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A Tunable-Q wavelet transform and quadruple symmetric pattern based EEG signal classification method

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ABSTRACT

Electroencephalography (EEG) signals have been widely used to diagnose brain diseases for instance epilepsy, Parkinson's Disease (PD), Multiple Skleroz (MS), and many machine learning methods have been proposed to develop automated disease diagnosis methods using EEG signals. In this method, a multilevel machine learning method is presented to diagnose epilepsy disease. The proposed multilevel EEG classification method consists of pre-processing, feature extraction, feature concatenation, feature selection and classification phases. In order to create levels, Tunable-Q wavelet transform (TQWT) is chosen and 25 frequency coefficients sub-bands are calculated by using TQWT in the pre-processing. In the feature extraction phase, quadruple symmetric pattern (QSP) is chosen as feature extractor and extracts 256 features from the raw EEG signal and the extracted 25 sub-bands. In the feature selection phase, neighborhood component analysis (NCA) is used. The 128, 256, 512 and 1024 most significant features are selected in this phase. In the classification phase, k nearest neighbors (kNN) classifier is utilized as classifier. The proposed method is tested on seven cases using Bonn EEG dataset. The proposed method achieved 98.4% success rate for 5 classes case. Therefore, our proposed method can be used in bigger datasets for more validation.

Introduction

In the human brain, there are billions neurons and these neurons communicate to each other by using tiny electrical signals. By using these electrical signals, brain activity is measured and these signals are called Electroencephalogram (EEG) [1–4]. The main objective of the use of EEG signals is to diagnose brain diseases. Epilepsy is one of the most commonly seen brain diseases and more than 70 million people suffer from epilepsy worldwide [5,6]. Epilepsy causes seizures and these seizures reduce quality of life. In order to predict the seizures of epilepsy patients and improve their living standards, seizures should be predicted by using EEG signals. Therefore, many machine learning based Epileptic EEG signal classification and recognition methods have been proposed to solve this problem [7–9]. Some studies about EEG classification are given below.

Richhariya and Tanveer [10] proposed a universum support vector machine (SVM)-based intelligent system for EEG classification. Their method consisted of feature extraction with ICA or wavelet transform, feature reduction using PCA, calculation of class discrimination ratio and classification with universum SVM. The results were presented with variable parameters and success rates were compared. Yilmaz et al. [11] presented quasi-probabilistic-based EEG Classification method. They used BCI dataset [12] to test the performance of their method. Accuracy, sensitivity, specificity and F-Measures parameters were utilized as performance metrics. Raghu and Sriraam [13] introduced a tool for focal and non-focal EEG signals classification. This method consisted of pre-processing, feature extraction, feature selection and classification phases. They extracted 28 features and these feature sets involved using the statistical attributes of EEG signals. Neighborhood Component Analysis (NCA) was utilized as feature selector. SVM, kNN, Random Forest (RF) and AdaBoost were used as classifiers. Rincon et al. [14] proposed an EEG detection method using supervised classification method for real time applications. Statistical attributes and wavelet filter were used together in the feature extraction phase and alpha, beta theta, gamma and delta band were obtained. Approximately higher than 95% accuracy was calculated for each band using this method and authors also indicated that this method had a short execution time. Shin et al. [15] suggested a robust EEG signal classification method against noise. They used a noise reduction method as a pre-processing step. They used SVMs and Spearman representation-based classification method as classifiers. Acharya et al. [16] presented a review about EEG classification methods based on computer aided detection (CAD). An

