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ORIGINAL RESEARCH

Surface EMG signal classification using TQWT, Bagging and Boosting for hand movement recognition

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Abstract

Hands play a significant role in grasping and manipulating different objects. The loss of even a single hand have impact on the human activity. In this regard, a prosthetic hand is an appealing solution for the subjects who lost their hands. The surface electromyogram (sEMG) plays a vital role in the design of prosthesis hands. The ensemble classifiers achieve better performance by using a weighted combination of several classifier models. Hence, in this paper, the feasibility of the Bagging and the Boosting ensemble classifiers is assessed for the basic hand movement recognition by using sEMG signals, which were recorded during the grasping movements with various objects for the six hand motions. So, the novelty of the current study is the development of an ensemble model for hand movement recognition based on the tunable Q-factor wavelet transform (TQWT). The proposed method consists of three steps. In the first step, MSPCA is used for denoising. In the second step, a novel feature extraction method, TQWT is used for feature extraction from the sEMG signals, then, statistical values of TQWT sub-bands are calculated. In the last step, the obtained feature set is used as input to an ensemble classifier for the identification of intended hand movements. Performances of the Bagging and the Boosting ensemble classifiers are compared in terms of different performance measures. Using TQWT extracted features along with the presented the Adaboost with SVM and the Multiboost with SVM classifier results in a classification accuracy up to 100%. Hence, the results have shown that the proposed framework has achieved overall better performance and it is a potential candidate for the prosthetic hands control.

Keywords Prosthetic hand control · Surface electromyography (sEMG) · Multi-scale principle component analysis (MSPCA) · Tunable Q wavelet transform (TQWT) · Ensemble classifiers · Bagging · Boosting

Abbreviations

sEMG	Surface electromyography
MMI	Man–machine interaction
HMR	Hand movement recognition
MSPCA	Multi-scale Principle Component Analysis
TQWT	Tunable Q- factor wavelet transform
DWT	Discrete Wavelet Transform
SVM	Support Vector Machine
k-NN	K-Nearest Neighbors
NB	Naive Bayes
ANN	Artificial neural network

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1 Introduction

1.1 Background

The surface electromyography (sEMG) signals acquired from the skin surface are produced by the electrical activity of muscle fibers during contraction. These signals are used to identify the subject's intended movement since each activity related to a precise activity of muscles (Zhang and Sup 2014). In fact, sEMG signals possess a significant information about the muscular activity and are frequently employed as an input of the myoelectric control systems. The EMG is an electro-diagnostic technique used in medicine, healthcare and man–machine interaction (MMI) (Merletti and Di Torino 1999). It records and analyses the electrical signals yielded by the skeletal muscles (Robertson et al. 2013). One of the EMG applications is the development of MMI for disabled people like a virtual world, a virtual mouse, electric wheelchairs, prosthesis etc. (Abdullah et al. 2017).

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The sEMG signals are used to recognize the different types of myoelectric signals. The variation of EMG signals affects the performance of a classifier due to the different categories of contraction. To eliminate such variations, different signal processing techniques, feature extraction and machine learning algorithms can be employed (Tsai et al. 2014; Phinyomark et al. 2013; Chowdhury et al. 2013).

The hands of human being play an imperative role in grasping and manipulating different objects. The loss of even a single hand can significantly affect the human activity. In this context, a prosthetic hand is an appealing solution to equip the armless subjects. In (Lee et al. 2018) authors have proposed a multi-channel sEMG knit band sensor for myoelectric prosthesis. In (Stango et al. 2015) the High Density (HD) EMG model is utilized for controlling upper limb prostheses. In (Ma et al. 2015) a muscle synergies based method is proposed to control a prosthetic hand. The non-negative matrix factorization (NMF) algorithm is used to map the muscle activities.

Generally, the sEMG based control system framework is divided into four stages namely (1) data acquisition, data segmentation and denoising, (2) feature extraction/dimension reduction, (3) classification and (4) controller. The sEMG signals are collected from the human muscles and then denoised to eliminate the artifacts. In the second step, the signal collected from the previous stage is transformed into a feature vector. Then, dimension reduction is applied to eliminate the redundant information from the feature vector. The third stage is the classification where classes are recognized from the reduced feature vector by using different machine learning techniques. The final stage is the controller in which decisions taken from the classification stage are interpreted as control commands (Rechy-Ramirez and Hu 2015).

In this study, the sEMG signals are employed for the prosthetic hand movement control. The upper limb prosthesis is mainly based on the myoelectric control. It exploits the sEMG signals which are originated during the contraction of muscles on the skin surface. The majority of muscles which control the motion of fingers are located on the left side of a stump. Therefore, after a hand amputation the activity of these muscles can be used to control the prosthesis motion. The prostheses control is based on a set of repeatable muscle contraction which can be differentiated from ordinary arm function. Some valuable features can be extracted from the myoelectric signals which provide information about muscle activity for prosthesis control. The sEMG signals can be investigated in terms of their amplitudes, phases in time domain and frequency. The extraction of sEMG features can be realized by using several methods including signal amplitude, autoregressive model coefficients, frequency characteristic and power spectrum, and time–frequency characteristics (Oladazimi et al. 2012; Asadi et al. 2011). In (Guo et al. 2017) seven features are extracted per instance. Four time-domain features, mean absolute value, zero crossings, slope sign changes and waveform length (WL), are extracted. Three near-infrared spectroscopy (NIRS) features, mean absolute value, waveform length and variance, are extracted. In (Wojtczak et al. 2009) energies and zero crossings are extracted. In (Subasi et al. 2018) the DWT decomposition is used to extract subbands coefficients. In (Subasi et al. 2018) the WPD subbands coefficients are extracted as pertinent features.

1.2 Research motivations

The research motivation of this study is twofold: employment of tunable Q-factor wavelet transform (TQWT) for feature extraction and the utilization of bagging and boosting ensemble models in hand movement recognition. The new research tendencies are changing towards employing single machine learning methods in developing ensemble models (da Silva-Sauer et al. 2016). Tsai et al. (2014) stated that the ensemble models based on the combination of diverse classifiers accomplish a better classification performance by eliminating the other classifiers' errors (Gicić and Subasi 2019). In biomedical signal classification different ensemble classifiers are employed to create homogenous classifier ensembles and the algorithm using an ensemble classifier revealed better performance (Blankertz et al. 2006). Since the ensemble methods decrease the effect of signal variability by averaging classifier outputs (Rakotomamonjy and Guigue 2008), there are several studies for hand movement recognition performance enhancement in terms of training time and accuracy. El Dabbagh and Fakhr (2011) employed an ensemble classifier to enhance the classification performance using an ensemble of weighted SVMs. However, these algorithms accomplished minor enhancements (Lee and Kim 2018). Subasi et al. (2018a, b, c) proposed a signal classification framework to combine the bagging ensemble classifiers with different classifier models to achieve a better classification performance. Hence, the main motivation of this study is to employ the ensemble classifiers in hand movement recognition.

