ANALYSIS OF EMG SIGNALS USING MACHINE ALGORITHM FOR PROSTHESIS

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ABSTRACT: Myoelectric Signals are formed by physiological variation in muscle fiber membranes. Electromyography (EMG) is a technique used for measurement and recording the electrical activity produced by skeletal muscles. EMG signals are typically time varying signal. In case of loss or amputee of upper limb myoelectric devices called prosthesis play vital role in rehabilitation. These devices sense EMG signals, on muscle contractions in upper limb, using electrode which are amplified for use as control signal in externally powered prosthesis. The signals acquired are processed before using it for controlling any device. Different methods are available for processing signals. Objective of this paper is to evaluate the feature extraction and classification of EMGs signals. In present work wavelet transformation is used for feature extraction and then SVM is applied for classification of the feature vector set.

Keywords- Electromyography, Feature extraction, Classification, SVM, machine learning.

I.INTRODUCTION

Muscle and joints are two major groups of organs that support human body movements. A failure or degeneration of any muscle could lead to severe problem in human life. There are more than 10 million physically handicapped people in India. A majority of them belong to poor strata of the society. In the present condition prosthetic fitment centers are not sufficient to deal with such large amputee population. Children are mostly victim of society in low per capita income country in general. Children with congenital amputation, loss of limb with street accidents/trauma, frost bite etc. need special attention for the prosthetic fitment. As children are in the growing age, the prosthetic device is required to be changed frequently.Even for a normal people, enhancing muscle functionality would be highly desirable, for either daily life or specific motions such as in sports, dancing, instruments, etc.The history of prosthetics and amputation surgery begins at the very dawning of human medical thought. There is a necessity of more research work on this area to help society. Myoelectric prostheses of the upper limb increase range of motion and improve overall function of the upper limb for people with missing hands. These prostheses function via surface electrodes which are placed in the socket to detect and amplify muscle action of the residual limb.

A terminal device, which is either a hand or a hook, is operated by a small electric motor and sometimes accompanied by a microprocessor. The technology of the upper limb prosthesis improved dramatically with the advances in electronics.A EMG signal controlled artificial hand uses muscle contractions as a signal to activate the prosthesis. The Electrical activity of muscle of residual limb is detected by surface electrodes these signal are amplified for use as control signal in externally powered prosthesis.EMG signals are extensively used as control signal in man-machine interface application. The feature extraction and classification of EMG Signal find application control of multifunction prosthesis and many virtual instrumentation. Three basic Steps to develop such a multifunction system involve. Acquisition and pre-processing of myoelectric signal from enduring muscle amputee, Feature extraction of acquired myoelectric signal and determine the class output or classification.The method of extracting useful information from EMG signal after removing the noise is known as feature extraction. In this stage raw signal is converted into feature vector set. Once the feature vector set made classifier is used to discriminate among the feature vector. Then these obtained categories are used as control command in controller.The objective of this study is to evaluate features of EMG Signal and study feature vector using classifier. The result of this study can be applied in clinical and engineering application.

II. DATA ACQUISITION

EMG signal can be acquired by two methods (i) invasively by inserting a needle electrode into the muscle or (ii) noninvasively by using a skin or surface electrode placed directly on skin surface above the muscle. In this study EMG signal where measured by noninvasive method. Ag-AgCl EMG electrodes are standard sensor used for best trace. Myotrace 400 (MT400) was used to acquire signal. EMG signal are passed by USB cable to PC no driver installation is required as MT 400 uses standard windows HID driver communication over USB port. MRXP software is used for acquiring the signal for analysis. A sample period of 20 millisecond at 1 KHz was taken. Two muscles of upper limb Flexor carpi radialis and Biceps Brachii caput longus are taken into consideration for measurement. Samples were collected from twenty persons of age group 20-25. A pair of electrode is used one on each muscle and a reference electrode is also used to minimize the effect of interference. The signal is generated by taking the difference between signals from adjacent electrodes place at a distance of 5-8 cm which help to attenuate noise.Two Movement of both Left and Right Hand have been take into consideration (i) Elbow Flexion, (ii) Elbow Extension