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intelligent EEG classification method consisted of pre-processing, feature extraction, feature ranking and classification phases and it was claimed that it is a widely used method. Ghayab et al. [17] proposed a wavelet scheme using Q-factor and this wavelet transform was used in feature extraction. They presented results for many classes of the EEG. Kocadagli and Langari [18] presented an EEG signal classification method using wavelet and fuzzy and used genetic algorithm. Kaya et al. [19] proposed a 1D local binary pattern (1D-LBP) to extract the features of EEG signals. They used BayesNet, SVM, Artificial Neural Network (ANN), logistic regression and functional tree as classifiers. Kaya and Ertugrul [20] introduced a stable and discriminative feature extraction using 1D ternary pattern. Orhan et al. [21] presented an approach using neural network and K-means for EEG signals. In this study, seven cases were defined as A-B-C-D, E, A, A-B, C-D-E, C-D, A-D-E and confusion matrixes were given to demonstrate the performance of the classification. Bhattacharyya et al. [22] presented a method for epilepsy detection from EEG signals. Wavelet transform was used to obtain feature set. Entropy of EEG signal was also calculated in this study. Support vector machine was utilized as classifier. Comparative results were presented according to SVM classifier. Sharma et al. [23] proposed a method for epileptic seizure diagnosis. The proposed method is based on fractal dimension and wavelet transform. Eight cases were defined as A-E, B-E, C-E, D-E, AB-E, CD-E, AB-CD, ABCD-E and the results were compared with current methods in literature. Tzallas et al. [24] presented an approach using neural networks and time-frequency analysis methods. The main objective of the study was to automatically detect the diagnosis of epileptic seizure. EEG signals were used for this objective and time-frequency analysis of these signals was performed. Gandhi et al. [25] proposed a method for EEG signal classification. In this method, wavelet transform and neural network were used to effectively extract features of EEG signals. The results were presented according to support vector machine classifier. Nicolaou and Georgiou [26] suggested an approach using support vector machine and permutation entropy. The results were presented according to average sensitivity, accuracy, specificity and time. Peker et al. [27] proposed a method based on wavelet transform and neural networks for EEG signals. These methods have been preferred for effective feature selection. The main objective of the study was to detect epilepsy disease automatically. Bhattacharyya et al. [28] presented an approach for EEG signal analysis. In this study, wavelet transform was used. Support vector machine and random forest were selected as classifiers. Sharma et al. [29] introduced a method for EEG signal classification using wavelet filters. CD-E, ABCD-E cases were defined for experiments. The comparison results were presented according to accuracy, specificity, and sensitivity. Higher order spectral (HOS) and deep learning-based methods have also been widely used in EEG signals classifications [30–33] As seen from related articles, most of them failed to give classification accuracy results for all of the five classes. Deep learning methods have high classification ability but high computational complexity. To solve these problems, a method based on 1D descriptor and multilevel wavelet is presented. The characteristics and contributions of this paper are given below.

In this study, TQWT and QSP based feature extraction network is presented. The main objective of this paper is to achieve high classification accuracy using EEG signals. The characteristics and contributions of the proposed method are given below.

- As we know from the literature, the pooling methods are not effective for machine learning [34]. Therefore, different methods should be used instead of pooling methods. In this study, TQWT is utilized as pooling method. Five Q values are used to generate frequency coefficients of the EEG signal to obtain high classification accuracy.
- In this study, an image descriptor is utilized as feature extractor and effectiveness of it is clearly shown. Because, descriptors extract both distinctive features and have low computational complexity [35–37]. In this study, QSP which is an image descriptor is utilized as feature extractor for EEG signals.
- NCA based feature selection method is used and variable features are selected to test the proposed TQWT and QSP based EEG classification method. By using variable size of features, high EEG classification capability of the proposed method is clearly shown.
- The proposed TQWT and QSP based method are tested using seven cases. Especially, the proposed method has very high results for five classes and achieved 98.40% classification accuracy.
- A multilevel learning method is presented and the proposed method has low computational complexity. Because any meta-heuristic optimization method is not used in the proposed method to achieve high classification accuracy. Therefore, the proposed TQWT and QSP based method is a cognitive method.

Background

In this study, a multilevel feature extraction network is presented. To construct this network, TQWT, QSP and NCA are used together. The used methods are explained in this section to better understanding the proposed method.