The hand prostheses are mostly controlled by sEMG signals. In fact, after the loss of a hand, a significant number of the muscles remain in the stub of arm. Therefore, it is possible to control the prosthetic hand by exploiting the sEMG. However, a robust recognition of hand movements by using the sEMG signals has different problems. In order to eliminate these problems and increase the classification accuracy, an appropriate combination of the feature extraction methods and the dimension reduction techniques must be used. Furthermore, a suitable classifier with a better performance to improve the classification accuracy must be employed. In (Kurzynski et al.) recognition of the EMG and the mechanomiographic (MMG) biosignals is realized by using a Multi Classifier System (MCS). It works in a two-level structure with a dynamic ensemble selection (DES). The biomedical signals are of multi-dimensional nature. Therefore, it is difficult to find a robust feature extraction and machine learning algorithm for the MMI (AbdelMaseeh et al. 2016; Ju et al. 2013; Young et al. 2013). Time–frequency methods, such as short-time Fourier transform (STFT), and wavelet transform (WT) decompose the signal in both time and frequency domain. WT is a popular feature extraction method for the EMG signals (Wang et al. 2006; Liu and Luo 2008; Subasi 2012). Machine learning algorithms have the ability to distinguish different type of signals. Boyali and Hashimoto (2016), proposed a myoelectric pattern recognition system using Spectral Collaborative Representation based classification to yield a higher classification accuracy for a hand gesture. Tsai et al. (2014) proposed a novel STFT-ranking feature for various muscle contractions. More than 90% classification accuracy is attained by using the SVM algorithm. AlOmari and Liu (2015), classified eight hand motions by using the sEMG signals using Genetic Algorithm and Particle Swarm Optimization. They integrated these optimization algorithms with Wavelet transform (WT). In addition, four different dimensionality reduction methods are used with an SVM classifier.

The sEMG signals contain significant information about the muscular activity and are extensively used for the myoelectric control (AlOmari and Liu 2014). Different intelligent methods have been suggested to recognize the neuromuscular activities in prosthetic devices control (AlOmari and Liu 2015; Rechy-Ramirez and Hu 2015). Most of the rehabilitation devices and assistive robotic systems have an old-style user interface, such as keyboards and joysticks, many disabled people have struggled in using them, hence the innovative human–machine interfaces become necessary (Rechy-Ramirez and Hu 2015). Karimi et al. (2011), used the artificial neural network with a genetic algorithm to classify ten hand motions and achieved a high classification performance for the selected hand motions. Rafiee et al. (2011), employed a mother wavelet matrix (MWM) based technique for the recognition of intramuscular and sEMG signals taken from the upper forearm for ten hand motions. Also, they used a surface electrode matrix (SEM) and a needle electrode matrix (NEM) to determine the appropriate sensors for each motion. They employed the statistical features, extracted from wavelet packet transformation of the sEMG signals, for supporting amputees to train their artificial limbs for different motions. In, Xing et al. (2014), proposed a real-time sEMG classification system to identify six types of wrist motions. He employed a hybrid system with wavelet packet transform, non-parametric weighted feature extraction (NWFE) and support vector classifier.

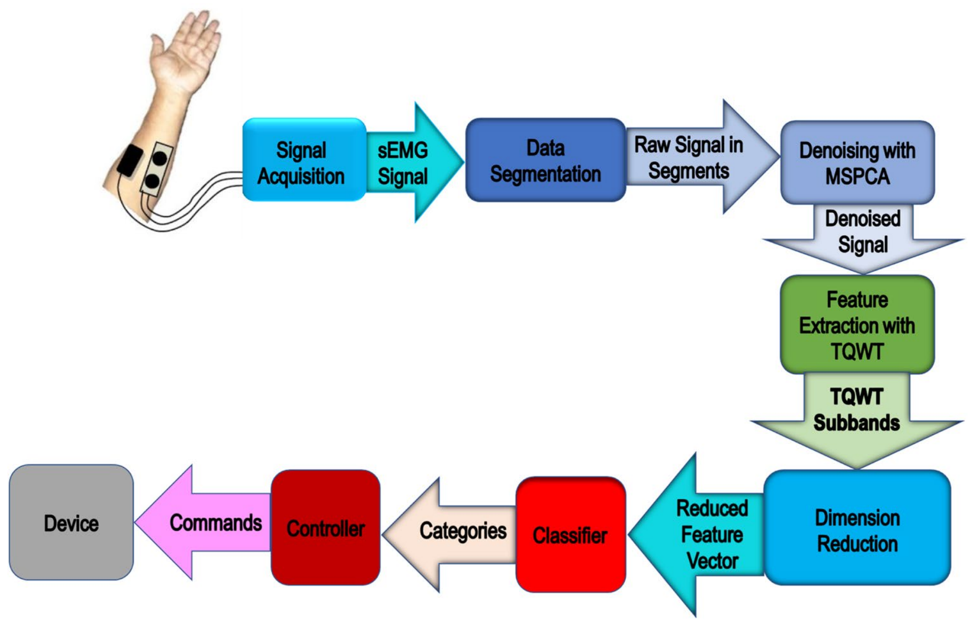
Recently, the ensemble classification methods have been employed for the Computer Aided Design (CAD). Ensemble machine learning techniques are methods which combine opinions of the multiple learners to achieve a better performance. It allows to use a group of simple predictors while achieving a better classification performance. The ensemble classifiers are supposed to have better performance than individual classifiers (Brown 2011; Kuncheva 2004), and they have been used for high-dimensional data sets (Valentini 2004; Valentini and Dietterich 2004). An ensemble classifier is formed by classifiers built on a different feature subset, sampled randomly from the original feature set, by taking the majority vote of the base classifiers. Ensemble classifiers have been used for problems with large dimensionality and excessive feature-to-instance ratio (Skurichina and Duin 2002). Furthermore, ensembles are inherently parallel, so they can be much more efficient at training and test time if they have access to multiple processors (Daumé, 2012). In (Wan et al. 2016a) a multi-label predictor based on ensemble linear neighbourhood propagation (LNP) is proposed. It weights hybrid sequence-based feature information from both labeled and unlabeled proteins for predicting localization of both single and multi-label chloroplast protein. In (Saha et al. 2014) SVM, Random Forest, Decision Tree and NB are used to build an ensemble learning method based on majority voting for prediction of protein interactions. In (Wan et al. 2016b) an ensemble transductive learning method is utilized to tackle multi-label protein sub chloroplast localization. In (Peng 2006) authors proposed an ensemble machine learning approach for the development of robust microarray data classification.

1.3 Contribution

Based on the above motivations, a new hand movement recognition model based on ensemble classifiers is suggested with the objective to improve the performance of the classifier. The contribution of this study is to utilize the tunable Q-factor wavelet transform (TQWT) feature extraction with bagging and boosting ensemble classifiers for hand movement recognition. To the best of the author's knowledge, the bagging and boosting ensemble classifiers has not been previously employed for the hand movement recognition. Furthermore, enhancement of the classification performance of the proposed model is also achieved by the TQWT feature extraction, not only at the classifier level.

Hence, in this study, a hand movements recognition based on sEMG signals recorded from subject's forearm is proposed. The MSPCA is used to denoise the sEMG signals. The features are extracted from the denoised signals by using TQWT and then the Bagging and Boosting ensemble machine learning methods are investigated for hand movement recognition. An innovative mechanism is presented

Fig. 1 General framework for the proposed hand movement recognition system



which let the use of robust classifiers. Besides, various experiments are conducted in order to compare the Bagging and the Boosting ensemble classifiers performance for the hand movement recognition.

1.4 Organization

The remainder of the paper is organized as follow. In the next section, information about the subjects is given and the methods applied in each step of the sEMG signals classification process are presented. Section 3 provides a complete experimental study of the Bagging and Boosting ensemble machine learning models based on the sEMG signals classification scheme. Finally, the work is concluded in Sect. 4.

2 Materials and methods

The proposed system block diagram is shown in Fig. 1. Different system modules are described in the following subsections.

