

EEG-based emotion recognition using tunable Q wavelet transform and rotation forest ensemble classifier

Abdulhamit Subasi^{a,b,*}, Turker Tuncer^c, Sengul Dogan^c, Dahiru Tanko^c, Unal Sakoglu^d

^a Institute of Biomedicine, Faculty of Medicine, University of Turku, Turku, Finland

^b Department of Computer Science, College of Engineering, Effat University, Jeddah, 21478, Saudi Arabia

^c Department of Digital Forensics Engineering, College of Technology, Firat University, Elazig, 23119, Turkey

^d Computer Engineering, College of Science and Engineering, University of Houston – Clear Lake, Houston, TX, 77058, USA

ARTICLE INFO

Keywords:

Electroencephalogram (EEG)
Emotion recognition (ER)
Tunable Q wavelet transform (TQWT)
Machine learning
Rotation forest

ABSTRACT

Emotion recognition by artificial intelligence (AI) is a challenging task. A wide variety of research has been done, which demonstrated the utility of audio, imagery, and electroencephalography (EEG) data for automatic emotion recognition. This paper presents a new automated emotion recognition framework, which utilizes electroencephalography (EEG) signals. The proposed method is lightweight, and it consists of four major phases, which include: a reprocessing phase, a feature extraction phase, a feature dimension reduction phase, and a classification phase. A discrete wavelet transforms (DWT) based noise reduction method, which is hereby named multi scale principal component analysis (MSPCA), is utilized during the pre-processing phase, where a Symlets-4 filter is utilized for noise reduction. A tunable Q wavelet transform (TQWT) is utilized as feature extractor. Six different statistical methods are used for dimension reduction. In the classification step, rotation forest ensemble (RFE) classifier is utilized with different classification algorithms such as k-Nearest Neighbor (k-NN), support vector machine (SVM), artificial neural network (ANN), random forest (RF), and four different types of the decision tree (DT) algorithms. The proposed framework achieves over 93 % classification accuracy with RFE + SVM. The results clearly show that the proposed TQWT and RFE based emotion recognition framework is an effective approach for emotion recognition using EEG signals.

1. Introduction

Emotions are among the most distinctive features of humans; they affect a person's behavior and actions [1,2]. Understanding and analyzing human emotions is important part of human life. Recently, there has been an increased interest in automatic emotion classification by machine learning and artificial intelligence, since this could be used in human-computer interfaces (HCI) with a variety of applications [3–5]. These studies have shown that successful understanding of human emotions can lead to successful interactions between humans and computers, and potentially artificial emotional intelligence could be implemented by computer systems [6,7].

In order for an artificial emotional intelligent system to be successful, the system needs to possess a good knowledge about the human emotional understanding and the relationship between the affective expression and emotional expression [8]. Human-machine interfaces

and collaboration exist in many domains such as health, therapy, gaming, to name a few. Researchers are constantly trying to increase the flexibility and efficiency of the interaction between computers and humans, and they strive to achieve high levels of satisfaction among users. Therefore, HCI systems require the ability to achieve a thorough understanding of different human emotions and emotional expression. Human thoughts and emotions can be expressed through verbal or nonverbal expressions, therefore, HCI systems need to understand, discern and analyze nonverbal expressions of humans. Recently, HCI systems have shown promise in helping understand the emotional behavior of a person, which is called “emotional computing” [9].

Electroencephalography (EEG), which can measure the neural activity in the brain with the use of contact electrodes that are placed on the scalp, has emerged as an important technology for HCI systems to utilize. EEG experiments have been used for decades to detect electrical signals from brain cortex while participants undertake different tasks or

* Corresponding author at: Institute of Biomedicine, Faculty of Medicine, University of Turku, 20520, Turku, Finland.

E-mail addresses: abdulhamit.subasi@utu.fi, absubasi@effatuniversity.edu.sa (A. Subasi), turkertuncer@firat.edu.tr (T. Tuncer), sdogan@firat.edu.tr (S. Dogan), sakoglu@uhcl.edu (U. Sakoglu).

<https://doi.org/10.1016/j.bspc.2021.102648>

Received 30 October 2020; Received in revised form 4 April 2021; Accepted 10 April 2021

Available online 16 April 2021

1746-8094/© 2021 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

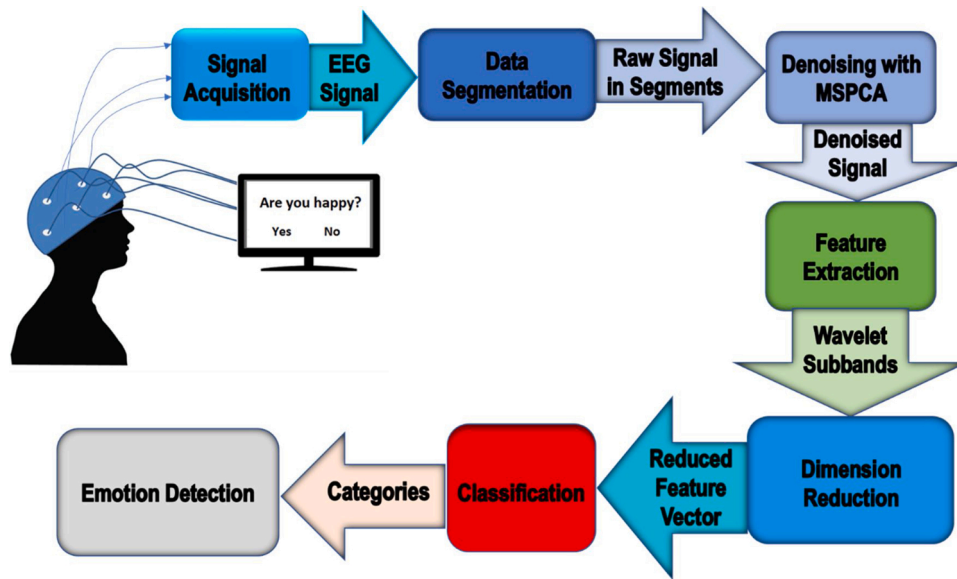


Fig. 1. EEG based Emotion Recognition Framework for HCI.

