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Research Article

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Features Selection for the EMG Classification for the Upper Limbs Prosthesis

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Abstract Electromyography (EMG) signals are important in the fields of engineering medicine and compensatory. The study of EMG is widely utilized in many areas like rehab, machine handling and more. EMG is a complex and non-stationary signal, therefore, hard to study. Nevertheless, it provides compensatory parties with high efficiency and helping humaneness in so several fields. Detection, processing and classification analysis in (EMG) so important. It allows a more standardized and precise valuation of the neurophysiological, habitational and assistive technological findings. In this paper: we will study a set of values for the demand of utilized wavelet transform for smoothing and extraction of features, to choose the better types of classifications to employ with the EMG signal. The objective of this study is to give us the better accuracy to control amputations and to preserve the best life. In this work will be considered the following types of classifications Support Vector Machines (SVM), K-nearest neighbor (K-NN) and Ensemble Classifiers.

Keywords EMG signal, SVM (Support Vector Machines), K-NN (K-nearest neighbor), DWT (Discrete wavelet transform)

1. Introduction

In recent years, the increase in the number of handicapped person as a result of traffic accidents, diseases, workshop and Most of them lose parts of their limb. So, to amelioration the life quality, several amputees tend to utilize external power for running artificial prosthesis or orthotic arms rather than cosmetic hands [1]. However, the major problem in facing researchers is how the amputees can control the artificial limb more simply, directly and intuitively, in another meaning, a normal sense of control is possible to be similar to that of the original life. So, electromyography (EMG) is that the electrical appearance inside the contracting muscles [2]. It is the easiest and direct approach to represent the contracting information of a muscle. Several attempts to utilize the EMGs signal as the instruction to the controller the prosthesis. By utilizing EMGs signals, it is necessary to distinguish various limbs and hand locomotion in the patterns of EMGs signals that are on record at the stump [3]. EMG was determined in the surface of the skin at the time of muscle contraction. The efficiency of the muscle can be measured noninvasively through the EMGs Therefore; it is beneficial in the areas both of engineering and medical.

Several active potentials from the motor units are superimposed on EMG thus, plural motions will be discriminated from little EMGs channels via variation of their waveforms. The differences are due to the number of muscle fibers made up of a single motor unit, the thickness of the skin and another muscle, and also the distance in the muscles implicated in the get about to the position of measurement. Wherein, this coefficient is not equal with various people, given the different individuals. Specifically, human’s motor skill differs in every individual. So, it's difficult for the technique excluding the individual difference from consideration to discriminate several motions in EMG [4]. EMG signal is a response of a neuromuscular system for an electrical stimulus produced either via brain or through the spinal cord. In this article interest the subject of onset detection within the context of a muscle activity. Evaluation relies on an EMG signal, it clear that at a muscle activity. Empty samples were cut off the dataset. The proposed estimation technique relied on EMG signal analysis and survey of modern solutions. So as to collate them with existing solutions simple comparison has been conducted EMG signal is burdened with comparatively big noise. As well as characterized via several single, almost randomly appearing amplitude picks [2]. Voltage rating and variance are various for among parts of muscles. Each the upon complicates the task of onset detection.

2. Backgrounds

A. EMG Signal

Muscle relaxation in natural conditions neutral electrically [5]. EMG is an electrical signal produced via human muscles during activity. Overvoltage ranges for these electrical units in 30 mv to 60 mV [6]. It will be measured via the electrical layout include electrodes accountable for the signal processing unit and measurement. The second is accountable for extracting, collecting and setting the EMG signal recorded from the output. Surface electromyography signals (EMGs) They are determined on the surface of the skin and are generated through the electrical efficacy of the muscle fibers during contraction, due to many movements compatible to a particular pattern of multiple activations of muscles, it can be utilized for multi-channel recordings EMGs, which are made utilized electrodes put on the muscles involved, to determine the movement [7]. This concept has been applied to the development of artificial limbs, where he fined control of the parties through classifying signals EMG. For this purpose, several pattern identify on schemes application, which composed of the extraction and classification coefficient. EMG surface signals are a summary of the action potential of the motor unit. The engine unit voltage capabilities that are collective and replicated are supported with a similar format over time. Thus, traditional representation techniques rely on self-modeling or temporal time features (decomposition in temporal sinus bases) may not be eligible for that type of signal. For this reason, it is suggested to employ the previous wavelets [8]. Where the fundamental functions to drop EMG signals to extract features and subsequent classification.