2.1 The surface electromyography (sEMG) database

For this study, sEMG for basic hand movements data set is downloaded from UCI Machine Learning Repository.[1] The sEMG database is prepared by conducting a sequence of experiments which uses the essential hand movements for grasping different objects. sEMG electrodes are respectively placed on Flexor Capri Ulnaris, Extensor Capri Radialis, Peronious Longus, Peronious Brevis and a reference electrode is also placed in the center of Longus and Brevis (Pinnington et al. 2005). For the data collection, five healthy subjects: two males and three females of approximately 20–22 years are asked to repeat the six movements: spherical, tip, palmar, lateral, cylindrical, and hook. The intended subjects are asked to repeat each basic movement, 30 times and each recording duration is 6 s, generated by the sEMG electrodes, placed on the body of the intended subject (Pinnington et al. 2005). The sEMG signal frequency contents lay within the range of [0; 500] Hz. However, the pertinent information exists within the range of [50; 150] Hz. In this framework, the analogsEMG signal is passed through a band-pass filter with respectively low and high cutoff frequencies of [50; 150] Hz. It avoids aliasing during the post-acquisition process. Additionally, it removes the line interference artifacts (Sapsanis et al. 2013b). The band limited analog signal is acquired at a rate of 500 Hz by using the National Instrument's (NI) data acquisition card and a Labview based programming kernel (Dong and Lin 2005).

2.2 The Multiscale Principal Component Analysis (MSPCA)

The appealing features of the wavelet analysis and of the Principle Component Analysis (PCA) are combined in the MSPCA. It employs the wavelet analysis to extract the deterministic features of measurements. Later on, it performs the PCA. It decorrelates these features by extracting a linear relationship among them. To conclude, at each scale, the

[1] https://archive.ics.uci.edu/ml/datasets/sEMG+for+Basic+Hand+movements#.

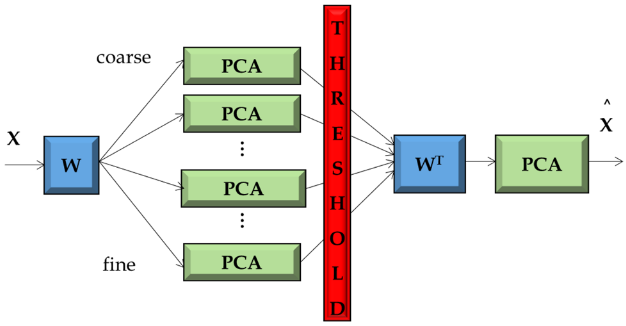


Fig. 2 The procedure for MSPCA

MSPCA performs the principal component analysis of the extracted wavelet coefficients (Fig. 2). The multiscale feature makes the MSPCA suitable for analysis and de-noising of the time–frequency varying signals. The MSPCA allows focusing only on the relevant scales where the finding of noteworthy events occurs. It is achieved by adjusting the deterministic variations detection limits. It results into an efficient finding of such changes in the intended data. Moreover, it allows filtering the residuals and scores in an effective and adaptive fashion. The MSPCA not only improves the detection of deterministic changes but at the same time it extracts the features who signifies anomalies (Bakshi 1998).

2.3 Tunable Q-Factor Wavelet Transform (TQWT)

The Tunable-Q Wavelet Transform (TQWT) is an effective tool for the oscillatory signal analysis (Selesnick 2011a, b). It can be easily adjusted as a function of the targeted application. Its primary tunable parameters are Q, r, and j. Here, Q denotes the Q-factor, r denotes the oversampling rate and levels of decomposition are denoted by j. The count of oscillations of the wavelet are managed by Q. The undesired excessive oscillations are controlled by r. The TQWT is conceived on the base filter banks. These filters can be easily specified in the frequency domain. These are non-rational transfer functions and are known for their effective realization (Selesnick 2011a, b; Patidar and Pachori 2014).

Theoretically, a suitable value of the Q-factor is decided as a function of the intended signal oscillatory behavior. Therefore, while analyzing the oscillatory signals like EEG, ECG and EMG, the wavelet transform should have a relatively high Q-factor. In other case, low Q-factors are employed while dealing with minor or non-oscillatory signals like the photographic image scan line. The dyadic wavelet transform is a suitable candidate in this context (Daubechies 1992). Mostly the wavelet transforms, except continuous wavelet transform, show a slight ability to tune the Q-factor. Because of this limitation, their usage is limited to the specific applications. In this context, the TQWT is devised. The perfect reconstruction over-sampled filter banks, with real scaling factors, are employed to realize the TQWT. The discrete time TQWT treats the finite length sampled signals. It is based on the short time Fourier transform and is efficiently realizable with Fast Fourier Transforms (FFTs). According to Selesnick (2011a, b), an effective realization of the TQWT can be achieved with modest oversampling ratio. The sampling rates of around three to four folds of the Nyquist sampling criterion are frequently employed as a function of the intended application (Selesnick 2011a, b).

The TQWT's key parameters are the **Q**-factor, redundancy (***r***), and number of levels (or stages, ***J***). The **Q**-factor, denoted as ***Q***, affects the wavelet's oscillatory behavior; specifically, ***Q*** affects the degree to which the wavelet's oscillations are sustained. Q is approximately a function of the number of oscillations produced by the wavelet. For Q, a value of 1.0 or greater should be chosen. The oscillatory pulse Q-factor meaning is the ratio of its center frequency to its bandwidth $Q = \frac{f_0}{BW}$. The parameter ***r*** is the TQWT redundancy when calculated employing infinitely many levels. The "redundancy" means the total number of wavelet coefficients divided by the length of the signal to which the TQWT is being applied. The defined ***r*** value is suggested that a value of 3.0 or greater. The theoretical redundancy would be very different from ***r*** since only a finite number of rates can actually be used to calculate the transform. The number of wavelet transform levels (or stages) is represented by ***J***. The transformation is composed of a series of two-channel filter banks, with each filter bank's low pass output being utilized as the input to the successive filter bank. Parameter ***J*** denotes the number of filter banks. Every output signal forms one sub-band of the wavelet transform. $J+1$ sub-bands will exist, which are the low-pass filter output signal of the final filter bank and the high-pass filter output signal of each filter bank (Selesnick 2011a, b). The TQWT based N level signal decomposition is shown in Fig. 3a and b shows the first stage of filters bank. Where, *LPS* stands for the Low Pass Scaling with a scaling factor α and *HPS* stands for the High Pass Scaling with a scaling factor β. In this study we used tried several values of Q, r and J. The best performance is achieved with $Q=3$, $r=4$, $J=15$.

2.4 Dimension reduction

Since, the wavelet-based feature extraction algorithms produce the feature vector which has a bigger size and is not efficient to be used as an input to a classifier, the dimension reduction techniques are used to extract a lesser number of features from the wavelet coefficients. The six statistical features are implemented for the dimension reduction which are:

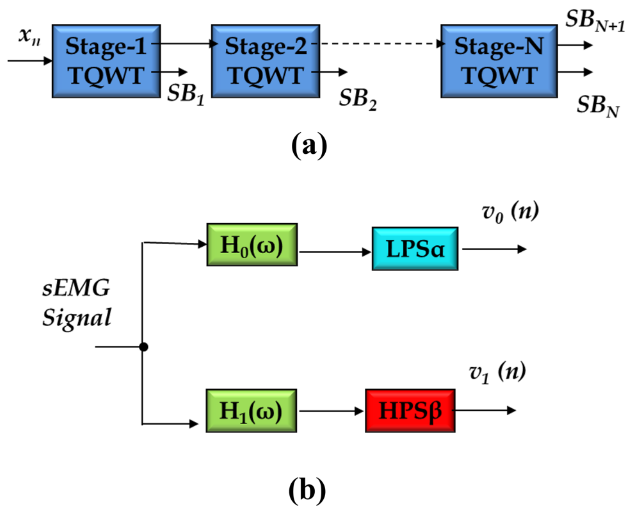


Fig. 3 TQWT decomposition of a sEMG signal. **a** N level TQWT decomposition, **b** First stage of filters bank

1. Mean absolute values of coefficients found in each sub-band,
2. Average power of the coefficients found in each sub-band,
3. Standard deviation of the coefficients found in each sub-band,
4. Ratio of the absolute mean values of coefficients of adjacent sub-bands,
5. Skewness of the coefficients found in each sub-band,
6. Kurtosis of the coefficients found in each sub-band.