view different stimuli. EEG signals are usually highly-varying and noisy voltage signals, hence the features extracted from EEG usually vary dramatically. A great advantage of the EEG, though, is its temporal resolution: EEG's temporal resolution is much finer/faster than the speed of emotional changes, therefore, EEG can potentially capture, track and discern between emotional changes. Due to the fuzzy boundaries between different emotions, EEG-based emotion recognition (ER) is still very difficult. This is why there has not been much research done on ER using ensemble classifiers. Within this article, we offer a short summary of the related study on emotional models, the role of movie within emotional induction and different methods for EEG-based emotion classification. We utilize EEG signals and apply a novel signal processing and analysis methods to evaluate the output from EEG data in classifying three emotion states. We use the TQWT technique to identify neural signs and steady trends for diverse emotions and assess the steadiness of our models of emotion recognition. Our approach is similar to a recently developed method which combined feature extraction method to recognize six basic emotional states, including irritation, objection, terror, sadness, happiness, and surprise [10].

A framework of emotion recognition system is presented in Fig. 1, which establishes the methodological framework in this study. In the methodology presented in Fig. 1, a multiscale principal component analysis (MSPCA) is utilized for removing the various types of the artifacts and disturbances after acquisition and segmentation of the signal [11]. In the second stage, useful features are extracted, and they are used to train the classifier using TQWT. Subsequently, dimension reduction is employed to decrease unnecessary features in order to accomplish better recognition performance [12]. The framework, using ensemble classifiers, can consequently achieve improved classification accuracy.

The research motivation of this study is threefold: employment of MSPCA for noise removal, TQWT [13] for feature extraction, and employment of rotational forest ensemble classifier for classification. Even though these methods are not novel on their own, the combination as a framework represents a novel framework. Current studies are drifting towards the developing ensemble classifiers [14]. For example, Tsai [15] identified the reliability of the ensemble classifiers on the mixture of different classifiers to achieve a higher performance by removing each "oversight" in a single classifier [16]. Diverse harmonized models are used to build homogenous classifier ensembles in biomedical signal classification and the learning algorithm utilizing the harmonized model achieved a higher classification accuracy [17]. Since ensemble techniques diminish the effect of variation in the signal by

averaging classifier outputs [18], there are numerous researches on optimizing the recognition rate of the emotion recognition systems in terms of the classification accuracy and training time. Alickovic and Subasi [19] used an ensemble model to improve the classification performance utilizing SVM-based ensembles. Nevertheless, these algorithms achieved minor improvements [20]. Subasi et al. [21] suggested a signal recognition system by using bagging ensemble models having diverse classification models in order to accomplish better recognition accuracy. Subasi et al. [22] also employed Adaboost ensemble classifier in healthcare application.

Yang et al. [23] suggested a hierarchical structure of the network with other network branches to differentiate 3 human affective states or emotions: 1) positive; 2) negative; and 3) neutral. Every branch inside the network, which consists a considerably large number of nodes that are hidden, may be practical as an autonomous invisible layer for representing features. The experimental findings from using two separate EEG datasets indicate that a positive outcome is achieved by employment of both single and multiple modalities of the proposed technique. Y.-J. Liu et al. [24] developed a diverse collection of 16 emotional film clips, chosen from over 1000 film excerpts. Based on the emotional classes convinced by these film clips, they suggested an emotional recognition system induced by real-time video to recognize the emotional states of a person through brain wave analysis. Thirty subjects participated and watched 16 structured film clips characterizing emotional interactions in real-life and emphasizing seven distinct emotions and neutrality. These findings show the advantage in terms of classification accuracy over current high performing, real-time ER systems from EEG signals and the potential to identify related affective states close to the 2-dimensional valence-arousal domain. Various other feature selection and feature reduction methods have been proposed in the literature [25–30]. Similar studies presented in this field in the literature are presented in Table 1 below.

Our study presented in this paper employs a rotation forest ensemble classifier on emotion classification. To achieve the stated aims, a new emotion classification framework which relies on rotation forest ensemble classifier is introduced and it aims at improving the ER accuracy. Hence, the contribution of this research to studies on emotion recognition is employing TQWT feature extraction technique combined with rotation forest ensemble (RFE) classifier in emotion classification. Prior to this work, RFE models have been rarely used for EEG signal-based ER research. Moreover, usage of the TQWT-based feature extraction technique improved the accuracy of the suggested model. In

Table 1
Review of existing emotion recognition techniques from physiological signals.

	Problem	Method	Dataset	Evaluation Criteria
[31]	Emotion recognition from EEG	Fast Fourier transform, Bayes' theorem and supervised learning	DEAP [32]	Accuracy
[9]	Emotion recognition from multimodal physiological signals	Ensemble deep learning model	DEAP [32] multimedia database	Accuracy, Boxplot analysis,
[33]	Emotion recognition from EEG	Differential entropy, rational asymmetry, power spectral density, differential causality differential asymmetry, asymmetry	DEAP [32] and SEED [34] datasets	Accuracy
[35]	Emotional Feature Extraction	Dual-tree complex wavelet packet transform, SVD, SVM, F-ratio	DEAP [32]	Accuracy
[36]	EEG signal classification	Wavelet decomposition, PCA and SVM	Collected dataset	Accuracy
[37]	EEG emotion recognition	The recalibrated speech affective space model	Collected dataset	Accuracy
[38]	Emotion classification and recognition	The wavelet transform	DEAP [32] emotion database	Accuracy, Euclidean distances
[39]	Emotional state recognition	Multivariate synchrosqueezing transform	DEAP [32]	Accuracy
[40]	Emotion recognition	The deep belief network	Collected dataset	Accuracy
[41]	EEG signal classification	Circular back propagation and deep Kohonen neural networks	DEAP [32]	Accuracy, sensitivity, specificity
[42]	EEG-based emotion classification	Machine learning	DEAP [32]	Accuracy
[43]	Human emotion recognition	Deep Belief Network, Fine Gaussian SVM	DEAP [32]	Accuracy, Confusion matrix
[44]	Emotion and personality recognition	ASCERTAIN framework	Collected dataset	Accuracy

this paper, RFE classifier is proposed to achieve emotional EEG signal classification with high accuracy. RFE classifiers can suitably better acquire the essential features of EEG signals. Novelities of the presented work are given as below.