In this study, the DWT will be applied with the ideal utilization of the corresponding representation space via identifying the mother wavelet signal. The DWT signal is a set of fundamental functions that are measured and purified the first function versions. Mother wavelet detection the projection space, executable, can get it infinite distances of the DWT signal is a set of fundamental functions that are measured and purified the first function versions [9]. The mother wavelet determines the projection space, the capacitor, infinite distances of DWT can get with varying waves of the mother. The single element can be find employ a wave or standard (e.g. Daubechies (db)), or determined for ideal discrimination. Different waves of the mother are foreseeable to have the ability to distinguish among classes, suitable to detect wavelet-based signal detection.

The purpose of classification, the standard natural optimization error is estimated of the training group classification signals, effective way to explore a lot family of functions wavelets are wavelet coefficient to impose conditions on the measurement filter in a multi-resolution analysis (MRA) frame [10]. The optimization proposal rely on the signal at DWT to identify patterns by our group for simulation signals EMG, where the primary concentrate on the feature space while the method of a simple classification application (the nearest representative) was applied in a single channel and two-layer context. In this work, the propose a technique relies on improving the representation space in combination with a powerful classifier (SVM), in state of multi-channel signals, in the context of a multi-layered. Moreover, the technique will be applied to the pilot signals recorded during the four hand movements [11]. The main objectives are

(1) demonstrate that the representation of the signal wavelet is a suitable field to control myoelectric prostheses and

(2) that the choice of the mother wave affects the ability to distinguish in wavelet features properties and therefore need to be clarified on thus, the need for signal-based optimization

Methodology Four steps applied to the MATLAB program which is illustrated in Figure.

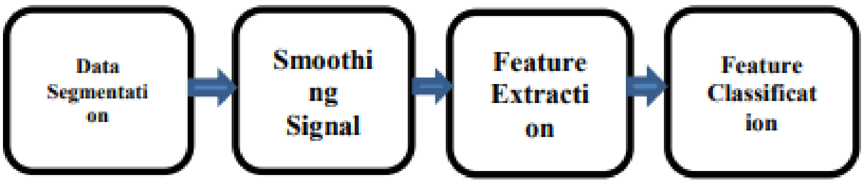


Figure 1: Sequence of processing

A. Data Segmentation

In the beginning, when we entered the whole signal as illustrated in Figure. 1, and applied in four stages, the accuracy ratio was 25%, so it was necessary to make a apportionment of the signal as illustrated at Figure. 2. and then the ratio of accuracy. It is also considered in the segmentation that contains every the detail of the movement and that the time is fixed for every of the movements combined until the signal processing is correct.