III. SIGNAL ANALYSIS

Whether EMG signals are used for controlling assistive or rehabilitative the most challenging is to able to process signal and identify the intention of user.Different pattern recognition method has been used to address the problem. After acquiring the signal into digital format in the computer, MatLab is used for analysis of pattern recognition in EMG Signals primarily two stages feature extraction and classification. In this stage raw signal are transformed into feature vector set by reducing noise and artifacts. One of the major activity in this stage is dimensional reduction which is elimination of redundant data from feature vector.

(a) FEATURE EXTRACTION

Feature is a measurablediscrete property from observed EMG signal and collection of relevant information from the signal is termed as feature extraction. Feature extraction is one of the key function in processing and analyzing the EMG signals there are three distinct class categories in which features can be broadly classified into categories according to what information they may obtain. (i) time domain features (ii) frequency domain (iii) time-frequency domain features. Qualitative features are indicative only of relative sizes or magnitudes, rather than their numerical values which quantitative features will give.Intime domain feature values are calculated based on signal amplitude and represent waveform amplitude, frequency and duration but unable to identify high frequency variations which is common in EMG Signals due to vigorous movements. The frequency domain features are on the basis of estimation of power spectrum density of signal. It requires parametricmethods for calculation takes more time and are complex. The frequency domain method is not that effective as it is unable to give time resolution for dynamic EMG signals. On the other in time-frequency domain feature can localize the energy of signal in time and frequency which give in-depth and accurate representation of signal. The time frequency is preferred technique over the other two and needs transformation.

The signal can be represented in another form by its transform by retaining the original information same. The Short Time Fourier Transform (STFT) is one of the popular method used but as it uses a fixed size window size it has to make compromise between time and frequency resolutions. The limitation of STFT is overcome by using wavelet transform which represent the dynamic signal into function of time and frequency with advantage to analyze different frequencies with different resolution with technique called multi-resolution. The size of window can be varied according to need of time and frequency resolution. Wavelets localized waves as there energy is concentrated in time therefore are bestappropriate for the analysis of dynamic signal. Another transformation mostly used for feature extraction is discrete wavelet transform (DWT) and provides high dimension of data.

The Discrete Wavelet Transform (DWT) is easier in implementation, takes less time in computation and uses sub-coding method. DWT uses digital filtering technique to represent signal in time scale and the operation is carried out by using multiple filter with rescaling. The signal with different frequency components is passed through the filters of different cutoff frequencies at different scales. The filter are used to sense in depth information of signal. The scale of filter is decided by the decimation and interpolation method. At each step of decomposition, In half band high pass filtering, the frequency resolution doubles by a decimation factor 2 and halves the times resolution as it produces the signal with half the samples without any loss of data while in the half band low pass filtering, the frequency resolution reduced by 2 as half of the frequencies are removed by which it doubles the time resolution by decimation of factor 2.

It is a multi-resolution approach where we get significant time resolution is at high frequency and good frequency resolution at low frequency. DWT is finally calculated by combining the detail coefficient and approximate coefficients of all levels.In our study we used Daubechies wavelet of order of 2 with 4 level of decomposition. Each segment is decomposed into three resolution level with four detail wavelet coefficient (d1, d2, d3, d4) and one approximation wavelet coefficients (a4).The notations d1, d2, d3, d4 or a4 correspond to coefficients at first level, second level, third level and fourth level. The coefficient are recoded five separate in excel sheet with 20000 rows and 42 column.

