

## Performance evaluation of different K-NN algorithms for sEMG signal classification

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### Abstract

*The myoelectric signal is very popular in robotic rehabilitation due to its high success rate and robustness for controlling the robotic device. For controlling any biomedical signal inspired external robotic devices, classification accuracy plays a pivotal role. This paper presents the classification of elbow and four fingers movement by using K-Nearest Neighbors (K-NN) algorithms with Discrete Wavelet Transform (DWT) and Principle Component Analysis (PCA). In conjunction to this, DWT is utilised for feature extraction and denoising purpose whereas PCA is used for reducing the size of data before the classification. In DWT, Daubechies 4 ( $db_4$ ) wavelet filter is employed and forth level approximation coefficient of reconstructed signal ( $a_4$ ) is used for time scale feature extraction. The result shows that Fine K-NN has 95.67% accuracy which is best among the other K-NN algorithms with selected frequency domain, time domain, and time-frequency domain (time scale) features.*

*Keywords- sEMG signal, Discrete Wavelet Transform, K-NN algorithms, Principle Component Analysis, elbow movement.*

### 1. Introduction

Electromyography (EMG) signals are the most popular biomedical signal used in the various fields like robotic, engineering and medical education. EMG signals are produced due to the neuromuscular activities (contraction and flexion) performed by the human [1]. Neuromuscular activities cause some ionic current flow in muscles thereby generating the potential between muscles. This potential can be measured by putting surface electrode on specific acupressure point with the help of bio-potential acquisition device [2, 3]. Depending upon the type of acquisition electrode, EMG signals are categorized into two types: intramuscular EMG and surface EMG (sEMG) signals. Intramuscular EMG signals acquisition method required to place electrode directly into the muscle [4]. It is also called an invasive method of EMG acquisition whereas the sEMG signals are acquired with electrodes putting on the muscle skin, not inside the muscle, also called non-invasive method [5]. Surface electrodes can be active or passive. The sEMG signal acquired with Active electrode has more immune to noise due to pre-amplification circuitry available inside the electrode but passive electrode does not has any such option thereby a great chance of noise influence [6, 7]. EMG signal can be easily contaminated by electrocardiogram (ECG) or another muscle signal which make identification of intentional movement difficult [8]. Therefore, denoising of such a signal has become essential to achieve the desired objective of controlling the robotic device [9, 10]. After the EMG signal acquisition, generally the pre-processing are carried out and the signal is available for further action depending upon the application [11].

EMG signal contains the hidden information related to the movement which can be utilized for controlling the assistive device like an exoskeleton, wheelchairs, orthotic devices, and prosthetic devices etc. This hidden information can be estimated with the help of features of EMG signal [12]. Features of the signal play a big role for identification of movement performed by the subject while acquiring the signals. The feature of EMG signal can be classified into three types: Time Domain (TD), Frequency Domain (FD), and Time-Frequency Domain (TFD) or time-scale domain [13]. TD and FD features can be calculated by simple mathematical operation whereas TFD features can be obtained by using wavelet transform (WT) [14, 15]. TD features are the simplest feature and widely utilized due to their computational simplicity such as mean waveform length (WL), absolute value (MAV), root mean square (RMS), autoregressive coefficients (ARC), and zero crossing rate (ZC) etc [16]. Power spectral density (PSD) is used for calculating the FD features but they are not effective in class separability. EMG signal is considered as a transient signal which can't be completely characterized by TD or FD feature alone. After feature extraction of EMG signal classification process is performed [17].

Wavelet packet transform (WPT), WT, short-time Fourier transform (STFT), and Empirical Mode Decomposition (EMD) method are time–frequency analysis methods which are more suitable for providing both FD and TD information of EMG signal. Due to fixed window length technique, STFT is not able to increase both frequency as well as time resolution simultaneously whereas time problem can be easily solved with the help of WT [18, 19]. WT can be classified as Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). This paper proposes to use DWT method for extracting wavelet coefficient in the form of TFD features [20]. TD, FD, and TFD features are combined to frame the feature vector for the classifier [21]. So, as to diminish the computational weight for improving the system performance, the dimension of feature vector must not be gigantic. In this context, some feature reduction technique may be applied to get a better result. Simultaneously, PCA approach as an acclaimed strategy is utilised for feature reduction [22].