- A new emotion classification/recognition model which combines MSPCA denoising, TQWT-based feature extraction with rotation forest ensemble classifier is presented to provide a high classification performance from EEG data.
- This model is both highly accurate and computationally simple, when compared with various computationally demanding deep-learning based models which are used for emotion recognition from EEG data.

The paper is structured as follows: In Section 2, we elaborate on the details of the dataset, our classification model architecture and the overall framework. The results of the experiment are given in Section 3. Section 4 presents the conclusions and discussions.

2. Materials and methods

2.1. Participants and dataset

The publicly available SEED dataset [34] is used in this study. Fifteen test participants/subjects (seven males and eight females) with mean age of 23.3 and standard deviation (SD) of 2.4 participated in the experiments. The EEG dataset is composed of signals acquired from the subjects while the subjects were viewing emotional video tapes. To explore neural signs and notable reactions across different individuals and different EEG sessions, participants were asked to carry out the trials for three sessions each. This resulted in total of 45 experiment sessions in this dataset. The time interval between each session for each subject was a week or more. The facial expressions of the subjects were recorded during the EEG recording sessions ("facial videos"), concurrently. EEG signals were acquired employing an ESI NeuroScan System employing a sampling frequency of 1000 Hz from 62-channel active AgCl electrode cap in accordance with the standard 10–20 system. Selected emotional video clips were utilized as stimuli in the experiments for negative, positive and normal emotions. The time interval of every video clip is around four minutes. The EEG data were sampled down to 200 Hz. A lowpass frequency filter of 0–75 Hz was used [23,33,45]. Sample emotional EEG signals are given in Fig. 2.

2.2. Signal denoising with multi-scale PCA

PCA combines the variables as a linear weighted sum of transforms. The direction on the hyperplane which gives the highest achievable residual variance in the studied instances characterized by the principal components, whilst keeping orthonormality. Multi-scale PCA (MSPCA) is a combination of the principal component analysis and wavelets, and it eliminates the cross-correlation among instances [19,46]. In the implementation, Symlets four wavelet was utilized as a primary wavelet with 5 level decomposition.

2.3. Feature extraction with tunable Q wavelet transform (TQWT)

Reducing the input parameters to a classification algorithm, i.e. the number of features, to a number less than the number of samples, is important for a classification algorithm to perform successfully. For example, in electromyography (EMG), an electrical measurement technique similar to EEG, small number of carefully extracted features can help diagnose neuromuscular disorders. Wavelets are among the widely used techniques to reduce number of features in EEG and EMG. Using the TQWT, which simplify the signal into a series of simple functions, namely wavelets, we can obtain a signal decomposition with a high time resolution. The wavelets were computed from a single basis function ψ by expansion and translations of the basis function [47]. In general, the CWT (continuous wavelet transform) [48,49] for a continuous signal $x(t)$ is expressed as

$$CWT_x(\tau, a) = \int_{-\infty}^{\infty} x(at) \frac{1}{\sqrt{a}} \psi\left(\frac{t-\tau}{a}\right) dt, \quad (1)$$

where $\psi(t)$ is the primary wavelet function, a is the scale factor which translates the wavelet function across $x(t)$, and τ is a variable that has the role to tune the time scale of the wavelet function, ψ [48–50].

The TQWT is an imperative instrument for the moving signal breakdown or analysis. A TQWT has three main parameters, namely r , Q , and j which are tunable. Q represents the Q-factor; r represents the oversampling rate; and j represents the levels of decomposition. The amount of the wavelet oscillations are adjusted by Q , whereas r controls the unnecessary ringing to define the wavelet temporal localization while conserving its form [13,51]. Hypothetically, the appropriate wavelet transform Q-factor's value depends on the anticipated signal oscillatory behavior. Hence, the wavelet transform must possess a comparatively high Q-factor while breaking down and studying the oscillatory signals such as speech, electrocardiograph (ECG), EMG, EEG

