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EMG Signal Based Pattern Recognition of Grasping Movement Using MODWT And Weighted K- Nearest Neighbor

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Abstract*: This study purposed and evaluates a method based on weighted K-NN classification of surface Electromyogram (sEMG) signals. The sEMG signal classification plays the key role in designing a prosthetic for amputee persons. Wavelet transform is new signal processing technique, which provides better resolution in time and frequency domain simultaneously. Due to these wavelet properties, it can be effectively used in processing the sEMG signal to determine certain amplitude changes at certain frequencies. This paper propose a Maximal overlap Discrete Wavelet Transform (MODWT) approach for Weighted K-NN classifier for classification of sEMG signals based Grasping movements. At level 5 signal decomposition using MODWT, useful resolution component of the sEMG signal is obtained. In this paper Time-domain (TD) features set is used, which shows a decent performance. In WKNN, use a square-inverse weighted technique to improve the performance of the K-NN. Hence, a novel feature set obtained from decomposed signal using MODWT is used to improve the performance of sEMG for classification. MODWT was used for de-noising and time scale feature extraction of sEMG signals. Several WKNN classifiers are tested to optimize classification accuracy and computational problems. PCA is use to reduce the size of the level 5 decomposed data. WKNN performance evaluation on K=10 values with or without PCA. Six hand grasping movements have been classified, results indicate that this method allows the classification of hand pattern recognition with high precision.

Keywords: Weighted K-NN (WKNN), Maximal overlap discrete wavelet transform (MODWT), sEMG, Principal component analysis (PCA), gasping movement, feature extraction, hand movements, robotic arm etc.

I. INTRODUCTION

Biomedical Signal Processing is an important research field as different types of bio signals that are extensively used these days for diagnosis of various diseases. As the health care is being computerized, novel techniques and applications are being established. Various biosignals like, EMG (Electromyogram), ECG (Electrocardiogram), etc are very important physiological signals [1]. Recognizing gestures based on sEMG signals is a significant study of clinical application of sEMG. It is an effective and reliable recognition of gestures that can contribute to the development of a human machine interface (HMI).The information about the muscles activities can be analyzed by measuring the surface electromyogram (sEMG) signals. The sEMG signal is the summation of the electrical signal generated from muscles and controlled by the nervous system. Muscle action is proportional to the amount of potential for action recorded as EMG. This techniques is widely used in the application of clinical and industrial research. It is also used to control the prosthetic devices for the amputees and partially paralyzed persons. The amplitude of sEMG signal is too low in the range of millivolts and microvolts but it can be directly captured by the bio-signal acquisition devices for further processing and applications [2] [3].

Obtaining the sEMG signal is an advanced task. It require lowest noise and accurate filtration and amplification stages earlier and later digitization and signal processing. On the contrary, operate a prosthesis for everyday life needs good control so that the subject can apply the correct types of grip, such as grasping a ball, a book, a pen, a stick etc. [4]. This requires the progress of a low-channel separation classification architecture.

The EMG signals are of two types,

1. Intramuscular EMG.
2. Surface EMG.

Intramuscular EMG can be record by invasive electrodes and the sEMG by non-invasive electrodes. Nowadays, surface-detected signals are most popular for obtaining the desired information of muscle activation [5].

In clinical applications, EMG signals have employed a way for the diagnosis of nervous and muscular systems. The application of EMG signals in rehabilitation and biomedical engineering has been studied for controlling the activities of lower/upper-limb to help the disabled and elderly people for controlling many kinds of assistive devices and prostheses [6]. The accuracy of sEMG signal classification may be varied according to some factors, such as sampling, selection of a location for electrodes placement, features extraction, sEMG signal acquisition and processing [6].

A variety of noises and interferences are automatically added to the sEMG signal due to its very low amplitude. In the case of denoising, Wavelet Transformation (WT) plays a significant role in efficiently meaning of the sEMG signal.

In order to obtain better performance in the waveguide algorithm, an adequate choice of the mother wavelet is very important [7].

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A set of sEMG features over time, frequency and time-frequency. All Features are recorded in time domain. Frequencies based time are not available directly and come from time and frequency domains. After filter the several noises of the sEMG signal, extraction of features can be done to gather all the vital information of the sEMG signal. sEMG signals can provide significant information about different hand activities. To obtain high precision, numerous classifiers can be used to classification of hand actions (Phinyomark, 2012). Classification of neuro-muscular diseases in sEMG based features such as RMS, WL, SSC, MAV and Zero Crossing (ZC) [8].