We have total TQWT sub-bands, $J+1=15+1=16$. For each statistical feature we have 16 values except 4, which is 15 since it is the ratio of 2 sub-band. Hence, we have total 95 features for each trial, total 6 different of movements and we have for each subject $6\times30\times95$ input data matrix.

2.5 Single classification methods

Support Vector Machine (SVM) carries out a nonlinear mapping to increase the dimensionality of the training data. It allows the most appropriate classifier to be discovered which can correctly distinguish the test data between different classes. The decision is based on margin calculation. The ***k-Nearest Neighbors (k-NN)*** learns the test sample and defines it by comparing it with the training ones. The *k* Training instances are used to identify the intended sample. The decision is based on distance calculation. The ***REPTree*** builds a prediction tree where the missing labels are handled by dividing the given dataset into parts (Alpaydin 2014). The testing set is identified by using the templates through the added nodes coincidence removing effect (Alpaydin 2014). The ***Naive Bayes*** (NB) is a scalable classifier, and relatively fast. It simply depends on a bunch of calculations being carried out. Either binary or multi-class recognition can be done efficiently with NB (Alpaydin 2014). The ***C4.5*** decision tree is an algorithm evolution of the Ross Quinlan method (Alpaydin 2014). It creates decision trees that are subsequently employed for classification. The tree root is defined in the beginning. The property is then observed, defined by the node. It allows the tree to be dig down in relation to the attribute value of a given instance. This process continues until there is a leaf on it. Finally, the instances under examination are marked using features of the leaves (Alpaydin 2014). The ***Random Forest*** is based on a combination of predictors for the tree. That tree is based on values of a random vector which is sampled independently. Nonetheless, for all trees in the forest a common distribution is practiced. The classification error is a function of the accuracy and the connotation between different trees (Alpaydin 2014). The ***Rotation Forest*** is the classifier of an ensemble that prepares a finite number of decision trees. Such trees are independently trained using a collection of dissimilar features. The decision trees serve as the classifiers of foundation. They are immune to the rotation of the feature-axes (Alpaydin 2014). The outcome of rotating features axes is the usage of fewer trees in founding the high accuracy classification regions.

2.6 Ensemble classification methods

Ensemble learning methods allow the use of robust classifiers widely used in different pattern recognition area. Recently, ensemble classifiers have increasingly gained more attention in different pattern recognition applications. The ensemble classifications which focus on the entirely complex-valued relaxation neural networks applied to the classification of images. They apply multiple classifiers for the same classification problem. In this learning methods, the results of classifiers with different accuracy scores are combined with different methods (voting, average, etc.). Thus, it is possible to obtain better predictive results from a single classifier (Saraswathi and Srinivasan 2014). Voting is getting a linear combination of learners.

$$\mathrm{y}_i = \sum_{\mathrm{j}} w_j d_{ji} \text{ where } w_j \geq 0, \sum_{j} w_j = 1 \tag{1}$$

In weighted sum, d_{ji} is the vote of classifier *j* for class C $_i$ and w_j is the weight of its vote. Simple voting is a special case in which all voters have equal weight, namely, $w_j=1/L$. This is known as *plurality voting* in which the class taking the majority of votes is the winner. Moreover, if the voters may provide the additional knowledge of how much they vote for each class, then after normalization, these might be employed as weights in a *weighted voting* system. Consistently, if d_{ji} are the class posterior probabilities, $P(C_i|x,\mathrm{M}_j)$,

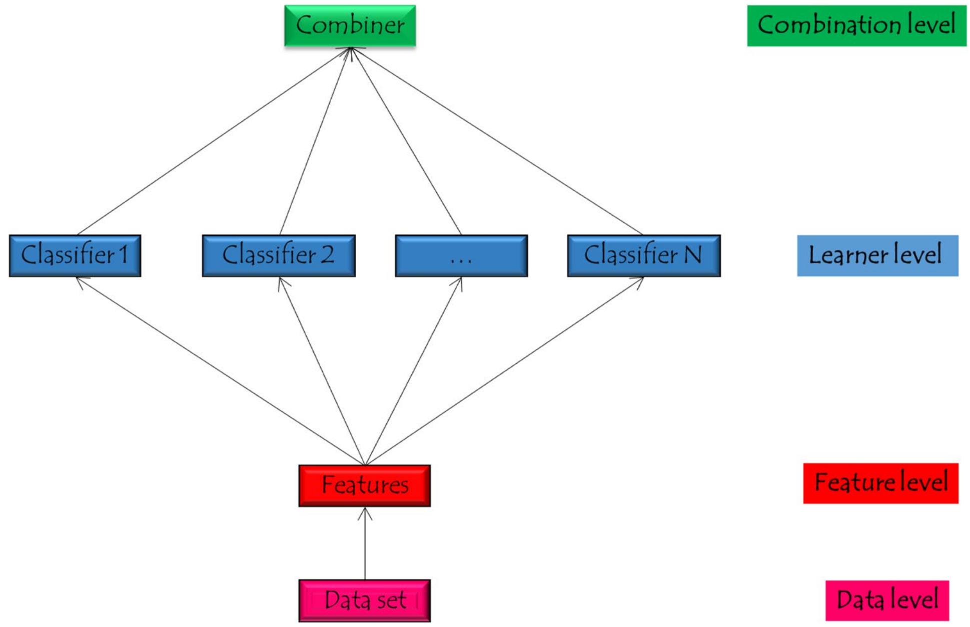


Fig. 4 Ensemble classifier framework

then they can be just summed up (w_j=1/L) and the class with maximum $y_i$will be selected. Median can be more robust to noise than the average. Another way might be to assess the accuracies of the learners on a distinct validation set and utilize that information to find the *weights*, so that more weights can be given to more accurate learners (Alpaydin 2014) (Fig. 4).

2.7 Bagging

In classification, decisions of different models can be easily merged by employing their votes. The weighted average of different model votes is employed in the case of numeric prediction. In the case of bagging, various unique size training data sets are randomly selected from the overall problem domain. Later on, a decision tree might be raised for each dataset by employing a specific machine leering tool. These trees might be expected to be essentially similar and to implement the same classification for every new test instance. However, this hypothesis is generally incorrect, especially if the training datasets are quite small since the decision tree induction is not a stable process. Therefore, small changes in the training data might simply produce a different attribute which is chosen at a specific node, with substantial implications for the structure of the subtree under that node. It indicates that there are some instances where several decision trees yield accurate predictions and others do not. Bagging tries to balance the instability of learning methods by simulating the procedure defined before employing a given training set instead of obtaining independent datasets from the domain. For each stage, the training data is altered by decimating certain instances and interpolating others. It avoids the complex process of selecting a new training data each time. The bagging produces a combined model, votes count based prediction, which generally produce moderately better than the single model created from the original training dataset (Hall et al. 2011).