For real-time EMG pattern recognition by using WPT, SVM classifier was used and the node energy of WPT coefficient for controlling multifunction myoelectric hands [23]. Artificial neural networks (ANN) classifier was used for the classification of EMG signal recorded during (i) an isotonic and anisometric contractions and (ii) isometric and isotonic with waveform length (WL), root mean square (RMS) and integrated EMG (IEMG) features [24]. A novel method based on One-Dimensional WPT and cubic SVM classification was suggested for elbow movement classification with 94.7% accuracy [10]. Transcranial direct current stimulation (tDCS) based EMG signal classification has also been done for amputees person. EMG signals were procured from influenced and flawless sides for wrist and hand motions with linear discriminant analysis (LDA) classifiers [25]. EMG signals acquired from transradial amputee and unblemished limbed have been analyzed with sequential forward selection (SFS) algorithm and different types of PCA [26].

This study explores a comparative investigation of various K-Nearest Neighbor (KNN) classification methods with DWT de-noising as well as wavelet-based coefficient extraction and PCA for dimensional reduction. Moreover, distinct execution parameters are utilised for evaluating the robustness of both classifiers. This paper is isolated into four sections: the first is the presentation of EMG signal with few classification strategies, the subsequent section portrays the material and methodology part which also describes the utilised feature extraction and classification

approach, the third section talks about the experimental results and the fourth section describes the conclusion of work.

**2. Materials and methods**

**2.1. Data acquisition and pre-processing**

15 healthy volunteers participated in the EMG data acquisition with the help of myotace400 device in Biomedical Laboratory of National Institute of Technical Teachers Training & Research, Chandigarh. Training and instructions were provided to all volunteers before data recording in front of the research team. EMG signals were acquired by using passive electrodes placed properly on specified acupressure points [27]. The volunteers performed four fingers movement and elbow movement. Each subject performed five trials of each motion with 8 times. For maintaining the isolation from the noise a band pass filter of 20 to 500 Hz transmission capacity was used [28]. The signal pre-processing circuitry had CMRR greater than 100, amplifier gain 500, input impedance more than 100M ohm and baseline noise level less than 1µV. Fig.1 show the systematic operation used for the sEMG signal classification.

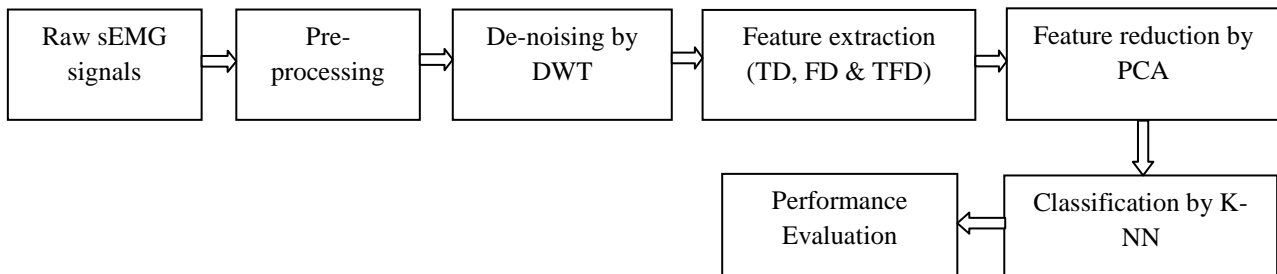


Fig.1. Block diagram of classification model using K-NN

**2.2 Feature Extraction**

After pre-processing step, sEMG signals features were extracted to make feature vector for classification purpose. TD, FD and TFD feature extracted were WL, RMS, standard deviation (STD), variance (VAR), kurtosis (KUT), fourth and sixth order ARC, slope sign change (SSC), median frequency (MDF), mean frequency (MNF) and wavelet based coefficient [29, 30]. Mathematical equations given in Table 1 were used for feature calculations. Fig. 2 shows the sEMG acquisition device with passive electrodes placed on the subject arm.