The easiest way to choose these bioelectric potentials areas of surface EMG (sEMG), where surface electrodes are located on the muscle groups. Surface Electromyography (sEMG) is a way of recording the electrical potential captured via muscular mass. In the area of biomedical instruments, the usage of MES (Myoelectric Signals) is the maximum significance for manipulating assistive devices including upper limb prostheses, wheelchairs and rehabilitation devices. Robotic applications used in rehabilitation exercise have rewards over conformist therapies because the applicant increases his/her inspiration to train and chance for executing uses freely in order to develop the quality of training [9].

Wavelet transform are two types, DWT as orthogonal and MODWT as non-orthogonal. DWT is used for decompose time series data of different frequencies. Whereas MODWT is a modified of DWT that use for sample rate. DWT compare with MODWT by using Haar, Daubechies, Symmlet and Coiflet functions that shows the MODWT makes better than DWT. MODWT is utilized for TFD feature extraction as well as de-noising purpose [10].

The method of extraction of the characteristics was implemented before the classification step. This will create complexities in the sEMG signal analysis. Therefore, there are some key issues that should be addressed carefully, including selecting or reducing features and designing the classifier to improve efficiency. Choosing the right features plays an important role succeeding a good classification accuracy as well as uninterrupted control device. The principle components analysis (PCA) is used to reduced the dimensions of feature vectors [11] [12].

This study investigates the feature extraction based accuracy of weighted K-NN from decomposed data for level 5 using MODWT.

The object of paper is to calculate the performance of weighted K-NN classifier which classify the sEMG signal using MODWT for the control of robotic arm prototype.

The section is divided into four divisions of this paper: first division is introduction, second division describes data recording, wavelet denoising and decomposition, Feature extraction, and introduction of classifier used, third division illustrate the result and, finally, in fourth conclusions are presented.

II. MATERIALS AND METHODS

The proposed system can be systematized in several inter-operating sections as described below:

A. EMG Dataset and Pre- Processing

In this paper, data were acquired from 15 healthy objects of the age of 20 to 24 at Biomedical Instrument Laboratory, National Institute for Technical Training for Teachers of Research and Development (NITTTR), Chandigarh. The clamping movements were performed by the subject according to the predefined protocol. The device has two recording channels in which a recording channel. The sampling frequency of sEMG signal was is 1000 Hz. 15 trails have been done by every object for movement with a delay of 5 sec with 10 repetitions. Figure. 1 illustrate the sEMG signal acquisition system.