2.8 Boosting

The boosting method combines multiple models by looking for models which complement each other. Like bagging, boosting also employs voting of employed decision trees in order to make the final prediction. However, unlike bagging the boosting is an iterative process. In boosting every new model is influenced by the performance of models built before whereas in the case of bagging individual models are built separately. It enhances the new model's performance for instances erroneously tackled by the previous models. It is realized by assigning higher weights to those instances. It allows the boosting to weight the contribution of a model by employing its confidence in place of assigning an equal weight to all models (Hall et al. 2011).

2.9 AdaBoost

AdaBoost can be employed for any learning process similar to Bagging. In order to simplify the process, it is assumed that the learning algorithm can update weighted instances which are positive numbers. The existence of instance weight changes the way where a classifier error is calculated. Normally, in this case it is computed by dividing the misclassified instances accumulated weights by the accumulated weights of all instances. The instances weighting allows the learning algorithm to focus on a specific set of higher weighted instances. These higher weighted instances become more important than others because there is a superior inducement to correctly classify them. The boosting algorithm starts by giving equal weights to all instances in the training data. Then it asks the classification algorithm to construct a model for training data and reweights each instance with respect to the model output. The weights of misclassified ones are increased and that of correctly classified instances are decreased. In the upcoming iterations classifiers are constructed by employing the reweighted data. The weights of instances are adjusted during each iteration. It is done as a function of the new classifier output. In the case of new data, better classifier precision can be achieved by employing the boosting approach as compared to the bagging method. Though, as compared to bagging, boosting occasionally fails in certain situations. It can result into an erroneous classifier as compared to the one constructed from the same data by employing the bagging approach (Hall et al. 2011).

2.10 MultiBoost

Since, bagging and AdaBoost employs different working mechanisms, a better performance can be achieved by combining these approaches. The bagging principally decreases the variance, while the AdaBoost decreases both the bias and the variance. However, it is evident that bagging is more efficient than AdaBoost at decreasing the variance (Bauer and Kohavi 1999). Therefore, their combination can keep decreasing AdaBoost's bias while adding bagging's variance reduction to that already attained by AdaBoost. It allows to get benefit from both sides and might results into a better performance as compared to one obtained in isolation. In this context, the MultiBoost technique is proposed which combines the interesting features of AdaBoost with the wagging. The Wagging is an enhancement of bagging (Bauer and Kohavi 1999). It employs a base learning algorithm which can exploit the training cases with differing weights. In place of forming the successive training sets by employing the random bootstrap samples, cases in each training set are randomly weighted by the wagging. In addition to the appealing features of wagging and Adaboost, the bias and variance reduction properties, the MultiBoost has the potential computational advantage over AdaBoost if it is implemented in parallel environment. In fact, in the case of MultiBoost, the sub-committees may be learned in parallel. On the other hand, the AdaBoost process is sequential in nature. It reduces the possibility of parallel computing. This interesting feature is achieved in the MultiBoost approach grace of wagging. It allows each classifier to learn independently of the rest, allowing parallel processing, a property that MultiBoost inherits at the sub-committee level (Webb 2000).

3 Results and discussion

3.1 Performance evaluation measures

It is expected to assess a classifier's performance in terms of the error rate for any classification problem. The classifier predicts the class of each instance, a success is calculated in case of a correct prediction and an error is calculated otherwise. The error rate is defined as the percentage of errors achieved from the whole set of instances. It quantifies the classifier overall performance. The class of each instance in the training set is known. It allows to use this data for training. In order to predict the classifier performance on a new test set, it is required to know its error rate on a dataset that is not employed during the classifier formation. The repeated cross-validation is the most frequently employed method for predicting the performance of machine learning techniques. It is especially an effective choice in the case of limited-data situations. Comparing the performance of different machine learning techniques is another challenge. In practice the error rate of a classifier is quantified by employing the tenfold cross-validation. The data is split into ten parts randomly. In each part, every class is approximately denoted in the same amount as it is available in the overall data. Every portion is kept in turn and the learning process trained on the remaining nine ones. The error rate is calculated for each iteration. The process is repeated ten times. In this way, the learning process is carried out ten times on diverse training sets. At the end, the ten error estimates are averaged to produce an overall error estimate (Hall et al. 2011). In this study we employed tenfold cross validation.

The true negatives (TN) and true positives (TP) are correct classifications. A false positive (FP) happens when the result is not correctly predicted as a yes (or positive) when it is essentially a no (negative). A false negative (FN) happens when the result is not correctly predicted as a negative when it is essentially a positive (Hall et al. 2011). The success rate or accuracy is mostly utilized for measuring the performance of the classifiers. It can be computed by employing Eq. 2.

$$Accuracy = \frac{TN + TN}{TP + TN + FP + FN} \times 100 \tag{2}$$

Another performance measure is the F-measure. It can be calculated by employing Eq. 3.

$$F\text{-}measure = \frac{2 \times TP}{2xTP + FP + FN} \tag{3}$$

Table 1 The average accuracy and standard deviation of single classification methods

	F1		F2		F3		M1		M2	
	Average	SD	Average	SD	Average	SD	Average	SD	Average	SD
SVM	84.44	4.60	97.22	1.90	86.67	5.20	95.56	2.80	97.78	1.70
k-NN	81.11	5.80	95.00	3.30	79.44	5.70	94.44	3.90	95.00	2.90
NB	83.89	7.40	90.00	3.50	77.78	6.70	91.67	4.20	91.11	4.50
Random Forest	87.78	4.80	91.11	2.50	82.22	4.70	92.78	2.60	91.67	4.70
C4.5	81.11	5.90	89.44	3.60	88.89	5.80	86.67	3.90	82.78	6.10
Rotation Forest	87.78	3.80	95.00	2.20	87.78	4.60	93.89	2.70	97.22	1.50
REPTree	78.89	6.10	88.33	3.80	84.44	6.30	77.78	3.90	86.11	5.70
RandomTree	74.44	7.30	85.56	4.10	76.67	7.20	88.89	4.20	86.67	6.20

Table 2 The average accuracy and standard deviation of Bagging

	F1		F2		F3		M1		M2	
	Average	SD	Average	SD	Average	SD	Average	SD	Average	SD
SVM	84.44	3.60	95.56	2.10	86.11	5.10	94.44	2.40	76.11	4.10
k-NN	84.44	3.50	92.78	2.50	82.22	4.60	93.89	3.20	67.22	4.60
NB	0.82	4.80	88.89	3.90	77.22	4.90	91.67	4.40	97.78	1.50
Random Forest	86.11	3.40	92.78	2.20	87.78	3.70	92.78	2.30	90.56	4.10
C4.5	78.89	4.20	90.00	3.70	88.33	4.20	88.89	3.80	96.11	2.30
Rotation Forest	85.00	3.20	96.67	2.20	91.67	3.10	92.78	2.60	98.33	1.40
REPTree	84.44	4.10	90.00	3.50	88.33	3.90	89.44	4.10	89.44	4.20
RandomTree	81.67	4.00	91.11	3.90	82.22	4.30	92.78	3.90	90.56	3.80

The ROC curves represent the performance of a classifier regardless of the class distribution or error costs. They plot the TN rate on the horizontal axis against the TP rate on the vertical axis. The ROC line depends closely on the details of the specific sample of test data. This sample dependency can be decreased by employing the cross-validation approach. A simpler method is to add the predicted probabilities for all test sets along with the true class labels of the related instances and produce a single ranked list based on this data. It assumes that the probability estimates from the predictors which are built from the different training sets, are all based on equally sized random samples of the data. It is not easy to decide which technique is superior. But the latter one is easier to realize. It is also employed as area under the ROC curve (AUC). Normally, larger the area the better is the model and vice versa (Hall et al. 2011).

