amplified and has a gain of 1000 and bandlimited from 1 Hz to 1kHz. The sampling of signals is done using analog to digital converter at a frequency of 3 kHz.

The signals are recorded at seven distinct limb motions: wrist flexion, hand close, pronation, hand open, supination, and wrist extension, rest. Within every trail, every subject repeated the limb motion four times and held on three seconds. Data from first two tails were used for this paper. The auto regression coefficients and mean square root features are used as vector for features.

The window used for analysis is of size 256ms, the size can be up to 300ms as per the myoelectric control. The window is spaced 128ms for data used for training and 32ms for data used for testing. The recorded data that was 256ms length is removed (before or after) from training data set to avoid data transitions.

4. Results

The error after classification without feature reduction is 10.56%. To improve accuracy of classification, post processing techniques like majority vote can be used. The majority vote classification technique uses present classification result and previous eight classification results. It uses a sliding window of length 256ms with a spacing of 32ms. It makes the decision based on

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the output of majority class that appeared in the previous 8 classification results. The classification error decreases to 9.39% after majority post processing technique. It also eliminates spurious misclassification.

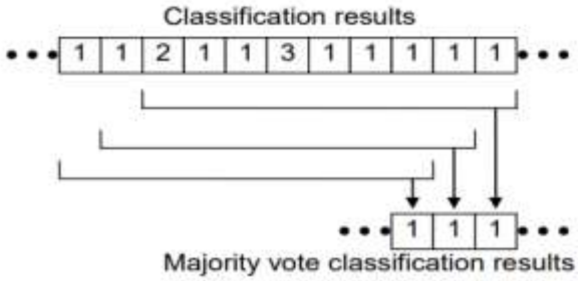

Fig 5: Majority vote post processing technique

We can see that recognition of pattern technique is very useful in classifying the MES signals. The error in the classification occurs due to the transitions. These transitions are due to the system contractions. If we can remove the transition period from the analysis window, we can improve the classification accuracy. In order to improve classification accuracy, we remove the 256ms period before and after the transitions. By doing this method we can get classification error up to 7.46%.

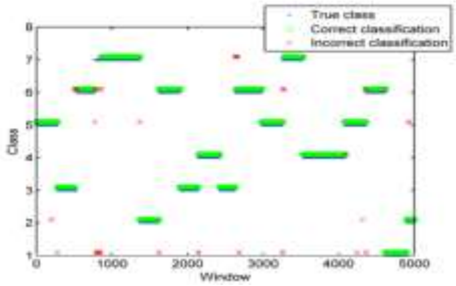

Fig 6: Sequence used for classification

Feature reduction can be eliminated when these two conditions are satisfied. First one, when we have rich training data set. As we know data set is the most important one in classification. Based on this only we can get the results with much accuracy. We can say that based on the training data set pattern only test data set is classified. Second one is having high dimensionality feature vector, which increases the probability of separating the features.

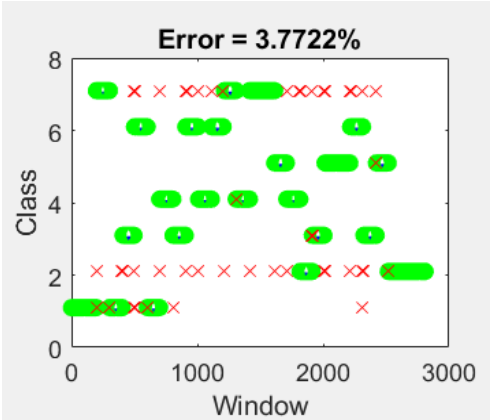

Fig 7: Error when ULDA feature reduction is done

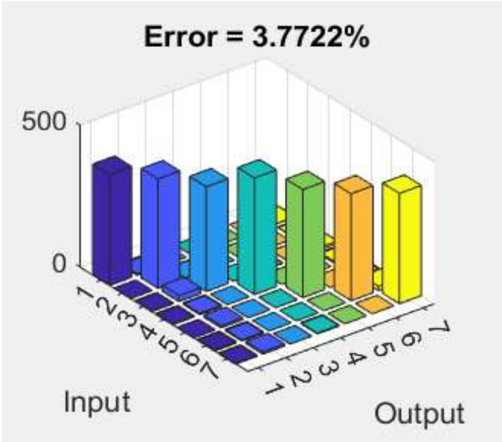

Fig 8: Representation of error using confusion matrix when ULDA feature reduction is performed

The above figures 7,8 shows the classification error when ULDA feature reduction is performed on the given data set.