Fig. 2. Complete EMG signals acquisition setup with myotace 400 device

**2.3 Feature Selection and Feature Reduction**

Feature selection acts as a significant role for accomplishing the better classification accuracy and system performance. Features were selected based on the different literature available for EMG signal classification [16, 31]. After the features selection, feature vector was formed for the classifier. PCA was applied for dimensional reduction for fast computation of classification system. It converted a high dimensional data to low dimensional data thereby reducing both time and space complexity [32, 33]. In PCA, first of all, mean and covariance matrix were computed and then corresponding eigenvalue and eigenvectors were calculated. The most significant eigenvectors were chosen and transposed matrix of eigenvectors was multiplied with mean adjusted data.

**2.4 Discrete Wavelet Transform**

The wavelet transform is an incredible tool for de-noising and multi-resolution examination of EMG signals. It tends to be characterized into continuous (CWT) and discrete (DWT). The selection of DWT was done on the basis of its concentration on real-time applications. A bank of high pass and low pass filter was employed in DWT for generating detailed ( $cD_k$ ) and approximation ( $cA_k$ ) coefficient subset where  $k$  depends on the level of decomposition of sEMG signals. For multi-resolution analysis, the sEMG signals were passed repeatedly through these filter bank until the desired final level was achieved. Fourth level decomposition was performed by DWT to obtain a set of approximation and details coefficient ( $cA_4, cD_4, cD_3, cD_2, D_1$ ) and further sEMG signals were reconstructed by performing inverse DWT operation [34]. In this way, reconstructed coefficient ( $D_1-D_n, A_n$ ) were obtained but for calculating the TFD feature of sEMG signals only fourth level reconstructed coefficient were selected. Daubechies (db) 4 wavelet filter was considered for calculating wavelet features given by the following Formulas [35].

(1) Mean of coefficients

$$\text{Mean} = \frac{\sum_{i=1}^n c_i}{n} \tag{1}$$

(2) Standard deviation of the coefficients

$$\text{Standard deviation} = \sqrt{\frac{\sum_{i=1}^n (c_i - \mu)^2}{n}} \tag{2}$$

(3) RMS of coefficients

$$\text{RMS} = \sqrt{\frac{1}{M} \sum_{m=1}^M c_m^2} \tag{3}$$

(4) Variance of coefficients

$$\text{VAR} = \frac{1}{N-1} \sum_{n=1}^N c_n^2 \tag{4}$$

In this way, total 14 features (TD, FD & TFD) were calculated in this study for providing input to the classifier. Fig.3. Show the de-noise signal and approximation coefficient obtained by DWT using db<sub>4</sub> wavelet filter.