The Kappa statistic expresses the outcome as a percentage of the total for a perfect classifier and converts this expected result into justification by removing it from the predictor's success. The maximum value of Kappa is 1, and the expected value for a random classifier with the same column totals is 0. Hence, the Kappa statistic is employed to check the agreement between observed and predicted categories of a dataset, while adjusting for an agreement which happens by chance. Nevertheless, it does not take costs into consideration like the plain success rate (Hall et al. 2011).

3.2 Experimental results

A summary of average classification accuracies and standard deviation obtained by using Single Classifiers (SCs) is given in Table 1 and Bagging is given in Table 2 for the five considered subjects. It is also visualized in Fig. 5. It shows that the highest classification accuracy of 98.33% is achieved by Rotation Forest with Bagging for the 2nd male subject using tenfold cross validation.

A summary of average classification accuracies and standard deviation obtained by using MultiBoost is given in Table 3 and AdaBoost is given in Table 4 for the five considered subjects. It is also visualized in Fig. 6. It shows that the highest classification accuracy of 100% is achieved by both SVM with MultiBoost and SVM with AdaBoost using tenfold cross validation.

It is evident from above results that MultiBoost and AdaBoost outperform SCs and Bagging in terms of the classification accuracies. Therefore, further evaluation is performed for MultiBoost and AdaBoost.

A summary of F-measure values, obtained by using MultiBoost and AdaBoost, for the five considered subjects,

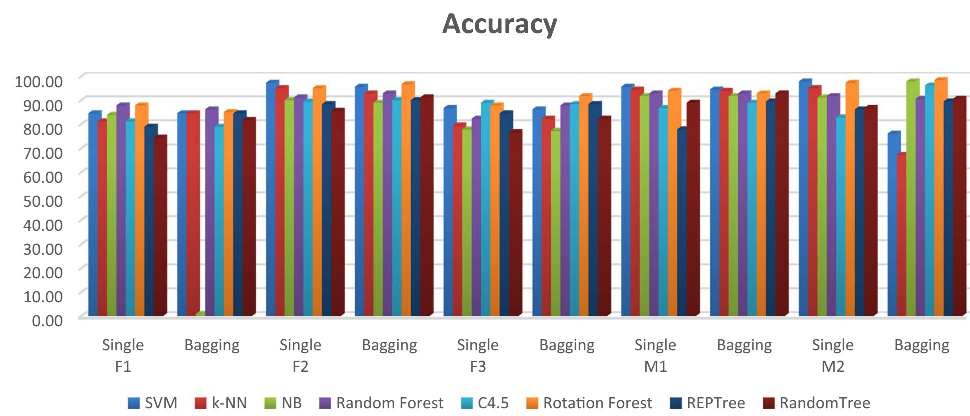


Fig. 5 Summary of the classification accuracies for SCs and Bagging

Table 3 The average accuracy and standard deviation of Multiboost

	F1		F2		F3		M1		M2	
	Average	SD	Average	SD	Average	SD	Average	SD	Average	SD
SVM	84.44	2.46	97.22	2.12	86.67	3.30	95.56	2.44	100	0.00
k-NN	78.33	3.10	95.00	2.50	79.44	4.90	95.56	2.44	93.33	3.30
NB	82.78	4.30	89.44	4.70	77.78	4.60	91.67	4.60	95.56	2.50
Random Forest	86.11	2.10	91.67	3.20	85.56	2.40	92.78	2.80	95.56	2.50
C4.5	81.11	3.90	91.11	3.48	90.00	3.70	88.89	3.94	92.78	3.80
Rotation Forest	87.22	2.50	96.11	2.50	91.11	2.50	95.00	2.50	98.89	1.10
REPTree	80.56	4.00	90.56	4.52	88.89	4.30	89.44	4.50	96.11	2.70
RandomTree	71.11	3.70	82.22	5.10	80.56	4.90	92.78	3.60	90.00	3.70

Table 4 The average accuracy and standard deviation of Adaboost

	F1		F2		F3		M1		M2	
	Average	SD	Average	SD	Average	SD	Average	SD	Average	SD
SVM	84.44	2.46	97.22	2.12	85	3.56	95.56	2.44	100	0
k-NN	81.11	3.28	95	2.5	81.11	4.88	95.56	2.44	96.67	2.3
NB	83.33	4.46	89.44	4.68	83.33	4.46	93.89	2.88	95.56	2.45
Random Forest	88.89	3.94	94.44	2.95	88.89	3.94	93.89	2.88	95	2.5
C4.5	82.78	3.83	92.78	3.24	82.78	3.83	88.33	4.96	97.78	2.64
Rotation Forest	86.67	4.24	96.11	2.1	86.67	4.24	91.11	3.98	92.78	2.85
REPTree	81.11	4.88	92.22	4.67	81.11	4.88	93.33	3.77	98.89	1.66
RandomTree	71.11	5.96	82.22	3.55	71.11	5.96	93.33	3.77	98.33	1.62

are presented in Table 5. It can also be visualized in Fig. 7. It shows that the highest F-measure value of 1 is achieved by both SVM with MultiBoost and SVM with AdaBoost.

A summary of AUC values, obtained by using MultiBoost and AdaBoost, for the five considered subjects, are presented in Table 6. It is also visualized in Fig. 8. It shows that the highest AUC value of 1 is achieved by SVM with MultiBoost, SVM with AdaBoost, Rotation Forest with MultiBoost and REP Tree with AdaBoost.

A summary of Kappa values, obtained by using MultiBoost and AdaBoost, for the five considered subjects, are presented in Table 7. It is also visualized in Fig. 9. It shows that the highest Kappa value of 1 is achieved by SVM with MultiBoost and SVM with AdaBoost.

Above results outlined that the employed assembly of MSPCA, TQWT and the SVM with MultiBoost or the SVM with AdaBoost delivers the highest classification performance for the case of 2nd female, 1st male and 2nd male

Fig. 6 Summary of the classification accuracies for MultiBoost and AdaBoost

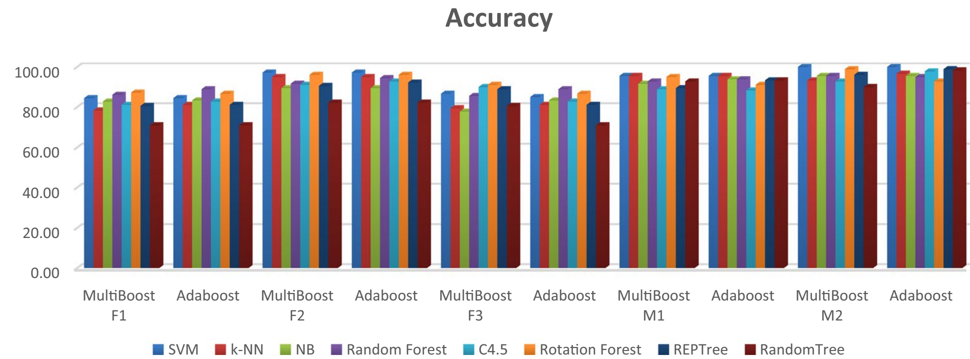
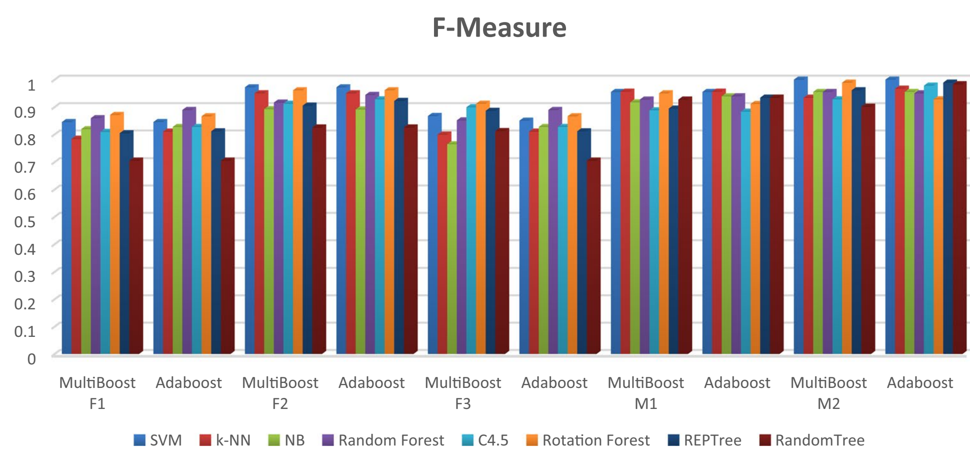