Tunable-Q wavelet transform

TQWT is one of the powerful decomposition methods in the literature and has a wide area of usage. TQWT is the improvement of traditional one single Q-factor wavelet transform [38]. It is carried out like discrete wavelet transform (DWT) with double channel multi-rate filter bank having low and high pass filters [39]. This method is proposed for discrete-time signal analysis for which the Q-factor is easily tunable and powerful transform for the analysis of oscillatory signals [40]. TQWT is fundamentally parameterized by its Q-factor and its redundancy to analyze signals with different oscillatory behaviors [41]. It has three main parameters which are Q-factor, oversampling rate (redundancy) and number of levels. It is also a reversible transformation. Q value represents oscillations of the wavelet. In Fig. 1, the analysis and synthesis filters of the TQWT are visually shown [42].

Analysis and synthesis low and high pass filters are sequentially $H_a(z)$, $G_a(z)$, $H_s(z)$ and $G_s(z)$. Low and high pass scaling operators are sequentially LPS and HPS. For perfect reconstruction, x = y is obtained. If f_s is input signal sampling rate, βf_s is sampling rate which low pass sub-band for level-1 decomposition. α and β (filter scaling factors) should be selected to meet the following requirements.

$$0 < \beta \leq 1 \quad (1)$$

$$0 < \alpha < 1 \quad (2)$$

$$\alpha + \beta > 1 \quad (3)$$

The filter banks are rate rollback, and the filter responses are well oriented locally and capable of perfect reconstruction. By altering α and β, the filter frequency responses can be adjusted to a desired frequency of interest. Tunable-Q wavelet transform of a given signal, x, is given by $w = \Phi x$, where Φ is the matrix regardful to the TQWT for a set of chosen parameters that are below.

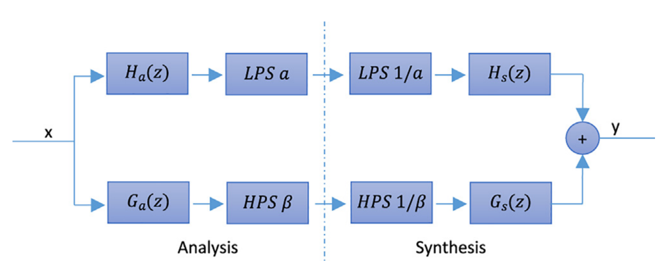


Fig. 1. Graphical demonstration of the analysis and synthesis filters for TQWT.

$$Q = (2 - \beta)/\beta \tag{4}$$

$$r = \beta/(1 - a) \tag{5}$$

$$Q = \frac{f_w}{B} \tag{6}$$

where Q is Q-factor, r describes over-sampling rate, f_w represents center frequency, B is bandwidth.

In the TQWT Q, r and number of levels are user defined parameters.

It has a wide area of usage including EEG classification, sEMG signal recognition, signal processing, signal decomposition, image processing [43–46].

Quadruple symmetric pattern

QSP is an image descriptor and it extract features by using 4 × 4 size of overlapping blocks and signum function. Then, 8 bits are extracted by using symmetric pixels of the blocks and signum function together. The extracted bits are converted to decimal values and these decimal values are used for feature signal construction. The histogram of the feature signal is extracted and the extracted histogram is utilized as feature vector with size of 256. This method is inspired by Chakraborty et al.'s method [47]. To better understand QSP, a numerical example about QSP is shown in Fig. 2.

As shown in Fig. 1, the QSP uses signum function to extract 8-bits features. Therefore, QSP extracts 256 features from a signal or image. The steps of the QSP is shown below.

Step 0: Load raw signal.

Step 1: Divide input signal into 16 sized overlapping blocks.

Step 2: Reshape each block into 4 × 4 sized matrix. This step describes vector to matrix transformation.