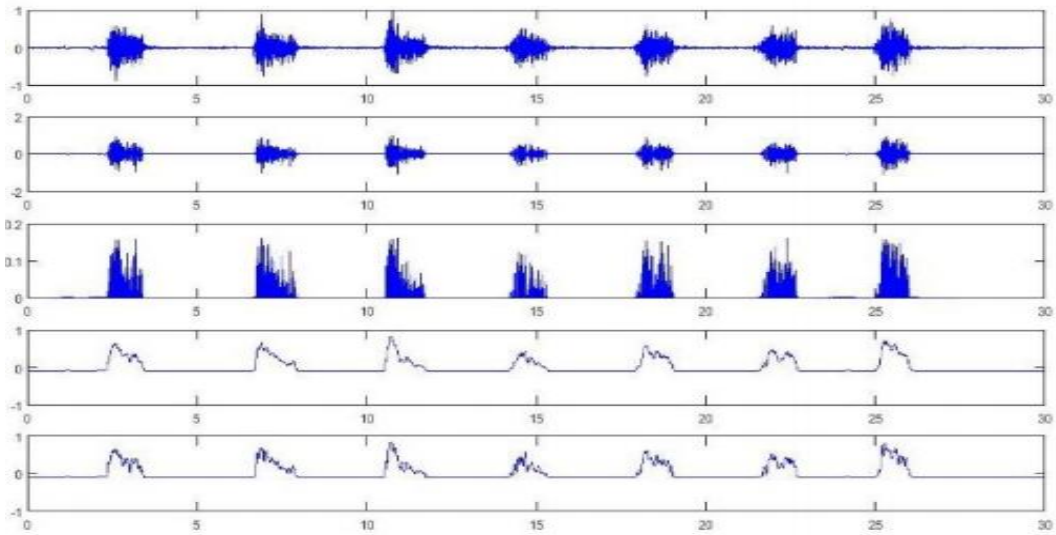


Figure 2.(a): The completed signal without segmentation

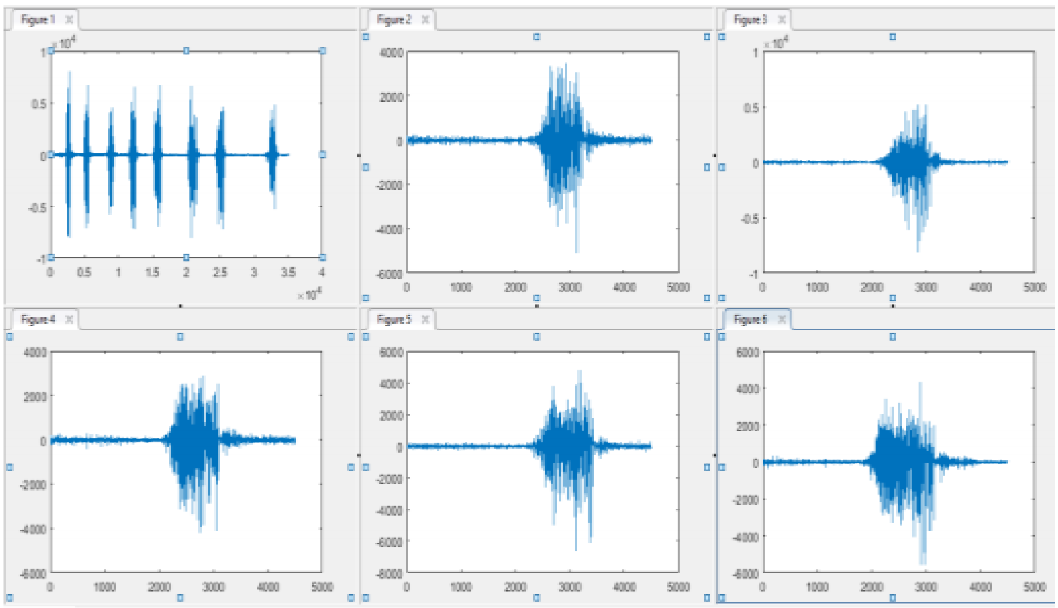


Figure 2.(b): Segmentation the signal with all the details of the movement

B. Smoothing Signal

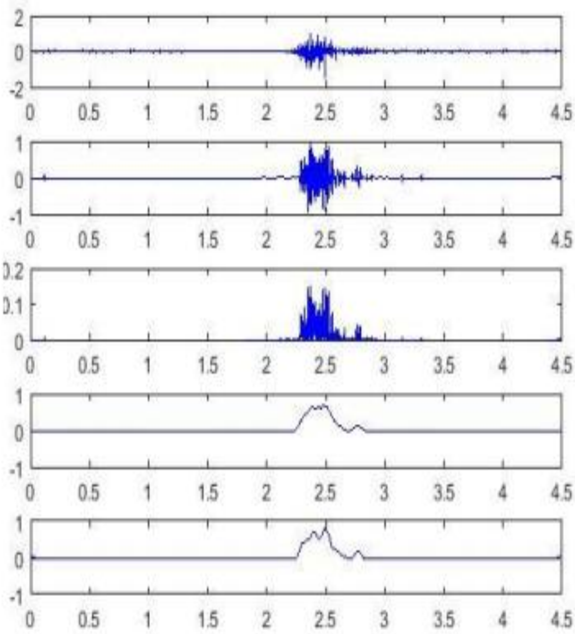
Smoothing may be utilized in two significant ways that can aid in data analysis via being capable to extract more information from the datum as long as the assumption of smoothing is credible and through being capable to extend analyses that are each flexible and robust. In this research, it utilized a signal filter utilized discrete wavelet Transform (DWT) as a candidate for the Filter of the signal and found rid of the high-frequency signal (noise). And that we control the threshold of value so that we draw the motion required in all its details and that help to increase accuracy. The following forms showed the shape of the smoothing done on the signal. In wavelet transform, the corresponding wavelets on the scale and time place y in the equation below, are given by:

$$\psi(a,b) = {}^{1}/_{\sqrt{|a|}}\,\psi\left(\frac{t-b}{a}\right) \qquad (1)$$

Where: (t) is the 'mother wavelet' which can be taken as a bandpass function. The factor $\sqrt{|a|}$ is utilized to preserve energy preservation, which is the same for every value of a and b. There are various ways of discretizing timescale coefficient (a, b), and both one produces a several type of wavelet transforms. Sequential high pass and low-pass filtering in the discretetime domain calculate the DWT. The general equation of DWT (Equation (4)), is given below:

$$X(t) = \sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty} d(k,l)2^{\frac{k}{2}}\psi\left(2^{-k}t-1\right) \qquad (2)$$

Where: k is related to an as: $a = k$; b is related to l as$b = 2kl$and (k, l), is a sampling of (a, b), at discrete points k and l. Most studies of EMGs analysis have concluded that the daubechies (db) wavelet family is the most suitable wavelet for EMGs signal analysis [11]. This study, the Daubechies orthogonal wavelets, Db1-Db10, which are commonly employed, were evaluated. It used the hand movements that we took from the Medical Engineering Laboratory in Cairo: Four hand movements that we took from the lab: 1) Open and close the hand 2) Thumb movement 3) Move four fingers 4) Move the wrist of the hand These movements are described in the following forms after the work of the smoothing utilizing daubechies wavelets db8. Figure. 3. (a,b,c,d) illustrates these movements:



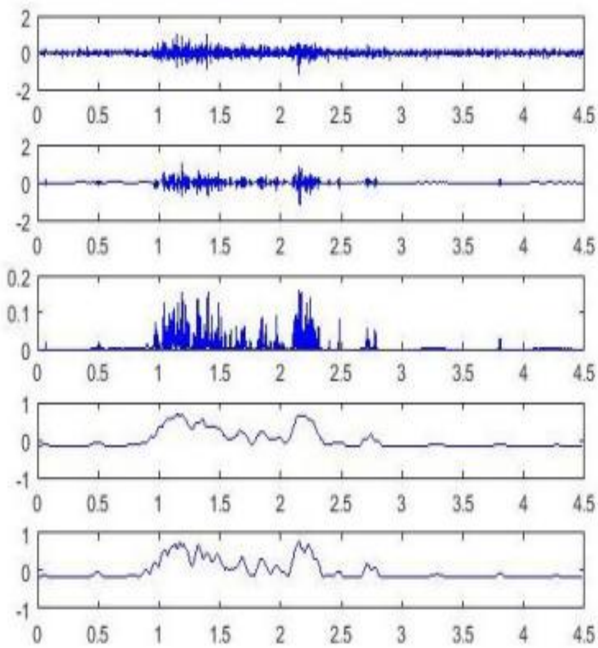


Figure 3.(a): Open and close the hand *Figure 3.(b): Thumb movements*

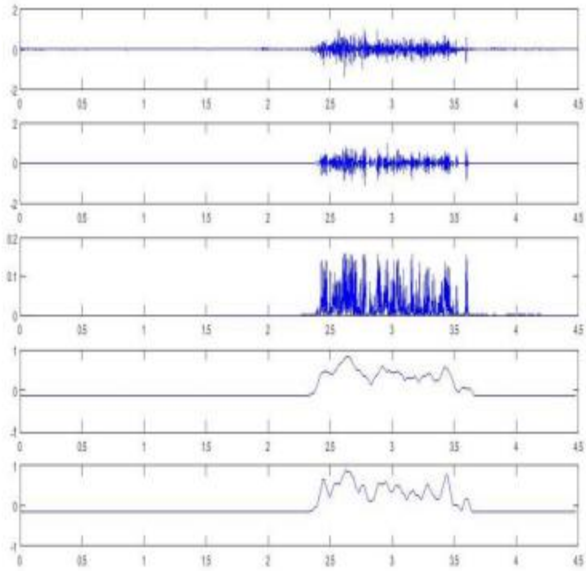


Figure 3.(c): Move four fingers

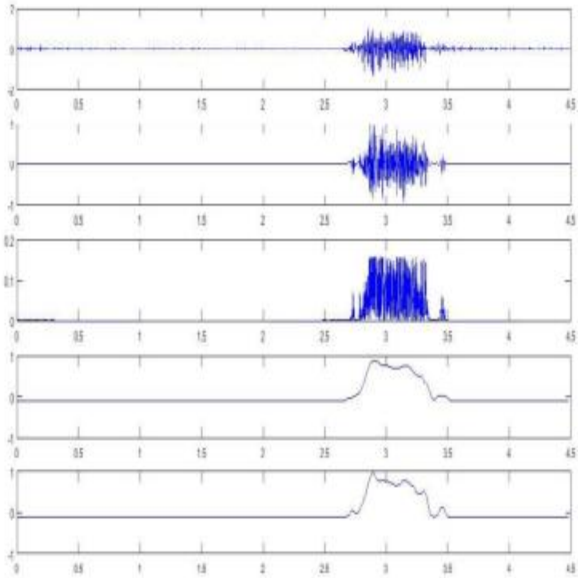


Figure 3.(d): Move the wrist of the hand

The previous forms illustrate the figure. 3.(a,b,c,d) signals illustrates a difference among each movement and the other according to the movement of muscle locomotion clearly illustrates that the movement of the thumb is the weakest among them, in addition to the signals contain many of the noise that covers the details of the signal until it was imported apply to smooth and reached the end form after the application of several things on the signal, namely: - Using wavelet transform Daebuchies (dB8) a filter and implemented on the signal (Average or mean value, stander deviation, and absolute value), and apply to smooth on the signal.

C. EMG Features

Because of the various noise and artifacts selected among the signals of EMGs, the require for information remainder a mixture of raw signals within the EMG. However, if the employ of these input signals as an input in the classification of SEMG, minimizes the efficiency of the classifier. To improve the evaluate performance of the classifier, the researchers utilized various types of the EMG features as an input to the classifier [12]. To improve ideal classification performance, the properties of the EMG feature space (eg, maximum degree separation, durability, and computational complexity) must be taken into account. There are three types of EMG features in different fields: time domain, frequency domain, and time domain frequency features. Advanced time domain features of EMGs. Absolute value (MAV), waveform lengths (WL), slope sign changes (SSC), mean absolute value slope, and zero crossings (ZC) were utilized to represent myoelectric patterns. D. Classification It has been an effective way to classify electromyography signal patterns (EMGs) and has been of interest to several researchers in modern times. There are various types of classifiers, which are effectively utilized for difference EMG applications, like K-NN, Ensemble Classifiers, Linear Discriminant Analysis (LDA) and SVM classifiers. The raw EMGs signal is represented as a feature vector in the feature extraction process, which is utilized as input to the classifier. Since raw EMG signals drawn directly into the classifier, they are not practical due to the randomness of the EMG signal [17]. The humans to perform their movements intended via the transfer of motor commands from the brain to the muscles. Note these commands are notification of the electromyogram (EMG) can be measured on the surface of the skins with noninvasive electrodes. The EMG signals contain information about how to perform movements, like that constrict the muscles and intensity. If we utilize this information, we can achieve the human and natural and intuitive interface to control the hand mechanism. Furthermore, through the application of this interface to prosthetic hands for the parties to a truncated, you can recover lost their works again. a) Support Vector Machines: Due to many advantages, SVM is one of the common ways of classification techniques in two categories It is known that SVM has good generalization properties and is known to be sensitive to immoderate training as well. furthermore, it is known to be resistant to the curse of dimensionality [13]. furthermore, SVM contains little hyper coefficient devices that require to be defined, like settlement C in SVM linear coefficient. • Classification with linear SVMs: it uses linear support vector machines to classify the vectors of the generated feature of the EMG data in chapters on which the crumbs are. SVMs have proven to be a remarkably strong rating method across a wide range of applications. The first, consider a classification constraint of two categories. Essentially, SVMs attempts to found the maximum "thickness" or margin that separates data points from two categories. b) K-nearest neighbor (K-NN): In pattern recognition, the nearest k-NN neighborhood technique is an unclassified method utilized for classification and regression. Receding. In each status, the entry composed of examples of the closest k-training in the feature space. The output relies on whether it is utilized as an NN class or regression. The K-NN technique, like other instance-based algorithms, is unusual from a classification perspective in the absence of a clear model training. One can weigh every neighbor through an inverse function behind him to the example of their classification [14]. The major advantages of the KNN are: 1) Implementation is very simple. 2) Strong with respect to the search area; for example, rows must not be linearly separable 3) An online workbook can be updated in verThe little cost as new cases are displayed with known categories. 4) Low parameters for synthesis: Metric and K surfaces. c) Ensemble Classifiers: Ensemble classification indicate to a collection of ways that learn a target function through training a number of individual learners and integrate their predictions [15]. Properties of Ensemble Classifiers: The diversity of Opinion – Multiple base classifiers must be available and able to of making classifications on a dataset. • Independence – all Base Classifier's decisions are not affected via any other fundamental Classifier. • Decentralization – fundamental Classifiers can be available to specialize on a certain subset of the dataset. • Aggregation – Some combining method exists for turning private judgments into a collective decision There are many coefficients that differentiate between the various ensembles ways [16].` Key factors are: 1) Inter-classifiers relationship - how it affects each classification on the other workbooks? Group can be divided into two main methods: serial and synchronous 2) Combining method - the technique of combining the working resulting from the induction technique the easy combination specify the output only from the output of individual inputs. 3) Diversity - generator in order to make an effective group, there must be some kind of diversity between classifiers. 4) Ensemble size - The number of classifiers in the ensemble. IV.