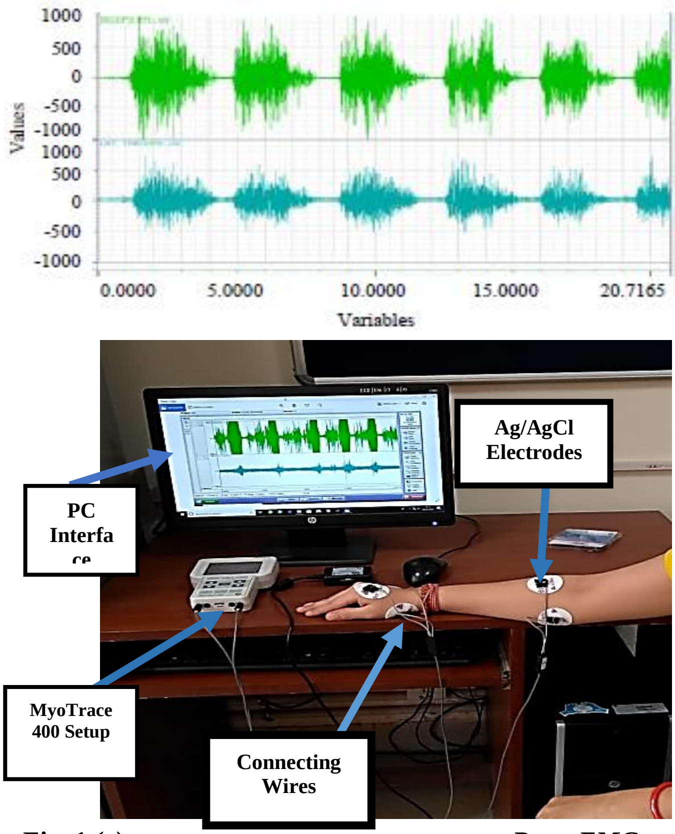

Fig. 1 (a) Raw sEMG signal (b) Data acquisition complete setup

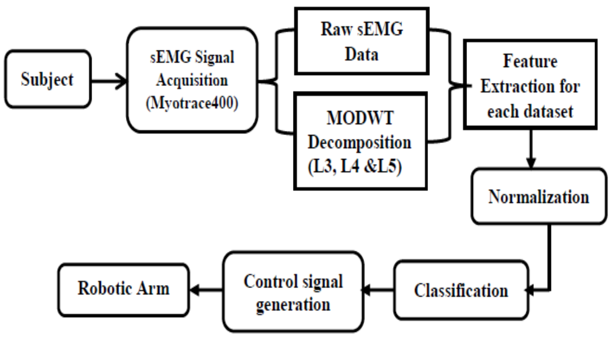

Fig. 2 Complete Steps of sEMG Signal Classification.

The electrode place is fixed at acupressure points of right handed upper arm based on the myotrace manual. The MYOTRACE400 device was used for data acquisition with signal processing techniques.

A sliding window analysis with a length of 150 msec was utilized for segmentation of combined sEMG data sheet [13]. The preprocessing stages, rectification, filtering, smoothing and normalization operation done by MYOTRACE400 device. For avoiding the noise, a bandpass filter of 20 to 500 Hz bandwidth was utilized. The six movements discuss here [14]-

1. **Cylindrical:** for grasping cylindrical objects like cane, bottle, glass etc.
2. **Tip:** for pinching or holding small objects like pen, spoon and other daily use material etc.
3. **Hook or Snap:** for supporting or pulling objects like briefcase, open door or heavy load etc.
4. **Palmar:** for grasping or holding tiny objects with palm facing.
5. **Spherical:** for holding or grasping spherical tools like tennis ball etc.
6. **Lateral:** for holding thin, flat objects like card etc.

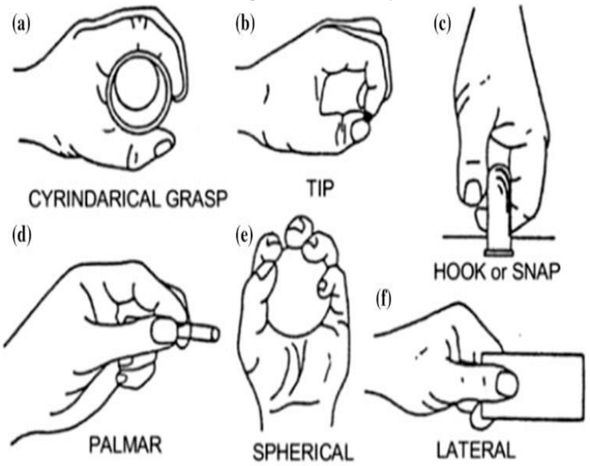

Fig.3. Representative Diagram of the Hand Movements

B. Feature Extraction and Selection

This paper extracts a set of 14 time domain features from original sEMG signal and MODWT subbands that were formed after preprocessing of sEMG signals. The purpose for using MODWT rather than EMD is that wavelet convolution is the best thing to find a good balance between time domain and frequency domain, i.e. we assume a better classification of sEMG signal assuming a time domain changes in power spectrum density of the signal [15]. Wavelet transforms have a continuous number of base components, now they are more suitable for decomposition. Element selection is an important and essential step for the myoelectric control design. The features should be able to show the properties of the sEMG signals for the clamping movements. With more features, there are some redundant features. So reducing the features is necessary to reduce redundant features. In this paper, the main components analysis (PCA) is used to reduce the characteristics [16].