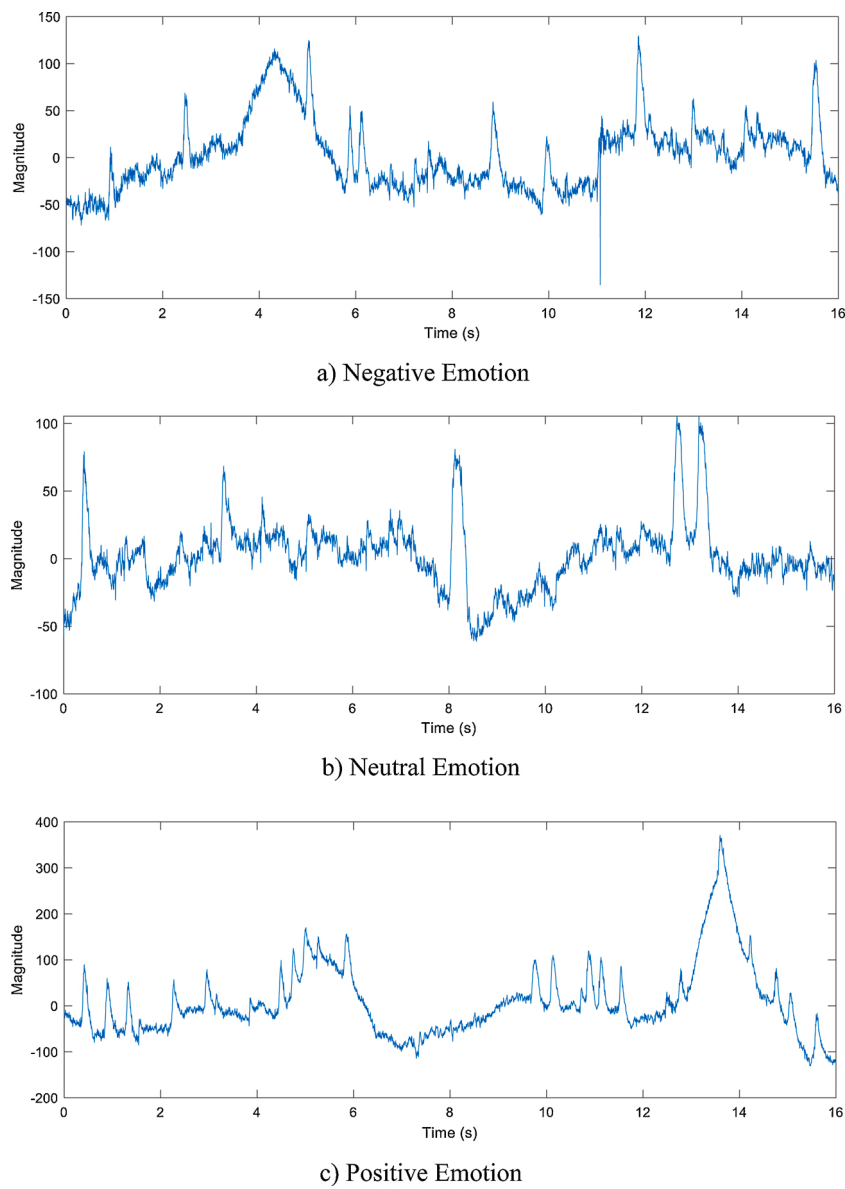


Fig. 2. Emotional EEG signals.

etc. Most of the time the wavelet transforms show an insignificant ability of tuning the Q-factor. Since they are limited to be used with certain applications, TQWT is proposed to overcome this problem. The exact rebuilding oversampled filter banks, with real scaling factors, are utilized to implement the TQWT. According to Selesnick [13] an effective implementation of the TQWT can be accomplished with a good over-sampling ratio. The TQWT has a significant similarity with the rational-dilation wavelet transform (RADWT) [52]. Similar to the RADWT, TQWT is discrete-time and moderately over-sampled to keep the perfect reconstruction capability. As compared to the RADWT, the TQWT is computationally more efficient because of its intelligent construction which is based on the radix-2 fast Fourier transforms (FFTs). Furthermore, it is easily configurable as a function of the intended application since the configuration can be done by tuning its three parameters, Q , r and j [13].

2.4. Dimension reduction

One method of reducing EEG data dimension is to use the 1st, 2nd, 3rd and 4th order statistics of the sub-bands, and the feature set being

minimized, which is computed from the sub-bands of the signal decomposition. Specifically, the following six statistical features were computed:

1. Mean absolute value (MAV) of each sub-band,
2. Average power of each sub-band,
3. Standard deviation of each sub-band,
4. Absolute mean values of adjacent sub-bands' ratios,
5. Skewness of each sub-band,
6. Kurtosis of each sub-band.

2.5. Rotation forest ensemble (RFE)

One ensemble learning approach that has the basic objective of constructing diverse but precise classifiers is the rotation forest ensemble (RFE). A bagging approach alongside random sub-space approach are combined with PCA to build an ensemble of decision trees. The input variables are spread in a random manner into k disjoint subsets in each iteration. To generate a linear combination of the subsets variables which are rotational movement of the foremost axes, PCA is

Table 2
EEG signal classification accuracy for three different emotional states without MSPCA Denoising.

Classifier	Single				Rotation Forest Ensemble (RFE)			
	Negative	Neutral	Positive	Average	Negative	Neutral	Positive	Average
SVM	0.903	0.858	0.855	0.872	0.932	0.537	0.68	0.716
k-NN	0.748	0.544	0.553	0.615	0.873	0.692	0.784	0.783
ANN	0.5	0.1	0.4	0.333	0.894	0.708	0.799	0.8
Random Forest	0.895	0.744	0.862	0.834	0.938	0.836	0.907	0.894
CART	0.835	0.689	0.807	0.777	0.934	0.846	0.898	0.893
C4.5	0.829	0.709	0.795	0.778	0.947	0.863	0.915	0.908
REPTree	0.836	0.621	0.797	0.751	0.938	0.847	0.898	0.894
LADTree	0.752	0.395	0.607	0.585	0.918	0.813	0.887	0.873

utilized for every subset in turn. To evaluate the values for the extracted features, k sets of principal components (PC) are utilized; at each iteration they provide the feedback to the tree learner. Owing to the preservation of all the components acquired on each subclass, the number of the generated attributes is as many as the original ones. PCA is utilized for the training examples from a selected sub-set of class values at random in order to avoid the creation of similar coefficients as a result of selecting same feature sub-set in different iterations. Although the values of the extracted features sent into the decision tree learning model are determined from all the examples in the training set. A small amount of the dataset can be produced in every iteration before implementing PC transformations, in order to further increase diversity. Experiments suggest that rotation forest can offer a comparable output to random forests, with a smaller number of trees. A recent study of diversity which is measured by the Kappa statistics that is employed in evaluating the agreement amongst classifiers against error for pairs of elements of an ensemble, indicates a marginal improvement in diverseness and a reduction in error in rotation forests compared to bagging, this seems to translate into considerably improved results for the ensemble in general [53].

We denote the training data matrix with X , and we assume L number of classifiers in the classifier ensemble D_1, \dots, D_L . F represents the feature set. The number L should be set beforehand as in most ensemble methods. We implement the following procedures in order to establish the training example for D_i :

1. Distribute F to K arbitrary separate subsets (K is set at the beginning) in order to obtain the maximum chance for the highest diversity. For a given number of samples N , all feature subset includes $M = N/K$ features (assuming K to be a factor of N for the sake of simplicity; if not, every feature subset includes roughly $M = N/K$ features each).
2. represent the j th subset of features for the training set of classifier D_i by $F_{i,j}$, pick arbitrarily subset of classes that are not empty for each subset and make a bootstrap of objects with the %75 of the dataset. Do PCA by making use of the M features in $F_{i,j}$ only, and the chosen subset of training data X . Save the coefficients of the PC, each of size $M \times 1$. There is possibility of some eigenvalues being 0 (zero), so we might not get all M vectors. Therefore, $M_j \leq M$. We run a PCA (principal component analysis) on a subset of classes so as to refrain from identical coefficients in the case that we have the exact feature subset for various distinct classifiers.