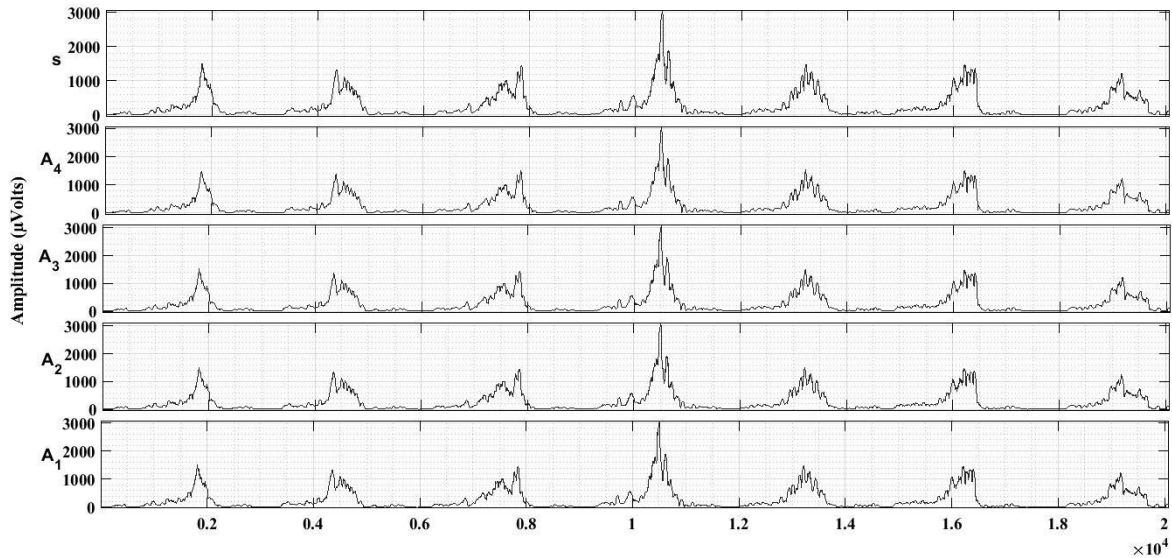


Fig. 3. De-noise signal (S) and fourth level approximation coefficients

Table1. Mathematical Equations

Feature extraction	Definition
WL	$WL = \sum_{i=1}^{M-1}  c_{i-1} - c $
RMS	$RMS = \sqrt{\frac{1}{M} \sum_{i=1}^M c_i^2}$
STD	$STD = \sqrt{\frac{1}{N} \sum_{i=1}^N (c_i - \mu)^2}$
KUT	$KUT = \sum_{i=1}^N \frac{(c_i - \bar{c})^4 / N}{STD}$
VAR	$VAR = \frac{1}{N-1} \sum_{i=1}^N c_i^2$
ARC	$ARC_i = -\sum_{i=1}^p a_i c_{i-1} + w_n$
MNF	$MNF = \frac{\sum_{j=1}^M f_j P_j}{\sum_{j=1}^M P_j}$
MDF	$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^M P_j = \frac{1}{2} \sum_{j=1}^M P_j$
SSC	$SSC = \sum_{i=2}^{N-1} [f[(c_i - c_{i-1}) * (c_i - c_{i+1})]]$ $f(x) = \begin{cases} 1 & \text{if } c \geq t \square res \square old \\ 0 & \text{ot} \square erwise \end{cases}$

where  $f_j$  and  $P_j$  is the power spectrum frequency when frequency is bin  $j$  and  $c_i$  is 4<sup>th</sup> level wavelet coefficient obtained by db<sub>4</sub> mother wavelet. Table 1 shows the various TFD feature obtained the present work from the wavelet coefficient.

**2.5 K-Nearest Neighbour classifier**

K-NN is a nonparametric supervised classification method which is based on the intuitive concept that same class data points should exist adjoining to each other in the feature space. If  $\{(x_1, y_1), (x_2, y_2) \dots (x_n, y_n)\}$  are the desired class for  $n$  point training dataset where  $x_i$ , and  $y_i$  represent feature vector and corresponding target class. For determining the class for new data point  $x$ , K-NN used the following relation [39]:

$$1\text{-NN}(x) = y_p, \tag{5}$$

where,  $p = \arg \min_i |x - x_i|^2$ .

A class can be determined by a majority voting of its neighbours. K-NN uses various distance function such as mahalanobis, Euclidean, cosine, chebychew, jaccard, hamming or spearman distance. In this study, we have utilised Fine K-NN, Medium K-NN, Coarse K-NN, Cosine K-NN, Cubic K-NN and Weighted K-NN. Table 2 shows the number of neighbors, distance metric, and corresponding distance weight.