Step 3: Use signum function and Algorithm 1 for binary feature extraction. The mathematical notation of the signum function is shown as Eq. (7).

$$S(k, l) = \begin{cases} 0, & k - l < 0 \\ 1, & k - l \geq 0 \end{cases} \tag{7}$$

where $S(.,.)$ is signum function, k and l are input parameters of the signum function.

Algorithm 1. Binary feature extraction procedure of the QSP.

```
Input: 4 × 4 sized overlapping block.
Output: Bits with sizes of 8.
counter = 1;
for i = 1 to 2 do
   for j = 1 to 4 do
      bit(counter) = S(block(i, j), blok(5 − i, 5 − j));
      counter = counter + 1;
   end for j
end for i
```

Step 4: Convert the extracted bits to decimal values by using Eq. (8) and construct feature values.

$$feat^S(t) = \sum_{i=1}^{8} bit_i x2^{8-i};\ t = \{1, 2, \cdots, length(signal) - 15\} \tag{8}$$

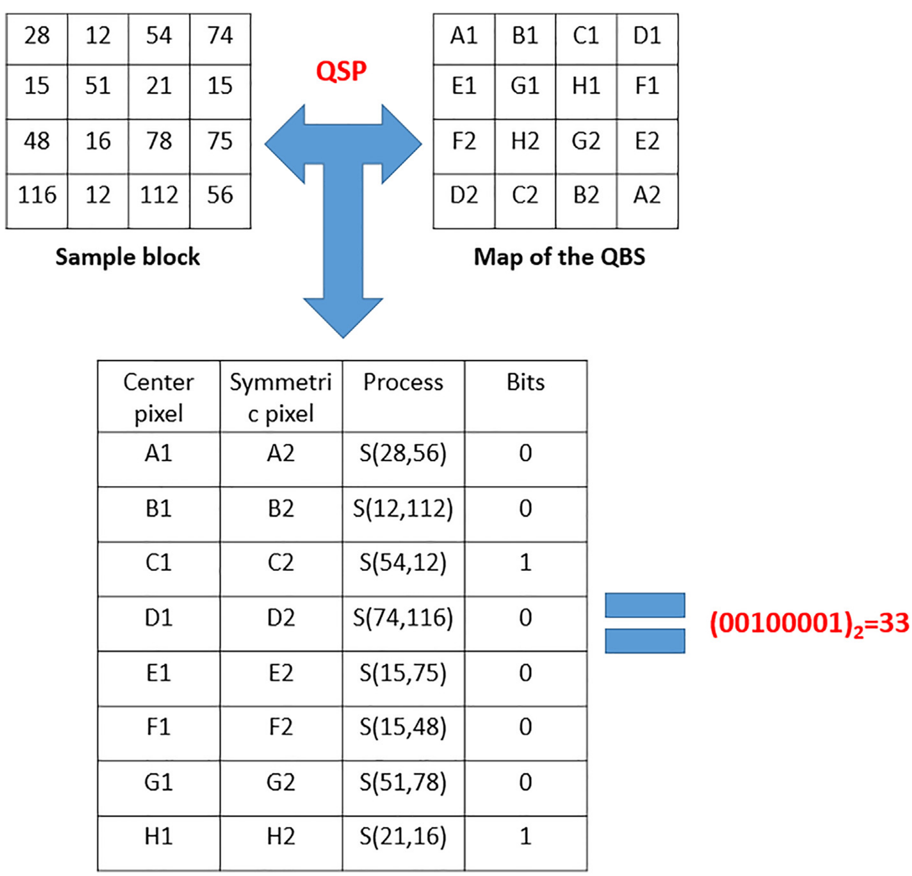
where $feat^S$ is feature signal.

Step 5: Extract histogram of the feature signal.

As seen from these steps, the QSP has a simple mathematical background. Therefore, its application is simple.