Table 3
F-measure, ROC area (AUC) and kappa statistic for EEG signal classification without MSPCA Denoising.

Classifier	F-Measure		ROC area (AUC)		Kappa	
	Single	Rotation Forest	Single	Rotation Forest	Single	Rotation Forest
SVM	0.873	0.713	0.928	0.884	0.808	0.5745
k-NN	0.616	0.782	0.711	0.917	0.4225	0.6745
ANN	0.306	0.799	0.497	0.934	0	0.7005
Random Forest	0.833	0.893	0.948	0.978	0.7505	0.8405
CART	0.776	0.892	0.854	0.975	0.6655	0.839
C4.5	0.778	0.908	0.844	0.982	0.6665	0.8625
REPTree	0.749	0.894	0.874	0.976	0.627	0.8415
LADTree	0.577	0.872	0.775	0.971	0.377	0.809

3. The extracted vectors with coefficients should be arranged in a scattered rotation matrix R_i . To measure the training example for D_i classifier, the columns of R_i are reorganized to match the original features. Designate the reorganized rotation matrix, which is of size $N \times n$ [54].

3. Results

3.1. Performance evaluation

For performance evaluation, we use basic performance measures such as overall accuracy, F-measure, kappa statistic (KS) and area under the ROC curve (AUC). True Negative (TN) and True Positive (TP) are the correct predictions while a False Positive (FP) just like the name implies, is falsely predicted as positive (whereas it is actually negative) and a False Negative (FN) is falsely classified as negative (whereas it is actually positive) [53]. The ROC curve is a graphical tool for evaluating classifier efficiency. ROC curves reflect a classifier’s output without taking into account the costs of error or the class distribution. In the ROC curve, the TP rate is denoted by the vertical axis while FP rate is denoted by the horizontal axis. If the class distributions and costs are not known, the area under the ROC curve is convenient, and one model is selected to denote all cases. The KS is an evaluation metric which takes into account the desired figure by extracting it from the accomplishments of the classifier, expressing the result as a percentage of the number of the noticed classes and the expected classes, while adapting to a relationship that happens by chance. Nevertheless, factors like the basic success rate are not taken into account [53]. Cohen [55] described the kappa statistic as an agreement index as follows,

$$K = \frac{P_0 - P_e}{1 - P_e} \tag{2}$$

where P_0 is the observed agreement and defined as

$$P_0 = \frac{TN + TP}{TN + TP + FP + FN} \tag{3}$$

The probability of random agreement is measured by P_e [10]. Total random agreement probability is the probability that they agree on either “Yes” or “No”, i.e.:

$$P_e = P_{YES} + P_{NO} \tag{4}$$

Table 4

EEG signal classification accuracy for three different emotional states with MSPCA Denoising.

Classifier	Single				Rotation Forest Ensemble (RFE)			
	Negative	Neutral	Positive	Average	Negative	Neutral	Positive	Average
SVM	0.941	0.9	0.934	0.925	0.952	0.906	0.936	0.931
k-NN	0.879	0.793	0.897	0.856	0.928	0.827	0.912	0.889
ANN	0.889	0.838	0.918	0.882	0.941	0.862	0.942	0.915
Random Forest	0.883	0.794	0.897	0.858	0.925	0.862	0.933	0.907
CART	0.781	0.701	0.84	0.774	0.927	0.834	0.895	0.885
C4.5	0.8	0.715	0.829	0.781	0.923	0.836	0.898	0.886
REP Tree	0.77	0.697	0.827	0.765	0.915	0.811	0.883	0.87
LAD Tree	0.803	0.727	0.824	0.785	0.896	0.812	0.891	0.866

Table 5

F-measure, ROC area (AUC) and kappa statistic for EEG signal classification with MSPCA Denoising.

Classifier	F-measure		ROC area (AUC)		Kappa	
	Single	Rotation Forest	Single	Rotation Forest	Single	Rotation Forest
SVM	0.925	0.931	0.957	0.982	0.8875	0.897
k-NN	0.856	0.888	0.915	0.973	0.7845	0.8335
ANN	0.882	0.915	0.963	0.983	0.8225	0.8725
Random Forest	0.858	0.906	0.959	0.983	0.787	0.86
CART	0.773	0.885	0.865	0.973	0.661	0.828
C4.5	0.781	0.885	0.837	0.976	0.672	0.8285
REP Tree	0.764	0.869	0.878	0.971	0.647	0.8045
LAD Tree	0.785	0.866	0.922	0.97	0.677	0.7995

where

$$P_{YES} = \frac{FP + TP}{TN + TP + FP + FN} * \frac{FN + TP}{TN + TP + FP + FN} \quad (5)$$

$$P_{NO} = \frac{FN + TN}{TP + TN + FP + FN} * \frac{FP + TN}{TN + TP + FP + FN} \quad (6)$$

3.2. Experimental results

Table 2 presents classification accuracy results using eight different classifiers e.g., Artificial Neural Network, k-NN, SVM, RF, C4.5, CART, REP tree, and LAD tree. The left half of the table presents single classifier results whereas the right half presents the RFE results. Table 3 presents the other aforementioned classification performance results, i.e., F-measure, ROC area, and Kappa values. The classifiers are run several times to achieve the highest performance with trial-and-error method. The best performance is achieved with RFE + SVM. In the implementation of the random forest ensemble classifier, the default values are used in WEKA.¹ In the the implementation of the SVM, the PUK kernel with a C value of 100 is used. As shown from the results in Tables 2–5, three main findings can be observed: a) the model with the highest performance (accuracy) uses the SVM, and the one with the lowest performance uses the LAD tree; b) the RFE always outperforms the single classification method; c) The MSPCA denoising increased the performance of the classifiers.