Implementation

Several types of validation have been applied to validate the following:

A. Cross-Validation:

Select a number of folds (or partitions) to divide the dataset via utilizing the slider control. This technique provides a good evaluation of the predictive accuracy of the final model trained with all data. It requires multiple periods but efficiently uses all data, so it is recommended for small sets of data.

B. Holdout Validation:

Select a percentage of the data to utilize as a test group via utilizing the scroll bar control. The application trains the model on the training group and evaluates the performance of the test group.

C. No Validation:

Do not protect against overfitting. The application utilizes both data for training and calculates the fault ratio on the same data.

3. Results and Discussion

Implemented the previous stages and those classifications on the reference taken from the laboratory College of the Medical Engineering University of Cairo and we have taken signals from the four movements referred to previously. Before we apply the above-mentioned classifications, it requires to know the order in daubechies wavelet, because it is utilized to smooth the signal and derive the advantages. Tested this on the classification of KNN, and we applied it to only two movements namely thumb movement and movement of open and close the hand, And we chose these two signals due to they differ in the form of the signal and it is natural that the accuracy is high. So we wanted to study the effect on them. It was observed in Figure 4 that the highest values in terms of accuracy were db8 and db10, the best values are db8 because it is easier and lower complex in execute. As a result, to apply all classifications to db8 in the smoothing and decoding of the signal to get the highest accuracy. Used the best types of classifications that gave us the best results in terms of accuracy, namely SVM and contains:- 1. Linear SVM 2. Quadratic SVM Used the best types in KNN and chose them:- 1. Fine KNN 2. Weighted KNN And also utilized the Eensemble type, which had high results in most status and chooses the following 1. Bagged trees 2. Subspace discriminant 3. Subspace KNN The following graphs illustrate the results us have obtained when detecting accuracy

$$\text{Accuracy} = \frac{\text{Number of correct classification}}{\text{Number of total classification}} * 100$$