C. Time Domain Features

A good classification pattern contains the acquisition of signals, filtration, feature reduction and classification. sEMG signals available for filtering through a 20 to 500 Hz bandwidth filter. Later, the features are extracted from the sEMG using many extraction methods [17]. The following time domain features:

$$\textbf{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2} \quad (1)$$

$$\textbf{Mean} = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (2)$$

$$\textbf{Variance} = \frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2 \quad (3)$$

$$\textbf{Skewness} = \frac{E(x-\mu)^3}{\sigma^3} \quad (4)$$

$$\textbf{Kurtosis} = \frac{\sum_{i=1}^{N}(x_i-\bar{x})^4}{(\text{RMS value})^4} \quad (5)$$

$$\textbf{Crest factor} = \frac{\text{Peak magnitude}}{\text{RMS}} \quad (6)$$

$$\textbf{Impulse factor} = \frac{\max(x)_{\text{absolute}}}{\text{mean}(x)_{\text{absolute}}} \quad (7)$$

$$\textbf{Shape factor} = \frac{\text{RMS}}{\text{mean}(x)_{\text{absolute}}} \quad (8)$$

$$\textbf{Waveform Length} = \sum_{n=1}^{N-1}(x_{n+1}-x_n) \quad (9)$$

If σ is the standard deviation of x, μ is the average of x. Therefore, a total of 9 characters were extracted from level 5 decomposed sEMG signal using MODWT and used to do training and testing of classifiers to be described in the next section.

III. WAVELET TRANSFORMATION

The wavelet transformation has been studied extensively in recent years as a promising tool for signal processing and noise elimination.

A. Maximal Overlap Discrete Wavelet Transform (MODWT)

As giving in [18], MODWT is a modified version of (DWT) in which the sub-sampling process of a resultant filter is absent. Consequently, the orthogonality property of the coefficient sets is gone, but the sum of gained components rebuilds the novel signal. MODWT is an invariable change and does not produce phase changes within detailed and approximate components. The MODWT module is invariably changing and does not produce phase changes within detailed and approximate components. In addition, the MODWT variance estimator is favored, since it has proven to be asymptotically more efficient than an estimator based mainly on DWT. Therefore, in this document, MODWT was observed with the wavelet function Daubechies8 (db8) for the signal sEMG.

IV. CLASSIFICATION PROCESS

In this paper, classification is made using WKNN. Classification of decomposed sEMG signal using MODWT for level 5, obtained from human muscles. The features are extracted and given to the WKNN to find the accuracy of the classification [17] [19]. In this, first intension was to verify the presence of functions of MODWT can r the increases performance of classifiers.

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However, using the best classifier, try to find the greatest algorithm for the planned work.

A. K-Nearest Neighbor (K-NN)

The K nearest neighbor (K-NN) is broadly classified due to the ease and simplicity of implementation. It is a nonparametric way of regression and classification. K-NN is also known as a lazy learning method, which does not require offline training. The extracted characteristics are used to classify the different conditions of the bearings using the nearest weighted K neighbor classifier (WKNN) [20].

B. WKNN

One of the most effective statistical classifiers studied in a wide range of model recognition is K-NN. This classifier has traditionally been used as the baseline classifier in several problem areas. K-NN classifiers have advantages such as the robustness of noisy workout data, the training phase, and easy learning of complex models. However, KNN also has disadvantages, such as the need to determine the K value and also the distance measure of the type to be used. If the dimensionality of data is greater than that of problems such as low computing efficiency, data gaps, false intuition and the need for a large number of data storage requirements [20]. The K- nearest neighbor classifier is a nonparametric classifier that is commonly used to classify a new unknown vector in which the calculation is done online. For an unknown vector, K-NN classifies the distances between the new vector and the training data set using one of the metric

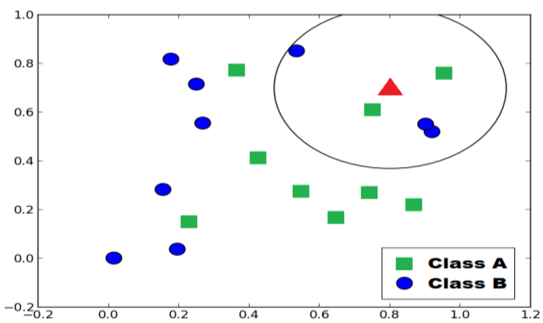

Fig.4. Classification Of New Data Point Using K Nearest Neighbour

distances, such as the Euclidean distance, to identify the nearest neighbor and to calculate the exit class. Assign a new vector to a class between one of the oldest classes k, where k is an integer value that represents the number of nearby points considered. Fig.4 explains the KNN Branch Methodology, a test point (like a triangle) surrounded by a number of vector training points (like squares and circles) representing two different classes. For point K = 1, the test point belongs to "class A" due to the minimum distance and if K = 5, the test point belongs to "class B" which is the majority class in the 5 closest points. To measure the distance between two points in the characteristic space, different distances were reported, such as distance Minkowsky, Correlation, Manhattan, Chi-square and Euclid, where the function of Euclidean distance is the most extensive used in the literature. To calculate the distance between points A and B in the characteristic space, the different types of values used are:

$$Eulicidean\,(A,B) = \sqrt{\frac{\sum_{i=1}^{m}(x_i - y_i)^2}{m}} \tag{15}$$

$$Minkowsky\,(A,B) = (\sum_{i=1}^{m}|x_i - y_i|^r)^{1/r} \tag{16}$$

$$Correlation\,(A,B) = \frac{\sum_{i=1}^{m}(x_i - \mu_i)(y_i - \mu_i)}{\sqrt{\sum_{i=1}^{m}(x_i - \mu_i)^2 \sum_{i=1}^{m}(y_i - \mu_i)^2}} \tag{17}$$

$$Mahalannobis(A,B) = \sqrt{(x-y)^T S^{-1}(x-y)} \tag{18}$$

$$Hamming\,(A,B) = \sum_{i=1}^{m}|x_i - y_i| \tag{19}$$

Where points A and B are represented by the feature vectors A $= (x_1, x_2, x_3, \dots \dots \dots x_m)$, B $= (y_1, y_2, y_3, \dots \dots \dots y_m)$, m represents the dimensionality of the characteristic space and S is the matrix of covariance. WKNN is an improved version of the conventional K-NN technique (where all features have the same weight) [20] [21]. In WKNN, the characteristics in the characteristic space are weights assigned according to their position. Remote weights are assigned to neighbors using the "square inversion".

V. EXPERIMENTAL WORK

An experimental setup was specially designed for acquiring sEMG signal from the human muscles using surface electrodes (Ag/AgCl) for the pattern recognitions of hand grasping movements. As shown in fig.5. The complete experimental setup.

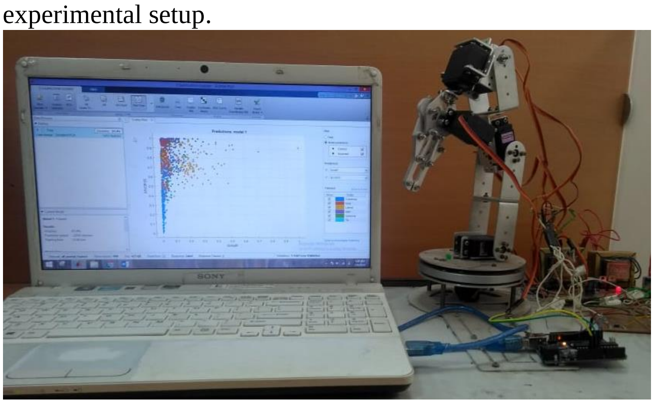

Fig.5. Experimental Setup

In this experiment, check the accuracy individual feature with or without PCA levels using MODWT with the help of classifier learner app given in MATLAB software to choose best one.

VI. RESULT AND DISCUSSION

The results of the classification were obtained by selecting the 25% retraction validation from the training data using a different number of characteristics. In the holdout method, two sets of data are randomly assigned, commonly called the training data set and test data set. The test data set size is generally 25% of the total data, which is used to test the trained model. The reduction in the characteristics of the extracted characteristics was implemented using the main component analysis technique (PCA) and its effect on classification accuracy was observed.

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It convert a number of variables that can be correlated with a set of uncorrelated variables called principal components. The new set of variables is linearly uncorrelated and usually has a smaller number that is used to reveal powerful patterns in data. The following sections describe the results for different cases:

A. Classification Results Obtained Without PCA

The extracted characteristics were tested for their ability to distinguish different hand movements using an individual precision of a piece with a weighted KNN pattern. The Euclidean distance metric was used to calculate the result of the model with the K value set at 10. Fig. 5 presents the specifications obtained for different features.

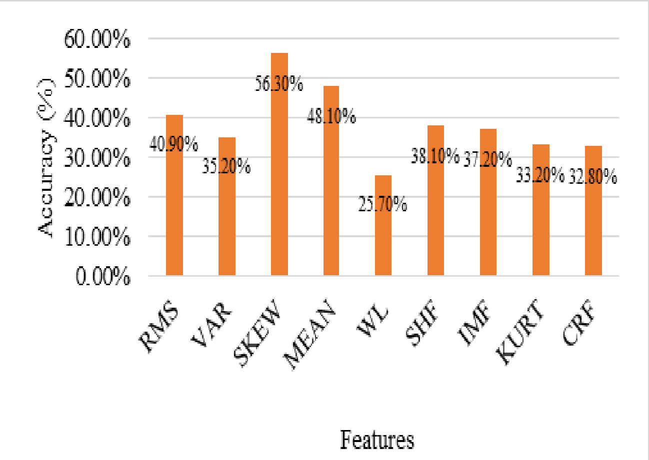

Fig. 5. Individual accuracies obtained for different feature using weighted 10- NN.