3.3. Discussion

This research presents a novel electroencephalography (EEG) based ER framework. The suggested approach consists of four major stages, namely MSPCA denoising, TQWT feature extraction, dimension reduction and classification with RFE. Eight different conventional classifiers models are used in the classification phase and a comprehensive benchmark is obtained. According to the obtained results from Tables 2–5, the classifier with the best result is the SVM with RFE

ensemble technique and the worst one is the LAD tree. To systematically assess the effectiveness of the suggested technique, the emotion recognition accuracy, F-measure, AUC and Kappa statistics are used. To show success of the suggested technique, different well-known methods are employed for comparison purposes. This paper is one of the first application which utilizes combined TQWT and RFE classifier framework for the EEG based emotion recognition. There are several studies which used various feature extraction and classification approaches. The accuracy of the suggested approach is also compared with seven widely used state-of-art methods in Table 6. It can be seen from the table that the suggested approach in this study outperforms the previous studies for EEG-based emotion recognition.

As shown in Table 6, the proposed framework outperforms in terms of emotion recognition accuracy. These results clearly show the effectiveness of the proposed framework in EEG based emotion recognition when compared to other existing methods. Also, the approach achieved approximately 18 % higher recognition rate than the deep learning method. The merits of the method are given as below.

- A novel lightweight approach is used because whole components of the proposed have basic mathematical background.
- The proposed approach can easily be employed to tackle signal processing hiccups because the proposed method is very simple.
- The proposed feature extraction method is very effective because high classification rates are achieved by using the suggested TQWT-based feature extraction method. This situation clearly shows that the features extracted are distinctive.
- A highly accurate EEG based emotion recognition framework is proposed. The comparisons are also shown the success of the proposed approach.

Demerits of the newly proposed method are;

- The method can be tested on bigger and heterogeneous datasets.
- In this dataset, we classified positive, negative and neutral emotions. Variable emotions for instance surprise, anger, sadness, disgust, etc. can be used to test the proposed TQWT based method.

¹ <https://www.cs.waikato.ac.nz/ml/weka/>

Table 6

Comparison of the classification accuracies achieved by previous studies and the proposed study.

The study reference	Feature Extraction Method	Classifier	Classification Accuracy
Yan et al method [56]	Sparse Learning	SVM	69.00
Li et al method [57]	Convolutional and LSTM Recurrent Neural Networks	SVM	75.21
Wu et al method [58]	Fast Fourier Transform	SVM	76.34
Chai et al method [59]	Adaptive Subspace Feature Matching	SVM	81.09
Alazrai et al method [60]	Quadratic Time-Frequency Distribution	SVM	83.1
Zhao et al method [61]	Support Vector Machine	SVM	86.11
Liu et al method [24]	Short-Time Fourier Transform	SVM	92.26
The Proposed Framework	MSPCA + TQWT	Rotation Forest with SVM	93.1

4. Conclusions

This study presents a novel TQWT and rotation forest ensemble classifier-based emotion recognition framework by using EEG signals. The proposed framework consists of MSPCA-based denoising, TQWT-based feature extraction, dimension reduction with statistical values and classification by using eight conventional classifiers widely considered as benchmarks. The proposed TQWT-based framework achieved 93.1 % classification accuracy using RFE + SVM ensemble classifier. In summary, in this paper, a novel and highly accurate EEG signal processing method for emotion recognition is presented. The proposed technique is lightweight and its mathematical models are simple. Since it is automated, there is no meta-heuristic optimization method involved in order to increase classification accuracy.

In the future studies, our novel TQWT-based RFE emotion recognition framework can be utilized to analyze other EEG datasets from different experiments, and other biomedical signals such as ECG and EMG. Testing and validating the proposed method on bigger and heterogeneous datasets is of interest. In this study, we only classified positive, negative and neutral emotions. Using a wider variety of emotions such as surprise, anger, sadness, disgust, etc. in order to test the proposed TQWT-based RFE emotion recognition framework would also be of great interest.

Funding

This work was supported by Effat University with the Decision Number of UC#7/28 Feb. 2018/10.2-44i (to Prof. Subasi), Jeddah, Saudi Arabia.

CRedit authorship contribution statement

All algorithm codes are written and run by Abdulhamit Subasi.
Part of Introduction and results are written by Turker Tuncer.
Part of Introduction and Conclusion are written by Sengul Dogan.
Part of Introduction, Methods and results are written by *Dahiru Tanko*.
Part of Introduction, Methods, Results and Discussion are written by Abdulhamit Subasi.
The whole manuscript revised by Abdulhamit Subasi and Unal Sakoglu.

Declaration of Competing Interest

The authors declare no conflict of interest.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at <https://doi.org/10.1016/j.bspc.2021.102648>.