Neighborhood component analysis

NCA [48] is one of the widely used feature selection methods. It is a distance based feature selector. To select most distinctive features, NCA



Center pixel	Symmetric pixel	Process	Bits
A1	A2	S(28,56)	0
B1	B2	S(12,112)	0
C1	C2	S(54,12)	1
D1	D2	S(74,116)	0
E1	E2	S(15,75)	0
F1	F2	S(15,48)	0
G1	G2	S(51,78)	0
H1	H2	S(21,16)	1

$(00100001)_2 = 33$

Fig. 2. Graphical illustration and numerical example of the QSP.

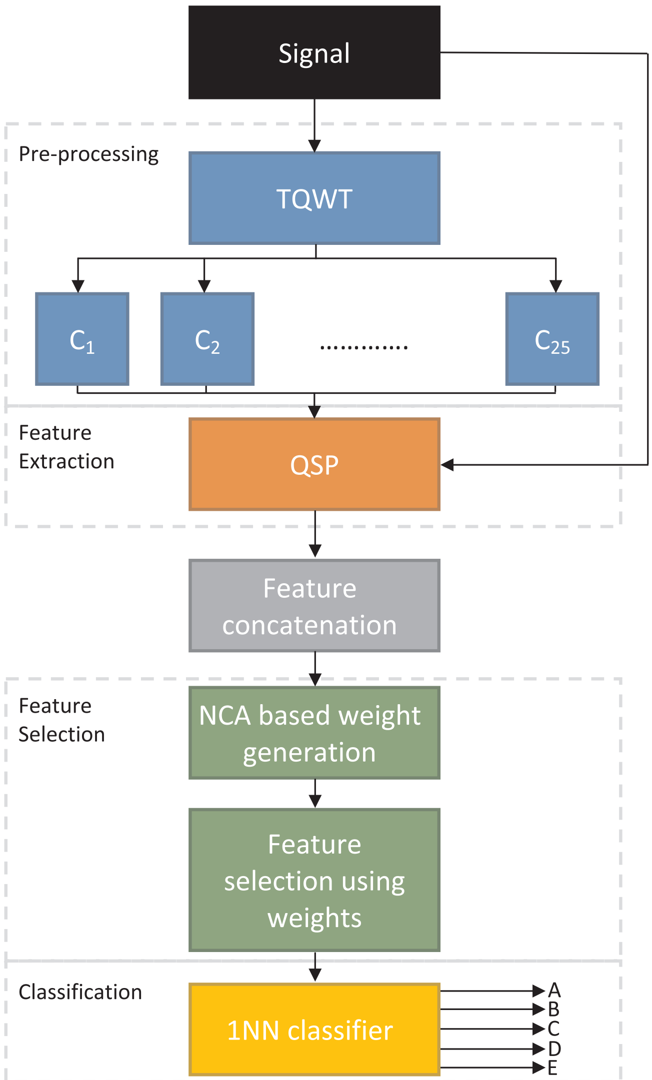


Fig. 3. The graphical outline of the proposed TQWT-QSP based method.

generates weights of the features. The generated weights are non-negative. Firstly, weights of features are randomly assigned. Manhattan distance are used as fitness function. By using stochastic gradient descend (SGD) optimization methods, weights are updated. NCA is a backpropagation and non-parametric method. In the NCA, bigger weights show more distinctive features and lower weights show redundant features [49].

The proposed method

In this paper, a TQWT and QSP based EEG signal classification method is proposed. The proposed TQWT and QSP based method is a multilevel method. The main objective of this method is to extract low, middle and high-levels features like deep learning methods with low computational cost. The effectiveness of TQWT is directly used.

The proposed multilevel method consists of preprocessing, feature extraction, feature concatenation and classification phases. The graphical outline of the TQWT-QSP based method is shown in Fig. 3.

As seen Fig. 3, the phases of the proposed are pre-processing, feature extraction, feature concatenation, feature selection and classification. These phases are clearly given in subsections.