A combination of the best features of the class has been tried to maximize the classification rate. It is observed that the best precision is obtained when all the characteristics are combined together. Table 1 shows the results of the various combinations of characteristics for the model. Achievements for combining different characteristics.

Table 1 Output accuracies obtained for different combination of features.

Features	Accuracy (%)
SKEW, MEAN	43.6
SKEW, RMS	46.3
SKEW,SHF	41.9
SKEW,IMF,VAR	49.4
SKEW,VAR,KURT,CRF	57.0
SKEW,MEAN,RMS,SHF,IMF,VAR,KURT,CRF,WL	61.7

B. Classification Results Obtained using PCA

To further improve the results and reduce the size of the data set, the reduction of the PCA-based features has been applied to the characteristics of MODWT 5 to generate new main components. Figure 6 shows the explicit percentage change for each component.

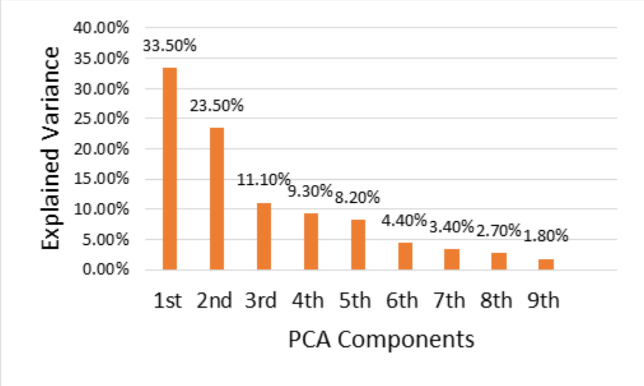

Fig. 6. Explained variance for PCA components

A different number of PCA components was used to find out the accuracies using WKNN (for K = 10), with distance weight to the inverse square and Euclidean distance metric. Figure 7 shows the corresponding results obtained:

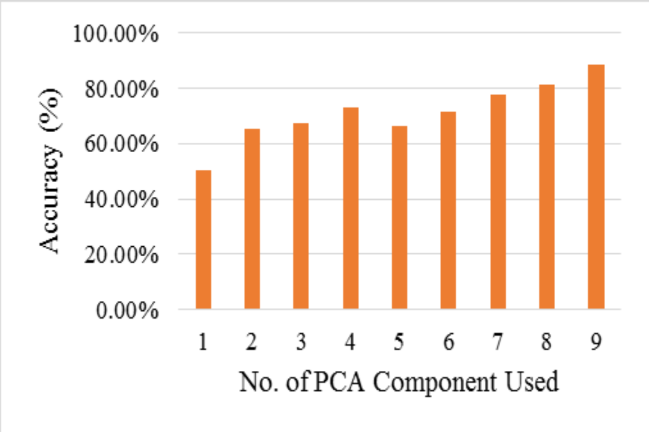

Fig. 7. Percentage accuracy obtained with different number of PCA components

VII. CONCLUSION

In this paper, a WKNN based sEMG signal based pattern recognition of grasping movement using MODWT and weighted kNN is proposed. The sEMG data is collected form the human subjects for classification purposes. The effectiveness of proposed method was tested using distance function such as Euclidean with k=10. After calculating the individual feature accuracy, Skewness time domain feature gives the highest accuracy in without PCA case. Same as in with PCA case is use to improve the classification accuracy. MODWT is used to decompose and denoise the sEMG data in the form of high and low pass filter, i.e. wavelet and scaling coefficient. The results obtained suggest the effectiveness of the proposed model recognition model. To further improve the accuracy of the classification, the results of several WKNN classifiers can be combined with different values of the nearest neighbor parameter. Classification can also be improved by merging classifiers using other types of classifiers, such as Support Vector (SVM), Decision Trees, and Artificial Neural Networks (ANN), etc.

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