References

- [1] P.C. Petrantonakis, L.J. Hadjileontiadis, Emotion recognition from EEG using higher order crossings, *IEEE Trans. Inf. Technol. Biomed.* 14 (2009) 186–197.
- [2] M. Murugappan, R. Nagarajan, S. Yaacob, Comparison of different wavelet features from EEG signals for classifying human emotions, 2009 *IEEE Symposium on Industrial Electronics & Applications: IEEE* (2009) 836–841.
- [3] C. Qing, R. Qiao, X. Xu, Y. Cheng, Interpretable emotion recognition using EEG signals, *IEEE Access* 7 (2019) 94160–94170.
- [4] F. Afza, M.A. Khan, M. Sharif, S. Kadry, G. Manogaran, T. Saba, et al. A framework of human action recognition using length control features fusion and weighted entropy-variances based feature selection. *Image Vis. Comput.* 106:104090.
- [5] M.A. Khan, S. Kadry, P. Parwekar, R. Damasevicius, A. Mehmood, J.A. Khan, et al., Human gait analysis for osteoarthritis prediction: a framework of deep learning and kernel extreme learning machine, *Complex Intell. Syst.* (2021).
- [6] Y. Dastdemir, E. Yildirim, S. Yildirim, Analysis of functional brain connections for positive–negative emotions using phase locking value, *Cogn. Neurodyn.* 11 (2017) 487–500.
- [7] A. Goshvarpour, A. Goshvarpour, EEG spectral powers and source localization in depressing, sad, and fun music videos focusing on gender differences, *Cogn. Neurodyn.* 13 (2019) 161–173.
- [8] S.N. Daimi, G. Saha, Classification of emotions induced by music videos and correlation with participants' rating, *Expert Syst. Appl.* 41 (2014) 6057–6065.
- [9] Z. Yin, M. Zhao, Y. Wang, J. Yang, J. Zhang, Recognition of emotions using multimodal physiological signals and an ensemble deep learning model, *Comput. Methods Programs Biomed.* 140 (2017) 93–110.
- [10] Y. Zhang, X. Ji, S. Zhang, An approach to EEG-based emotion recognition using combined feature extraction method, *Neurosci. Lett.* 633 (2016) 152–157.
- [11] R. Yuvaraj, M. Murugappan, Hemispheric asymmetry non-linear analysis of EEG during emotional responses from idiopathic Parkinson's disease patients, *Cogn. Neurodyn.* 10 (2016) 225–234.
- [12] A. Ghaemi, E. Rashedi, A.M. Pourrahimi, M. Kamandar, F. Rahdari, Automatic channel selection in EEG signals for classification of left or right hand movement in Brain Computer Interfaces using improved binary gravitation search algorithm, *Biomed. Signal Process. Control* 33 (2017) 109–118.
- [13] I.W. Selesnick, Wavelet transform with tunable Q-factor, *IEEE Trans. Signal Process.* 59 (2011) 3560–3575.
- [14] L. da Silva-Sauer, L. Valero-Aguayo, A. de la Torre-Luque, R. Ron-Angevin, S. Varona-Moya, Concentration on performance with P300-based BCI systems: a matter of interface features, *Appl. Ergon.* 52 (2016) 325–332.
- [15] C.-F. Tsai, Combining cluster analysis with classifier ensembles to predict financial distress, *Inf. Fusion* 16 (2014) 46–58.
- [16] A. Gicic, A. Subasi, Credit scoring for a microcredit data set using the synthetic minority oversampling technique and ensemble classifiers, *Expert. Syst.* 36 (2019), e12363.
- [17] B. Blankertz, K.-R. Muller, D.J. Krusienski, G. Schalk, J.R. Wolpaw, A. Schlogl, et al., The BCI competition III: validating alternative approaches to actual BCI problems, *IEEE Trans. Neural Syst. Rehabil. Eng.* 14 (2006) 153–159.
- [18] A. Rakotomamonjy, V. Guigue, BCI competition III: dataset II-ensemble of SVMs for BCI P300 speller, *IEEE Trans. Biomed. Eng.* 55 (2008) 1147–1154.
- [19] E. Alickovic, A. Subasi, Effect of multiscale PCA de-noising in ECG beat classification for diagnosis of cardiovascular diseases, *Circ. Syst. Signal Process.* 34 (2015) 513–533.
- [20] Y.-R. Lee, H.-N. Kim, A data partitioning method for increasing ensemble diversity of an eSVM-based P300 speller, *Biomed. Signal Process. Control* 39 (2018) 53–63.
- [21] A. Subasi, E. Yaman, Y. Somaali, H.A. Alyanabawi, F. Alobaidi, S. Altheibani, Automated EMG signal classification for diagnosis of neuromuscular disorders using DWT and bagging, *Procedia Comput. Sci.* 140 (2018) 230–237.
- [22] A. Subasi, D.H. Dammas, R.D. Alghamdi, R.A. Makawi, E.A. Albiety, T. Brahimi, et al., Sensor based human activity recognition using adaboost ensemble classifier, *Procedia Comput. Sci.* 140 (2018) 104–111.
- [23] Y. Yang, Q.-J. Wu, W.-L. Zheng, B.-L. Lu, EEG-based emotion recognition using hierarchical network with subnetwork nodes, *IEEE Trans. Cogn. Dev. Syst.* 10 (2017) 408–419.
- [24] Y.-J. Liu, M. Yu, G. Zhao, J. Song, Y. Ge, Y. Shi, Real-time movie-induced discrete emotion recognition from EEG signals, *IEEE Trans. Affect. Comput.* 9 (2017) 550–562.