(b) AUTOREGRESSIVE METHOD

The power spectral density shows the distribution of power with frequency. AR parametric model is a sort of linear prediction. This method is commonly used as parameters can be estimated easily and provides good stability for small length signal. A good spectral resolution is obtained. In small time periodsEMG signal can be viewed as stationary Gaussian process and can be represented in AR Model. The advantage of AR Parametric model is that sEMG signal can be represented by model parameters without original waveform data which reduces large data and specific feature are strengthened. In such models spectrum is estimated in two steps in first step process parameters are estimated and in second step this estimation is uses for calculating power spectral density (PSD). It can be defined by

$$\mathrm{x(n)} = \sum_{k-1}^{p} a_k\, x(n-k) + e(\mathrm{n})$$

Where x(n) is n^{th} output of AR model and x(n-k) is $(n-k)^{th}$ sampling data of N samples of EMG raw data, a_k is AR model parameter and e(n) is white noise signal. P is order of AR Model.

In the study we use AR6, AR8, and AR10 to get a total of 24 dimension feature vector. The power spectral density (PSD) by this method for the class A, Class B, class D and class E.

(c) MIXTURE OF FEATURES

Features set are extracted in time domain and frequency domain for each set of coefficient and approximation wavelet coefficients (a4). These features set are then appended to form feature vector. The combination of autoregressive (AR) model coefficients with time domain and frequency domain feature set is used for training classifier. After appending the feature vectors set final feature vector set of 84 x 40 column dimension is obtained.These mixture feature set taken to be effective signal representation for EMG pattern recognition with fairly low computational complexity.

IV FEATURE CLASSIFICATION

After extracting the features from raw signal and classifiers are used to differentiate between different groups among the reduced feature vector. In this work we used support vector machines (SVM) and K-nearest neighbor (KNN).KNN is widely used algorithm which stores all available cases and classifies new cases based on comparison of measure like distance function. It is mostly used in statistical evaluation and in recent time in signal processing as a non-parametric technique. Experimental result when KNN is used as classifier of EMG signal reported sensitivity up to 81% and specificity up to 72% on average across ten persons.Supportvectormachines (SVM) is a kernel based supervised learning algorithm and is being used popularly for bio-signal classification. In contrasting with neural networks they reduce the number of parameters introduced by user. In SVM each instance of data is represented as point in space and then a model is built to assign new instances to one group or another. Each data point is represented as a n-dimensional vector, to separate two classes a hyperplane of n-1-dimension is constructed with aim to maximize distance between hyperplane and data points on each side.The aim in SVM is to find best hyper plane.Data is represented as

$$(\vec{x}_1, y_1) \ldots \ldots \ldots \ldots (\vec{x}_n, y_n)$$

Where subscript takes value 1 or -1, which shows to which class x_i belongs. Here x_i is p-dimensional vector representing all of the characteristic values of x_i.The hyperplane used to separates the group of x_i vectors where $y_i = 1$ from the group of vectors where $y_i = -1$ is represented by

$$\vec{w}\,.\,\vec{x} - b = 0$$

Where $\vec{w}$ = normal vector to hyperplane

b = offset of hyper plane from origin

If the data points are linearly separable, the hard margin can be represented as

$$\vec{w}\,.\,\vec{x} - b = 1$$

And

$$\vec{w}\,.\,\vec{x} - b = -1$$

Figure 1 shows a maximum margin separation for linearly separable data. The samples that lie on the margin are called as the support vectors.