Table 2. Details of different K-NN methods

<b>Classifier name</b>	<b>No. of neighbours</b>	<b>Distance metric</b>	<b>Distance weight</b>
Fine K-NN	1	Euclidean	Equal
Medium K-NN	10	Euclidean	Equal
Coarse K-NN	100	Euclidean	Equal
Cosine K-NN	100	Cosine	Equal
Cubic K-NN	10	Minkowski	Equal
Weighted K-NN	10	Euclidean	Squared inverse

**3. Results and Discussion**

This particular section talks about the execution of different classification method and consequences of various K-NN algorithm utilized for elbow and four fingers movement identification by utilizing PCA and DWT approaches. De-noising and decomposition of sEMG signal were furnished by utilizing Daubechies 4 wavelet approach with four scale level decomposition. DWT based lingered features were consolidated to shape feature vector with TD and FD features. Classification accuracy and area under the curve (AUC) were utilised in benchmarking parametric evaluation of classification strategies however there are numerous

different parameters like sensitivity and specificity that can likewise characterize the exactness of different conditions. Fine K-NN demonstrated the best classification accuracy that’s why fine K-NN confusion matrix was indicated uniquely rather than all disarray frameworks. Following equation was utilized for correlating the performance of classifier:

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Population} \times 100 \tag{6}$$

Table 3. Performance comparison of K-NN

<b>Classifier Name</b>	<b>Accuracy (%)</b>	<b>AUC (%)</b>
Fine K-NN	95.67	99
Medium K-NN	93.1	98
Coarse K-NN	88.6	95
Cosine K-NN	93.7	98
Cubic K-NN	92.6	98
Weighted K-NN	94.0	98

Experimental work was performed by MATLAB<sup>®</sup> software with the help of Myotace 400 device and passive electrodes. Table 3 showed the comparative analysis of accuracy and AUC value. It is clear from the result that Fine K-NN is best among the other classifiers. The Fine K-NN achieved the 95.67% accuracy whereas AUC was 98%. The classifier performance was also shown graphically in Fig. 4. Table 4 indicated the confusion matrix of Fine K-NN classifier utilised with the end goal of accuracy parameter computation. Receiver operating characteristic (ROC) curve is another way to express classifier performance. Fig. 5 showed the ROC curve and corresponding AUC value obtained by Fine K-NN method.