- [25] F. Afza, M.A. Khan, M. Sharif, T. Saba, A. Rehman, M.Y. Javed, Skin lesion classification: an optimized framework of optimal color features selection, 2020 2nd International Conference on Computer and Information Sciences (ICIS): IEEE (2020) 1–6.
- [26] M.A. Khan, M.S. Sarfraz, M. Alhaisoni, A.A. Albeshier, S. Wang, I. Ashraf, StomachNet: optimal deep learning features fusion for stomach abnormalities classification, *IEEE Access* 8 (2020) 197969–197981.
- [27] A. Rehman, M.A. Khan, T. Saba, Z. Mehmood, U. Tariq, N. Ayesha, Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture, *Microsc. Res. Tech.* 84 (2021) 133–149.
- [28] M.A. Khan, M. Qasim, H.M.J. Lodhi, M. Nazir, K. Javed, S. Rubab, et al., Automated design for recognition of blood cells diseases from hematopathology using classical features selection and ELM, *Microsc. Res. Tech.* 84 (2021) 202–216.
- [29] H. Arshad, M.A. Khan, M.I. Sharif, M. Yasmin, J.M.R. Tavares, Y.D. Zhang, et al., A multilevel paradigm for deep convolutional neural network features selection with an application to human gait recognition, *Expert. Syst.* (2020), e12541.
- [30] M.A. Khan, Y.-D. Zhang, S.A. Khan, M. Attique, A. Rehman, S. Seo, A resource conscious human action recognition framework using 26-layered deep convolutional neural network, *Multimed. Tools Appl.* (2020) 1–23.
- [31] H.J. Yoon, S.Y. Chung, EEG-based emotion estimation using Bayesian weighted-log-posterior function and perceptron convergence algorithm, *Comput. Biol. Med.* 43 (2013) 2230–2237.
- [32] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, et al., Deap: a database for emotion analysis; using physiological signals, *IEEE Trans. Affect. Comput.* 3 (2011) 18–31.
- [33] W.-L. Zheng, J.-Y. Zhu, B.-L. Lu, Identifying stable patterns over time for emotion recognition from EEG, *IEEE Trans. Affect. Comput.* (2017).
- [34] <http://bcmi.sjtu.edu.cn/~seed/>.
- [35] D.S. Naser, G. Saha, Recognition of emotions induced by music videos using DT-CWPT, 2013 Indian Conference on Medical Informatics and Telemedicine (ICMIT): IEEE (2013) 53–57.
- [36] D. Iacoviello, A. Petracca, M. Spezialetti, G. Placidi, A real-time classification algorithm for EEG-based BCI driven by self-induced emotions, *Comput. Methods Programs Biomed.* 122 (2015) 293–303.
- [37] M. Othman, A. Wahab, I. Karim, M.A. Dzulkipli, I.F.T. Alshaikli, EEG emotion recognition based on the dimensional models of emotions, *Procedia-Social Behav. Sci.* 97 (2013) 30–37.
- [38] G.K. Verma, U.S. Tiwary, Multimodal fusion framework: a multiresolution approach for emotion classification and recognition from physiological signals, *NeuroImage* 102 (2014) 162–172.
- [39] A. Mert, A. Akan, Emotion recognition based on time–frequency distribution of EEG signals using multivariate synchrosqueezing transform, *Digit. Signal Process.* 81 (2018) 106–115.
- [40] S.-K. Kim, H.-B. Kang, An analysis of smartphone overuse recognition in terms of emotions using brainwaves and deep learning, *Neurocomputing* 275 (2018) 1393–1406.
- [41] D.J. Hemanth, J. Anitha, Brain signal based human emotion analysis by circular back propagation and Deep Kohonen Neural Networks, *Comput. Electr. Eng.* 68 (2018) 170–180.
- [42] D.D. Chakladar, S. Chakraborty, EEG based emotion classification using “Correlation based Subset Selection”, *Biol. Inspired Cogn. Archit.* 24 (2018) 98–106.
- [43] M.M. Hassan, M.G.R. Alam, M.Z. Uddin, S. Huda, A. Almogren, G. Fortino, Human emotion recognition using deep belief network architecture, *Inf. Fusion* 51 (2019) 10–18.
- [44] R. Subramanian, J. Wache, M.K. Abadi, R.L. Vieriu, S. Winkler, N. Sebe, ASCERTAIN: Emotion and personality recognition using commercial sensors, *IEEE Trans. Affect. Comput.* 9 (2016) 147–160.
- [45] W.-L. Zheng, B.-L. Lu, Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks, *IEEE Trans. Auton. Ment. Dev.* 7 (2015) 162–175.
- [46] B.R. Bakshi, Multiscale PCA with application to multivariate statistical process monitoring, *AIChE J.* 44 (1998) 1596–1610.
- [47] M. Vetterli, C. Herley, Wavelets and filter banks: theory and design, *IEEE Trans. Signal Process.* 40 (1992) 2207–2232.
- [48] I. Daubechies, The wavelet transform, time-frequency localization and signal analysis, *IEEE Trans. Inf. Theory* 36 (1990) 961–1005.
- [49] O. Rioul, M. Vetterli, Wavelets and signal processing, *IEEE Signal Process. Mag.* 8 (1991) 14–38.
- [50] N.V. Thakor, B. Gramatikov, D. Sherman, Wavelet (time-scale) analysis in biomedical signal processing, *Medical Devices and Systems*, CRC Press, 2006, pp. 113–138.
- [51] S. Patidar, R.B. Pachori, Classification of cardiac sound signals using constrained tunable-Q wavelet transform, *Expert Syst. Appl.* 41 (2014) 7161–7170.
- [52] I. Bayram, I.W. Selesnick, Frequency-domain design of overcomplete rational-dilation wavelet transforms, *IEEE Trans. Signal Process.* 57 (2009) 2957–2972.
- [53] I.H. Witten, E. Frank, M.A. Hall, C.J. Pal, *Data Mining: Practical Machine Learning Tools and Techniques*, Morgan Kaufmann, 2016.
- [54] J.J. Rodriguez, L.I. Kuncheva, C.J. Alonso, Rotation forest: a new classifier ensemble method, *IEEE Trans. Pattern Anal. Mach. Intell.* 28 (2006) 1619–1630.
- [55] J. Cohen, A coefficient of agreement for nominal scales, *Educ. Psychol. Meas.* 20 (1960) 37–46.
- [56] Y. Yan, C. Li, S. Meng, Emotion recognition based on sparse learning feature selection method for social communication, *Signal Image Video Process.* (2019) 1–5.
- [57] Y. Li, J. Huang, H. Zhou, N. Zhong, Human emotion recognition with electroencephalographic multidimensional features by hybrid deep neural networks, *Appl. Sci.* 7 (2017) 1060.
- [58] S. Wu, X. Xu, L. Shu, B. Hu, Estimation of valence of emotion using two frontal EEG channels, 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM): IEEE (2017) 1127–1130.
- [59] X. Chai, Q. Wang, Y. Zhao, Y. Li, D. Liu, X. Liu, et al., A fast, efficient domain adaptation technique for cross-domain electroencephalography (EEG)-based emotion recognition, *Sensors* 17 (2017) 1014.
- [60] R. Alazrai, R. Homoud, H. Alwanni, M. Daoud, EEG-based emotion recognition using quadratic time-frequency distribution, *Sensors* 18 (2018) 2739.
- [61] G. Zhao, Y. Ge, B. Shen, X. Wei, H. Wang, Emotion analysis for personality inference from EEG signals, *IEEE Trans. Affect. Comput.* 9 (2017) 362–371.