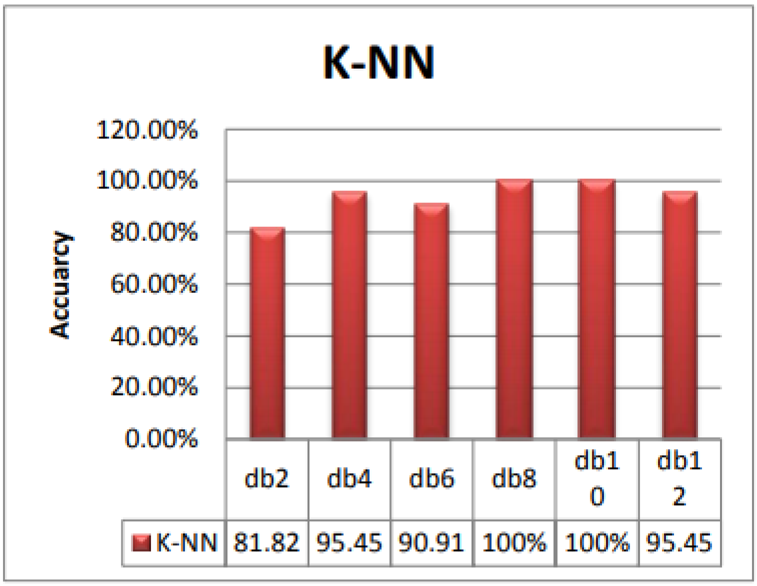


Figure 4: The accuracy of KNN

Table 1: Accuracy of the classifications

type of classification	cross 5fold	holdout 25%	NO
linear svm	80.90%	73.50%	89%
quadratic SVM	80.10%	96.30%	96.30%
fine Gaussian SVM	47.10%	50%	100%
fine KNN	77.20%	76.50%	100%
weighted KNN	47.10%	50%	100%
bagged trees	81.60%	79.40%	100%
subspace discriminant	83.10%	79.40%	88.20%
subspace KNN	69.10%	67.60%	100%

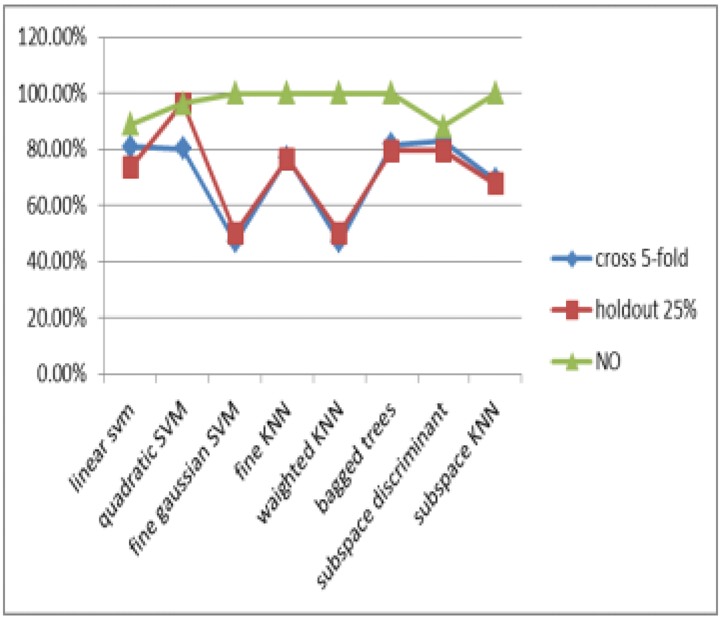


Figure 5: The accuracy of the classifications

Use the collected data to train the linear SVM classifier, and perform parameter selection by using across-session cross-validation error as the measure. Figure 3 illustrates the SVM classifier. From table (1) where he gave high results at Cross 5-fold where the division of the rudder is around 80.9% followed through quadratic SVM where he gave the value of is about 80.1%. But its best value was followed through the ensemble classifier, the subspace discriminant is around (83.1%) and the bagged trees is about (81.6%). Hence it is clear that the best among them was it subspace discriminant In the case of cross 5 fold in validation. As for the 25% Holdout in validation, the SVM was the best with 96.3% in the quadratic SVM type, and it was distinguished by the rest of the other types. For the application of NO Validation has given most of the classifications and gave the values of accuracy is 100%. These consequences are evident from the curve in Fig.5.

4. Conclusion

The segmentation of the signal is implemented so that splitting the signal will preserve all required information to control the limbs prostheses. The details of each movement are studied, segments, implementing the features extraction. The aim of this study is to obtain the highest accuracy of performance. This is done utilized wavelet even the smoothness of the signal and extraction of features to increase the accuracy and thus the increase of the efficiency in limbs prostheses. We utilized the (db8) signal smoothing because it gave them a better results and we also utilized it to extract the EMG signals for the upper compensatory sides In terms of classifications, the best values we got at cross 5-fold validation were 83.1% in type subspace discriminant. The better result in 25% holdout validation was in quadratic SVM 96.3%. It is clear to us that the best types used with the EMG signal in the classifications are SVM and ensemble classifier, which helps in compensatory limbs with the highest accuracy in performance.

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