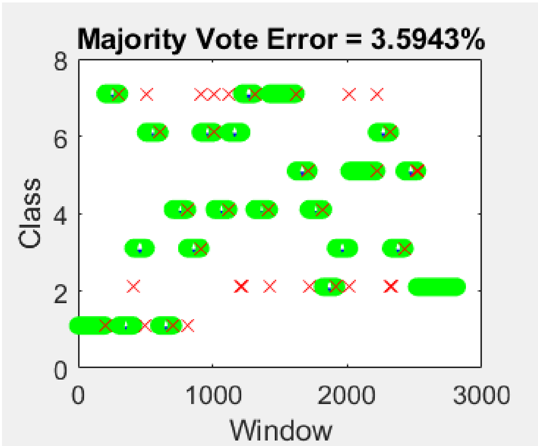

Fig 9: Error after ULDA feature reduction and majority post processing is performed

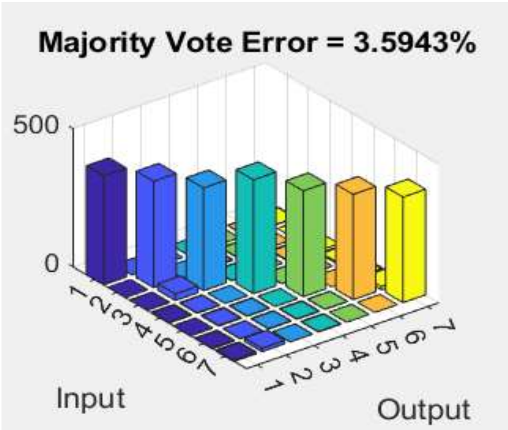

Fig 10: Representation of error using confusion matrix when ULDA feature reduction and majority vote post processing is performed

As discussed above we can see that post processing techniques improves the classification accuracy. Figures 9,10 shows the error after ULDA and post processing.

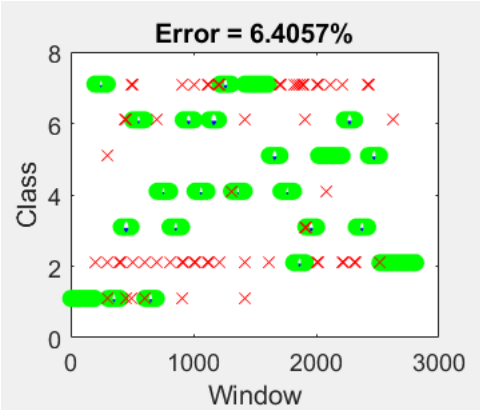

Fig 11: Error when PCA feature reduction is performed

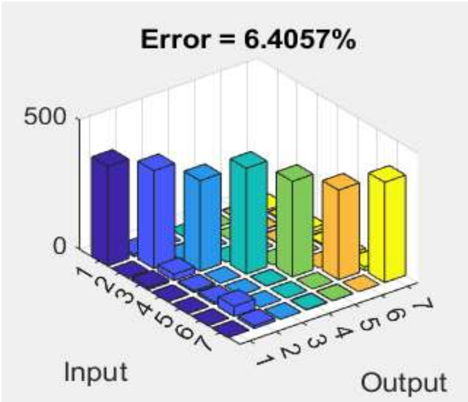

Fig 12: Representation error using confusion matrix when PCA technique is performed

The above figures 11,12 shows the classification error after PCA feature reduction is performed on the given test data.

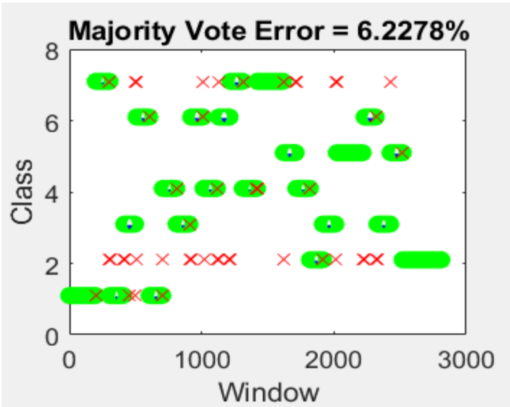

Fig 13: Classification sequence and error after post processing is performed.