Table 5 The summary of F-Measure for Multiboost and Adaboost

	F1		F2		F3		M1		M2	
	MultiBoost	Adaboost	MultiBoost	Adaboost	MultiBoost	Adaboost	MultiBoost	Adaboost	MultiBoost	Adaboost
SVM	0.845	0.845	0.972	0.972	0.867	0.85	0.955	0.955	1	1
k-NN	0.784	0.81	0.95	0.95	0.799	0.81	0.956	0.956	0.934	0.967
NB	0.819	0.827	0.892	0.891	0.765	0.827	0.917	0.939	0.955	0.955
Random Forest	0.859	0.889	0.916	0.944	0.851	0.889	0.927	0.939	0.955	0.95
C4.5	0.809	0.827	0.912	0.928	0.899	0.827	0.888	0.883	0.928	0.978
Rotation Forest	0.871	0.866	0.961	0.961	0.912	0.866	0.95	0.911	0.989	0.928
REPTree	0.804	0.811	0.905	0.922	0.886	0.811	0.894	0.934	0.961	0.989
RandomTree	0.705	0.705	0.825	0.825	0.812	0.705	0.927	0.934	0.901	0.983

Fig. 7 Summary of the F-Measure for MultiBoost and AdaBoost



subjects. The best performance is achieved for the 2nd male subject.

A performance comparison is also made between the proposed framework and the one based on DWT based features extraction (Subasi et al. 2018). Results are summarized in Table 8. It shows that the proposed assembly of TQWT with AdaBoost performs much better than the counterpart based on DWT with AdaBoost in terms of the classification accuracy.

3.3 Discussion

The classification results reported in above section shows that for the 2nd female, the 1st and the 2nd male subjects the highest classification accuracies are attained with the employed assemblies of the MSPCA, TQWT, and the SVM with Boosting. However, for other two intended subjects, a different assembly of classifiers achieves the best performance. It occurs because of the difference in force

Table 6 The summary of AUC for Multiboost and Adaboost

	F1		F2		F3		M1		M2	
	MultiBoost	Adaboost	MultiBoost	Adaboost	MultiBoost	Adaboost	MultiBoost	Adaboost	MultiBoost	Adaboost
SVM	0.962	0.962	0.994	0.994	0.965	0.965	0.984	0.984	1	1
k-NN	0.899	0.81	0.98	0.98	0.919	0.88	0.953	0.985	0.983	0.98
NB	0.937	0.925	0.972	0.962	0.87	0.925	0.992	0.984	0.992	0.968
Random Forest	0.968	0.972	0.984	0.986	0.977	0.972	0.995	0.984	0.998	0.998
C4.5	0.952	0.964	0.952	0.954	0.962	0.964	0.989	0.992	0.966	0.998
Rotation Forest	0.963	0.967	0.994	0.994	0.968	0.967	0.996	0.96	1	0.978
REPTree	0.954	0.964	0.983	0.992	0.975	0.964	0.983	0.96	0.997	1
RandomTree	0.827	0.827	0.893	0.893	0.883	0.827	0.978	0.871	0.94	0.997

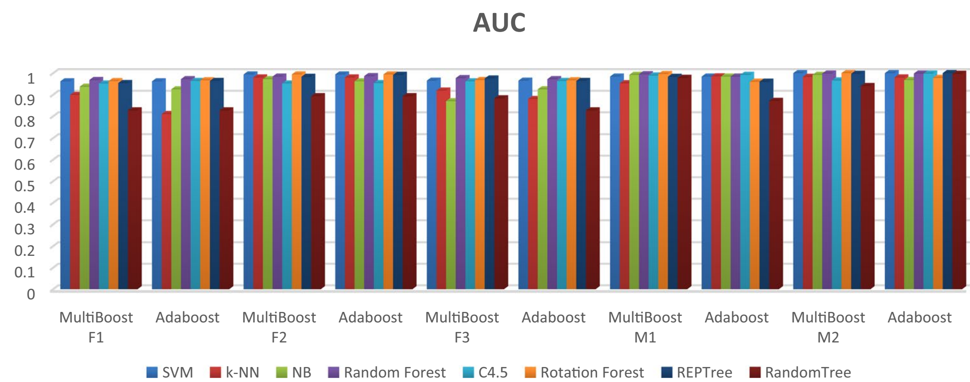


Fig. 8 Summary of the AUC for MultiBoost and AdaBoost

Table 7 The summary of Kappa results for Multiboost and Adaboost

	F1		F2		F3		M1		M2	
	MultiBoost	Adaboost	MultiBoost	Adaboost	MultiBoost	Adaboost	MultiBoost	Adaboost	MultiBoost	Adaboost
SVM	0.813	0.813	0.967	0.967	0.840	0.820	0.947	0.947	1.000	1.000
k-NN	0.740	0.773	0.940	0.940	0.753	0.773	0.907	0.947	0.920	0.960
NB	0.793	0.800	0.873	0.873	0.733	0.800	0.947	0.927	0.947	0.907
Random Forest	0.833	0.867	0.900	0.933	0.827	0.867	0.913	0.927	0.940	0.940
C4.5	0.773	0.793	0.893	0.913	0.880	0.793	0.867	0.860	0.913	0.973
Rotation Forest	0.847	0.840	0.953	0.953	0.893	0.840	0.940	0.893	0.987	0.913
REPTree	0.767	0.773	0.887	0.907	0.867	0.773	0.873	0.920	0.953	0.987
RandomTree	0.653	0.653	0.787	0.787	0.767	0.653	0.913	0.920	0.880	0.980

level, posed by muscles while grasping a unique object by different subjects. It results in different amplitudes of the sEMG signals, originated by different subjects and it influences the accuracy of classification process. Moreover, the response time of each subject could be specific. Therefore, a respective temporal misalignment occurs between the sEMG signals, originated by different subjects, while grasping a unique object. It affects the performance of post segmentation and features extraction processes and finally results in variations of the classification precisions for different subjects.