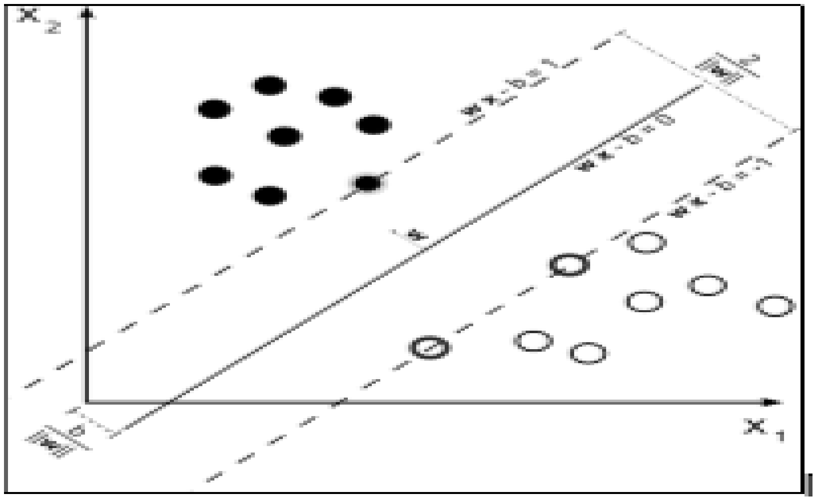


Figure 1: Linear SVM in 2D feature space

We use kernel based function in situation where data is not linearly separable wherein to adjust inner dot product of maximum margin hyperplane optimization algorithm is used. This transforms the data into higher dimensional space.

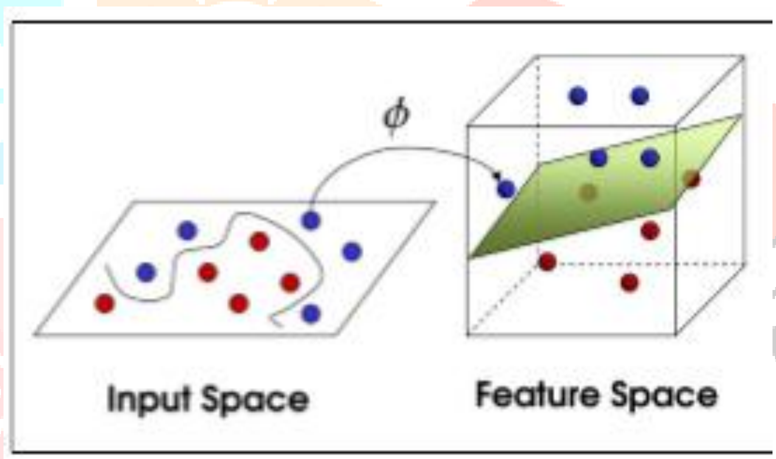


Figure 2: Transformation of features into higher dimension

V PERFORMANCE EVALUATION

The classification is done by using MATLAB software package. The feature vector set is involves a mixture of features computed from wavelet coefficient, approximation wavelet coefficients (a4) autoregressive (AR6, AR8, AR10) coefficients. The Feature vector set so developed are five in number of matrix size 69 rows and 38 column. The classifier uses a fivefoldcross-validation scheme is used to evaluate the classification performance. The experiment is conducted for all five feature set and confusion matrices for each decision is recorded overall classification accuracy is then calculated as percentage of correctly classified pattern over all the analysis patterns. The confusion matrix enumerates number of instances in test dataset classified as false positive (FP), true positive,false negative and true negative there by precision and sensitivity can be calculated.

$$Precision = \frac{True\ positive}{true\ positive + false\ positive}$$

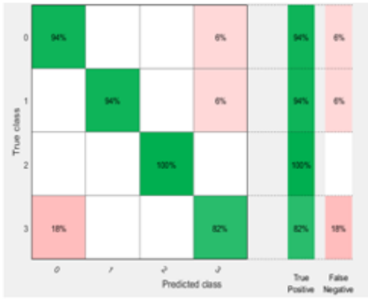
$$Sensitivity = \frac{True\ positive}{true\ positive + false\ negative}$$

$$Classification\ acurracy = \frac{Number\ of\ accurately\ classified\ testing\ data}{total\ no\ of\ testing\ data} \times 100\%$$