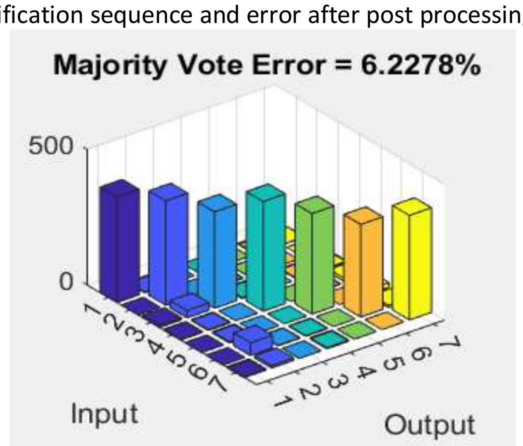

Fig 14: Representation of classification error using confusion matrix after post processing is performed.

Figures 13,14 represent the classification sequence and error after post processing is performed.

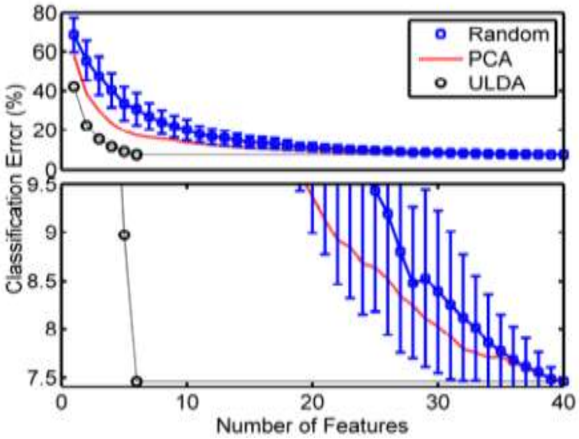

Fig 15: Classification accuracy calculated using feature vector dimension

Figure 15 is the plot of accuracy in classification based on the feature vector dimensions. Reduction of features was performed by selecting features randomly such as mean and standard deviation of 10 users.

As discussed above the classification error reduces as the feature vector dimensionality increases. The error will be minimized only when most of the features are used. PCA decreases the dimensionality of features by obtaining a new feature through the previous values mean and variance. The new feature is selected based on the previous eigen vectors with highest eigenvalues. This method will keep the parts with highest variance and these parts essentially contains the most information. But this method can be true always. As we can see in the figure 15 there is a large gap in the classification error when new principal component is added. This error did not reduce until we selected all the features.

In figure 15 we can clearly see that ULDA outperforms PCA technique. We do not expect this from PCA as PCA is a technique which is unsupervised whereas ULDA is technique which is supervised. Instead of selecting feature projections using variance or mean, ULDA selects the feature projections that decrease the class separation. The obtained feature vector will have dimension that are less than the number of classes that are chosen. In this system, the chosen classes are seven, in which ULDA attains minimum rate of classification with six features. The figure 15 plotted with features six or even less than six.

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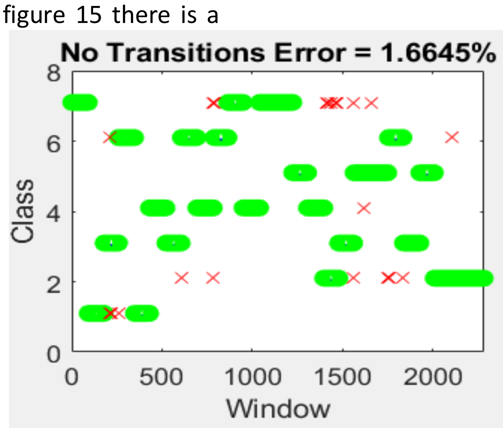

Fig 16: Error after removing transitions and when PCA technique is performed

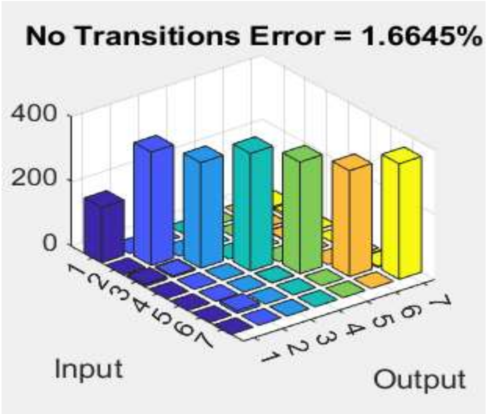

Fig 17: Representation of no transitions error when PCA technique is performed using confusion matrix

Figures 16,17 represent the classification error when there are no transitions and PCA feature reduction technique is performed.