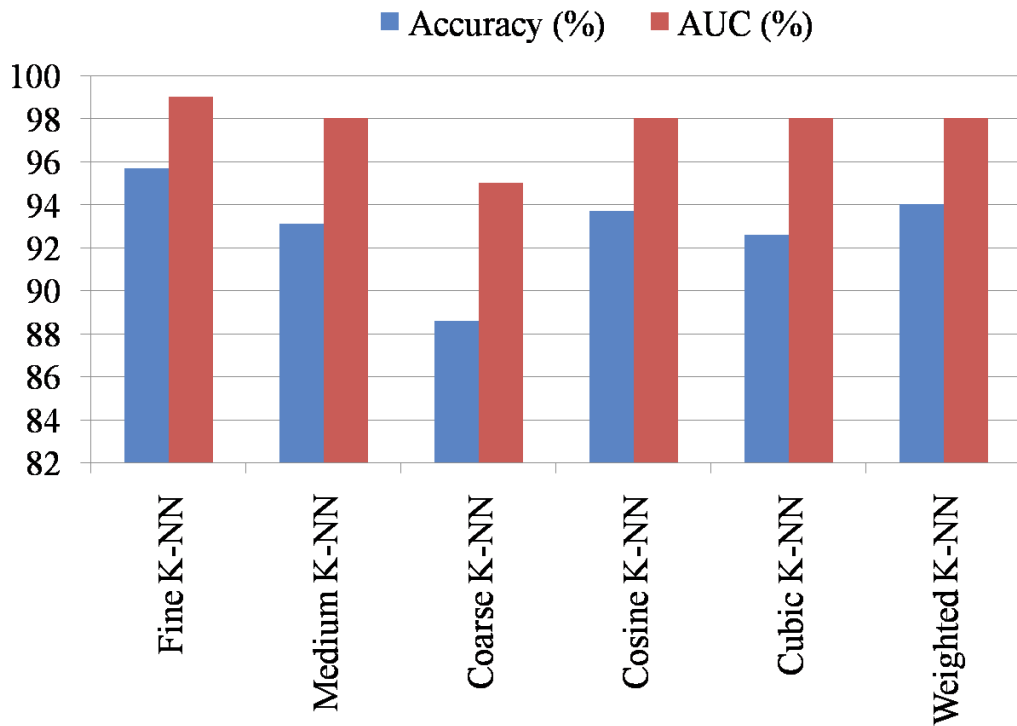


Fig. 4. Graphical representation of Accuracy and AUC

Table 4. Confusion Matrix of Fine K-NN method

96%	1%	2%	1%	0%	0%
1%	95%	3%	1%	0%	0%
0%	2%	93%	1%	1%	0%
0%	0%	0%	96%	2%	2%
1%	1%	0%	0%	97%	1%
2%	1%	0%	0%	0%	97%

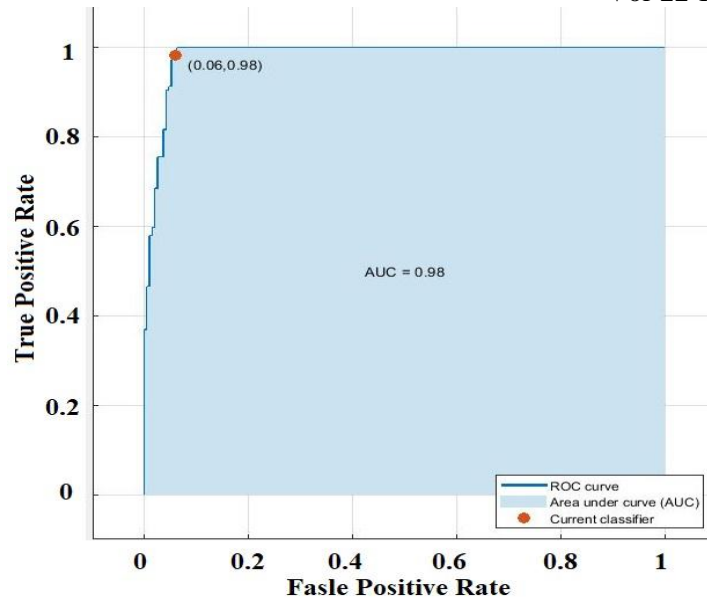


Fig. 5. ROC curve of Fine K-NN

**4. Conclusion**

This investigation proposes the TD, FD and TFD features extraction, de-noising by DWT technique and classification by utilizing distinctive K-NN approaches. The examination compares various K-NN techniques, for example, Weighted K-NN, Cubic K-NN, Cosine K-NN, Coarse K-NN, Medium K-NN and Fine K-NN. However, the exhibition of Fine K-NN was seen as best among them. Daubechies 4 wavelet filter was utilized for de-noising and time scale feature extraction, while PCA was used for dimension reduction. The sEMG signals were procured from 15 healthy subjects to classify the four fingers and elbow movement. The offline classification result showed that feature combination used in this study with PCA and DWT de-noising yielded good accuracy with Fine K-NN method. The outcome obtained in this work can be considered for controlling the fist and elbow movement in real time applications also. This methodology can be utilized for remote control of mechanical gadgets and automaton helicopters if the idea of the networked control system is joined with it. In near future, one could deploy empirical mode decomposition (EMD) and DWT techniques in conjunction to other for enhanced feature extraction alongside some differencing technique to make sEMG signal stationary with the goal that system execution can be improved.

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