The employed model of TQWT and MultiBoost and the Adaboost with SVM classifiers achieve the best performance for the hand movement recognition by using the sEMG signals. Similar studies employing the different feature extraction methods and machine learning algorithms for the hand movement recognition by employing the sEMG signals can be found in the literature like (Tsai et al. 2014; Phinyomark

Fig. 9 Summary of the Kappa for MultiBoost and AdaBoost

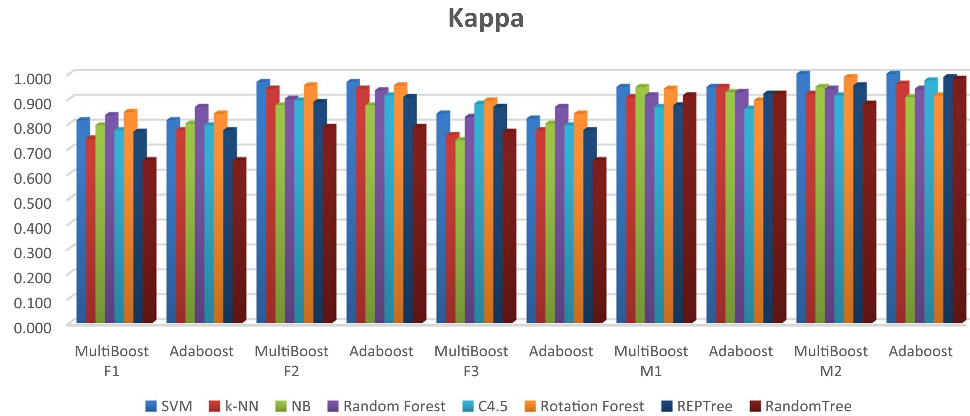


Table 8 Comparison of DWT with TQWT

	F1		F2		F3		M1		M2	
Adaboost	DWT	TQWT	DWT	TQWT	DWT	TQWT	DWT	TQWT	DWT	TQWT
SVM	74.44	84.44	75.00	97.22	86.11	85.00	93.89	95.56	97.22	100.00
k-NN	63.89	81.11	60.00	95.00	71.11	81.11	90.56	95.56	88.89	96.67
NB	78.33	83.33	79.44	89.44	83.89	83.33	91.67	93.89	90.23	95.56
Random Forest	78.89	88.89	82.78	94.44	86.67	88.89	91.67	93.89	96.11	95.00
C4.5	76.67	82.78	79.44	92.78	82.78	82.78	92.22	88.33	96.11	97.78
Rotation Forest	81.67	86.67	83.89	96.11	87.22	86.67	92.22	91.11	92.35	92.78
REPTree	75.00	81.11	77.22	92.22	81.67	81.11	91.11	93.33	95.56	98.89
RandomTree	63.89	71.11	67.22	82.22	72.22	71.11	86.11	93.33	86.66	98.33

Table 9 A summary of the classification accuracies achieved by the previous studies and the proposed study

The study reference	Feature extraction	Classifier	Classification accuracy
Sapsanis et al. (2013b)	Empirical Mode Decomposition	LDA	94.8%
Wojtczak et al. (2009)	Time Domain Features	ANN	98.6%
Sapsanis et al. (2013a)	Time–Frequency Features	LDA	95.16%
Zhang et al. (2014)	Wavelet Packet Decomposition	SVM	98.81%
Purushothaman and Ray (2014)	Time Domain Features + AR	Logistic model tree (LMT)	91.2%
Phinyomark et al. (2013)	Sample entropy (SampEn), the fourth order cepstrum coefficients, root mean square and waveform length	Linear discriminant analysis (LDA)	98.87%
Matsubara et al. (2011)	Root mean square	SVM	70%
Chowdhury et al. (2013)	Ensemble EMD (EEMD)	ANN	98.20
Khushaba et al. (2012)	Time Domain Features + AR	LIBSVM	95.2%
Mane et al. (2015)	Wavelet Transform	ANN	98.6%
Proposed method	Tunable Q wavelet transform (TQWT)	Boosting of Support Vector Machine (SVM)	100.00%

et al. 2009; Xing et al. 2014; Coelho and Lima 2014; Phinyomark et al. 2013; Ahsan et al. 2009; Zhang et al. 2014), etc. A summary of these findings is presented in Table 9. Table 9 shows that the proposed solution outperforms the previous ones by achieving the 100% classification accuracy for the 2nd male subject's sEMG data set.

The classification performance of the sEMG signals can be quantified in terms of the classification accuracy, the AUC, the F-Measure and the Kappa statistic values. It is found that the classification performances are noticeably improved when features of the considered sEMG signals are extracted by the TQWT and the ensemble classifiers are employed for the recognition of basic hand movements. It proves that the employed feature extraction and classification techniques possess a significant impact on the system overall accuracy and performance. The main advantage of the ensemble classifiers is their self-configurability as a function of the employed training dataset.

Based on the results obtained during this study, the followings points can be highlighted:

a. The TQWT based features extraction significantly improves the studied sEMG signal classification accuracy. It is because of the inherent robustness of TQWT against the input signal artifacts and noise.
b. The high classification accuracy of ensemble SVM classifier shows that by employing the features obtained with the TQWT leads towards a correct distinction among different sEMG signal classes.
c. The employment of TQWT with Rotation Forest, Random Forest and k-NN based classifiers are also suitable for the identification of the sEMG signals. However, the SVM based classifiers outperform due to their higher classification accuracy and robustness.
d. The selection of a proper non-linear function, which will accurately map the input to a higher dimensional space, is one of the main problems in the SVM classifiers training. A variety of nonlinear functions can be employed such as the Polynomial, the Gaussian, Puk etc. A suitable choice should be made as a function of the intended problem. Hence we tried polynomial, RBF and Puk kernels and Puk kernel, which is a non-linear function, achieved the best accuracy.
e. The obtained findings have confirmed a noticeable superior performance of the employed TQWT and ensemble SVM classifier for the studied sEMG signal classification as compared to other studied classification methods and the methods already existed in literature.
f. SVM is the best in combination with one of the boosting ensemble methods (Adaboost and MultiBoost) with high accuracy up to 100%.
g. Most of the classifier's accuracy increased at least one ensemble classifier. But in some cases, the accuracy is not affected even decreased.
h. As it can be seen easily from the tables, the ensemble classifiers improve the performance of weak classifier significantly as compared with other single classifiers.
i. The drawback of ensemble models is significant increase on the computational cost.
j. The average computational cost of Adaboost and multiboost almost the same (0.12 s) whereas the computational cost of Bagging is four times higher (0.5 s) than the boosting algorithms. But if we implement algorithms in a parallel environment the Multiboost can be faster than Adaboost. The AdaBoost is naturally sequential, which prevent the parallel computation, whereas, MultiBoost in which the classifiers are learned with wagging are independent of the others and makes parallel computation possible for MultiBoost.

4 Conclusion

Hands play an important role in gripping and handling the different objects. Just the loss of a single hand affects human activity. A prosthetic hand is an attractive alternative in this regard for the subjects who have lost their heads. The surface electromyogram (sEMG) plays a critical role in the construction of the prostheses hands. The hand prostheses are controlled mainly by sEMG signals. In addition, a small number of the muscles remain in the stub of the arm after the loss of a hand. Hence, the prosthetic hand can be controlled by leveraging the sEMG. However, there are various issues with reliable detection of hand gestures by using the sEMG signals. To alleviate these problems and improve the classification accuracy, a suitable combination of the feature extraction techniques and the classification method should be utilized.

In this paper a novel approach is presented for recognizing the sEMG patterns. It is based on the TQWT and the Bagging and Boosting ensemble classifiers. The TQWT features extracted from the sEMG signals are intelligently employed by the ensemble classifiers in order to achieve a higher degree of accuracy in recognizing each of the six targeted hand movements. A performance comparison is made between the single classifier models and the ensemble classifier models. Results have demonstrated that the ensemble classifier models outperform the single classifier models. A substantial enhancement in the classification performance is observed for all the considered subjects. The proposed ensemble classification model has relatively revealed the outstanding results. In this case, the maximum average classification accuracy, achieved with the TQWT extracted features is 100%. It can be concluded that the proposed boosting ensemble classifier model with the TQWT feature extraction can be effectively used in the recognition of complex hand movements and ultimately for the prosthesis hand control.

For the future direction, we are planning to include more subjects and also include deep learning models.

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