Fig 18: Error after removing transitions and when ULDA

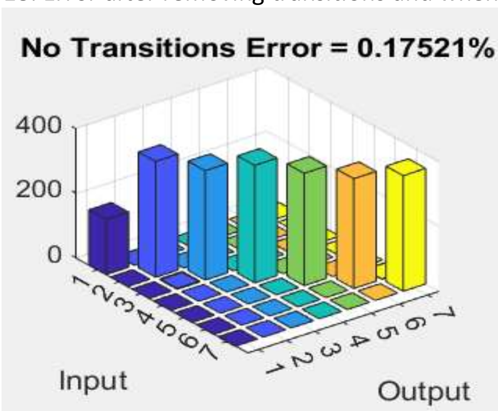

Fig 19: Confusion matrix representation of error when transitions are removed and ULDA technique is performed

We can say from the above figures that the classification accuracy increases if we remove transitions in the data.

After removing transitions, if majority vote post processing is performed it may not be of any help.

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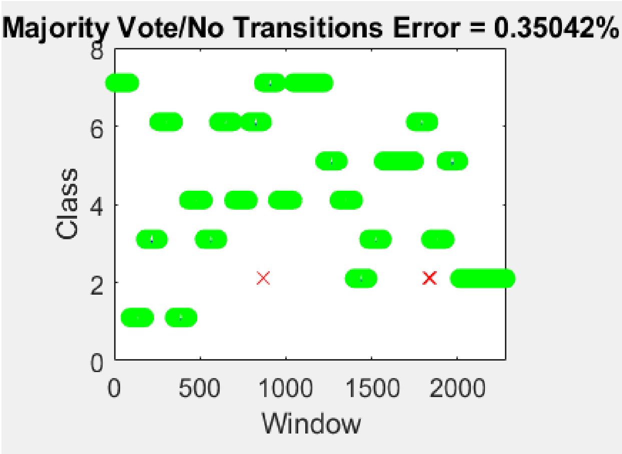

Fig 20: No transitions error when ULDA technique is performed.

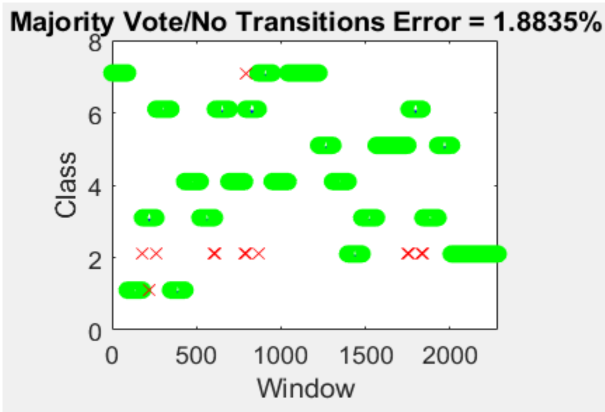

Fig 21: No transitions error when PCA technique is performed

5. Discussion

Based on the results, we can say that the classification accuracy can be improved by changing the techniques used in the recognition of pattern system. The usage of different classifiers, feature reduction techniques can or may yield a better classification accuracy. We achieved high accuracy with a simple pattern recognition system. The system used provides an accurate baseline for remaining systems to compare with this. The comparison of systems includes system complexity. These computational requirements are important in embedded systems where MES signals are used.

In this paper, we compare two reduction of feature techniques: ULDA and PCA. While PCA is expected to be performed better, because of its random selection and unsupervised method. But minimum classification error is not achieved with PCA.

Results clearly says that ULDA outperforms PCA. When ULDA is used, the feature vector can be decreased by a factor of seven without having any changes in the classification error. This reduces the work of a classifier. Thus, non-linear classifiers which are known for high accuracy can be omitted. And the classifiers need less time for training them with machine learning algorithms.

6. Conclusion

A simplistic pattern recognition system with high accuracy is presented. This system is used for upper arm prostheses or artificial upper arm. This system extracts features like RMS and auto regression coefficients in feature vector. Effective feature reduction technique is ULDA method. An accuracy of 92.54% is achieved over 30 subjects using linear discriminant classifier. And the classification accuracy can be improved by performing post processing and by removing transitions.

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