Preprocessing

As known from computer vision and deep learning methods, the effectiveness of pooling methods is not sufficient [34]. Therefore, variable methods should be used in this phase to increase the performance of machine learning method. In this study, we used TQWT in the preprocessing phase. The pseudo code of the TQWT-based preprocessing is shown as Algorithm 2.

Algorithm 2. TQWT-based preprocessing procedure.

Input: Input signal (S) with a size of L.
Output: 25 TQWT coefficient bands (R).
1: $cnt = 1$; // Counter defining.
2: **for** Q = 1 to 5 **do**
3: $R\{cnt: cnt + 4\} = tqwt(S, Q, 2, 4)$; // Creating TQWT coefficients of the signal using 5 different Q values
4: $cnt = cnt + 5$;
5: **end for i**

As shown in Algorithm 2, R has five coefficient signals for each Q value. Graphical examples of the proposed TQWT based preprocessing method are shown as Fig. 4.

As seen from Fig. 4, 25 sub-bands coefficients are generated by using TQWT. In the feature extraction phase, original signal and the generated 25 TQWT sub-bands are used as inputs of the QSP.

Feature extraction

In the TQWT based preprocessing phase, 25 signals with variable lengths are calculated. To extract fixed sized features, QSP is utilized as feature extractor. In this section, 25 TQWT signals and the original EEG signal are utilized as input. The QSP extracts 256 features from each signal and $256 \times 26 = 6656$ features are totally extracted. The QSP based feature extraction procedure is shown in Algorithm 3.

Algorithm 3. QSP based feature extraction process

Input: The original signal (S), data structure of the TQWT R.
Output: Feature (feat) with a size of 256×26.
1: $c = 1$;
2: **for** i = 1 to 25 **do**
3: $feat((c-1)x256 + 1: cx256) = QSP(R\{i\})$ // Feature extraction from TQWT sub-bands
4: $c = c + 1$;
5: **end for i**
6: $feat(25x256 + 1: 26x256) = QSP(S)$; // Feature extraction from original EEG signal.

Algorithm 3 defines both feature extraction and feature concatenation processes. Finally, a feature set with size of 6656 is obtained. A graphical representation of these features by using a sample EEG signal is graphically shown in Fig. 5.

Feature selection

In the feature extraction and concatenation phases, 6656 features are obtained. NCA based feature selection phase is used to select discriminative features. NCA is a nonparametric feature selection method. It generates non-negative weights for all features. To generate weights, it uses distance metrics [13]. The mathematical representation of the NCA-based weight generation is shown as Eq. (9). Prior to the weight generation, features are normalized using min–max normalization and it is shown as Eq. (10).