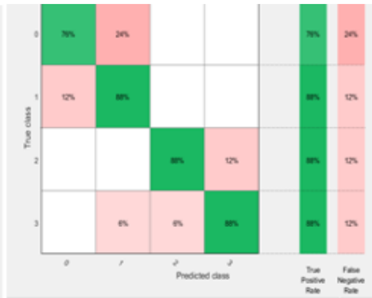
Table 1: Total classification accuracy

	CLASSIFIER	ACCURACY (%)	TYPE OF MOVEMENT			
			EXT(0)	FLX(1)	PRO(2)	SUP(3)
Data set 1	Weighted KNN	94.1	94	100	100	82
	SVM-Cubic	92.6	94	94	100	82
	SVM Quadratic	92.6	94	100	100	76
	Linear Discriminate	75.0	47	100	100	53
Data set2	Weighted KNN	85.3	94	94	82	71
	SVM-Cubic	85.3	76	88	88	88
	SVM Quadratic	86.8	82	94	82	88
	Linear Discriminate	64.7	47	53	94	65
Data set 3	Weighted KNN	88.2	100	82	88	82
	SVM-Cubic	98.5	100	100	100	94
	SVM Quadratic	98.5	100	100	100	94
	Linear Discriminate	98.5	100	100	94	100
Data set 4	Weighted KNN	88.2	100	100	76	76
	SVM-Cubic	83.8	100	82	82	71
	SVM Quadratic	79.4	100	82	65	71
	Linear Discriminate	76.5	100	53	88	65
Data set 5	Weighted KNN	86.8	100	100	65	82
	SVM-Cubic	94.1	100	94	88	94
	SVM Quadratic	94.1	100	94	88	94
	Linear Discriminate	79.4	100	53	94	71

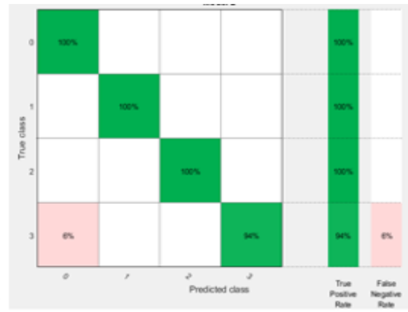
The performance of classifiers is evaluated using confusion matrices. The Table depicts comparison of classifier performance on four movements across all subjects. Fig.performance per class in the confusion matrix it gives an understanding how a classifier performed in each class which is recorded in table. Row show the true class and columns show predicted class where as diagonal cell show where true and predicted class match and if the cell are green and display a high percentage it is taken as classifier has performed well and classified the observation of true class correctly. In first data set top row shows that 94% of data is correctly classified so that 94% is true positive rate for correctly classified points in this class the data in green cells are true positive rate column.



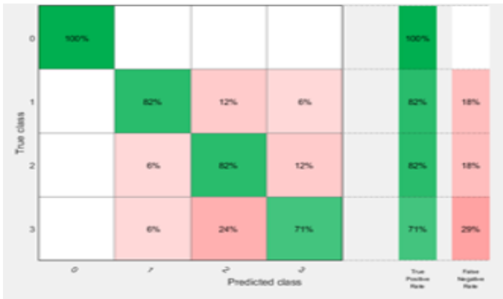
(a) Data Set 1 Accuracy 92.6%



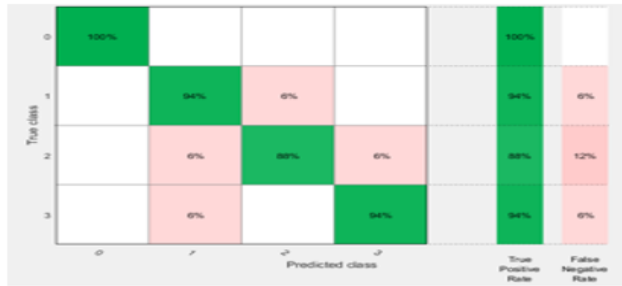
(b) Data set 2 Accuracy 85.3%



(c)Data set 3 Accuracy 98.5%



(d)Data set 4 Accuracy 83.8%



(e)Data set 5 Accuracy 94.1%

Fig.3 pattern classification of different movements

VIRESULT& DISSCUSSION

In this work after analysis of EMG signals acquired from both right and left hand of all 10 persons classification for all four movement based on feature set extracted it is clear that support vector machine out performed over other classifier. After evaluating the overallaccuracies of all four movement graph is used to scrutinize the data. In this graph accuracy in percentage form are depicted on y-axis where as five movement are shown in different colour on the x-axis. Table shows the performance on basis mean accuracy of four different classifier for four movement using five set of data. It is clear from analysis summary that accuracy of complete work is in the range of 89.14% -92.01% which is on a reasonably acceptable level. As lot of research work is going on this area scope of improvement of accuracies.

Table 2. Comparison of average accuracies of classifier

TYPE OF MOVEMENT	CLASSIFICATION AVERAGE (% Percentage)			
	W-KNN	SVM-CUBIC	SVM-Quadratic	LDA
EXTENSION	78.82	90.28	90.86	88.52
FLEXION	78.8	95.2	94	97.6
PRONATION	71.8	94	91.6	95.2
SUPINATION	94	87	91.6	82.2

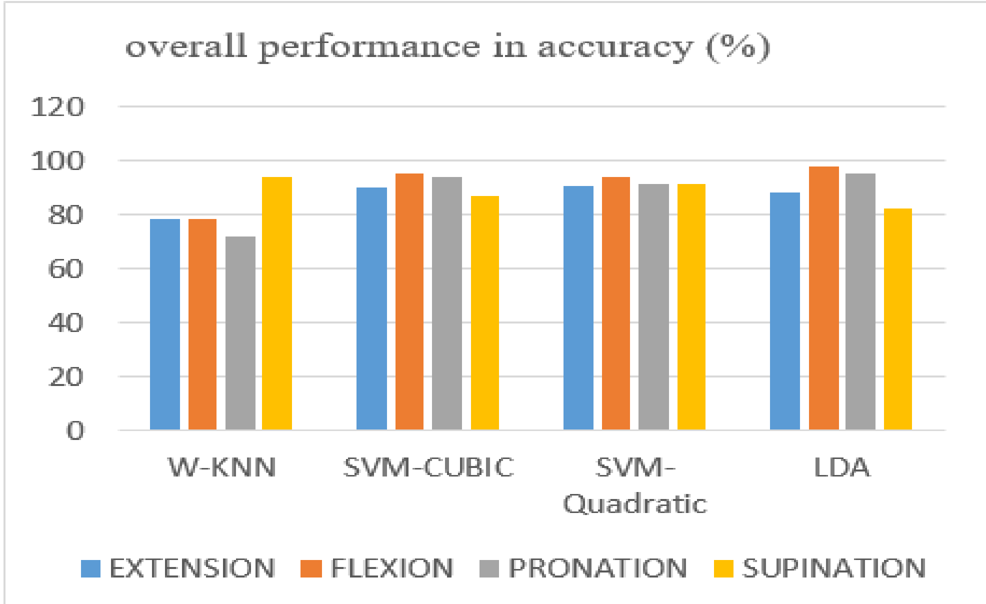


Fig. 4. Statistical representation of average accuracies of classifier

VII CONCLUSION

In this study analysis of surface EMG signal is done using discrete wavelet analysis method and Auto regression(AR). The final feature vector set was a mixture of time AR6, AR8, AR10, time domain and time frequency domain. It established that a classification of different movements using mixture feature vector set resulted with an accuracy of 92.02% which is at par with other technique used. The result revealed that dimension reduction can be left while using mean feature wavelet thus it is an alternate to principle component analysis. DWT when used solves serves two purposes one noise reduction and secondly feature extraction. Support vector machine are good alternative tool for classification in comparison to other classifier for biomedical problems. Results can be directly used for design rehabilitation devices as svm can clearly distinguish movements precisely. There is immense of scope and lot of work can be done for movement classification of limbs with better amount accuracy for increased number of movement including more than two muscles.

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