$$w = NCA(feat, target) \tag{9}$$

$$feat = \frac{feat - feat_{min}}{feat_{max} - feat_{min}} \tag{10}$$

where $NCA(.)$ is weight calculation function of the NCA and w

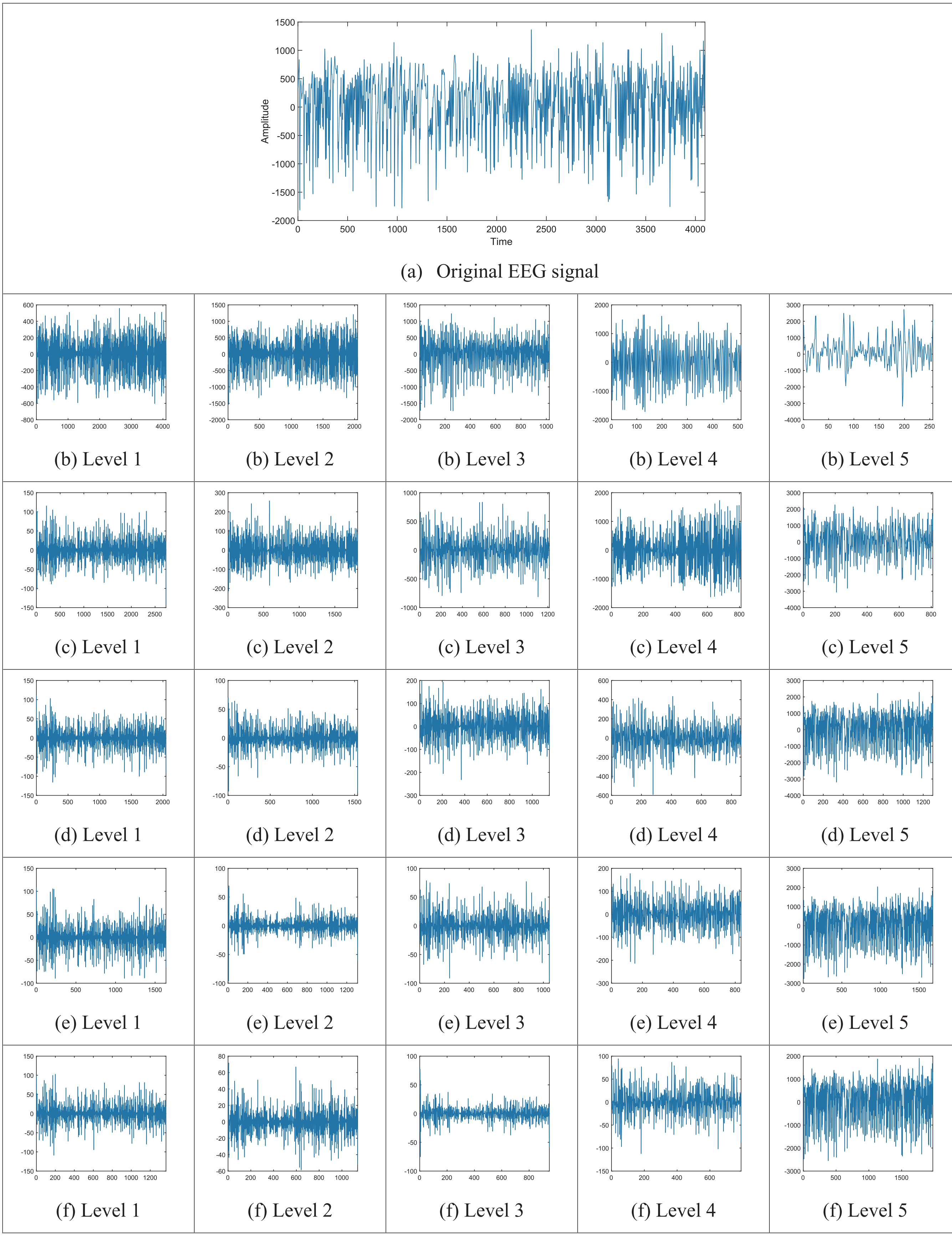


Fig. 4. An EEG signal sample and its TQWT coefficients (a) raw EEG signal, (b) Q = 1, (c) Q = 2, (d) Q = 3, (e) Q = 4, (f) Q = 5.

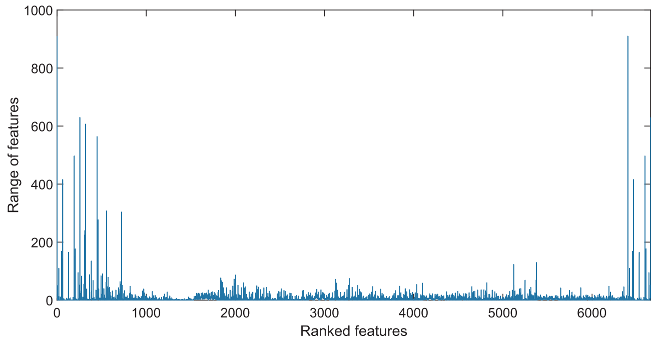


Fig. 5. A graphical example of the extracted features.

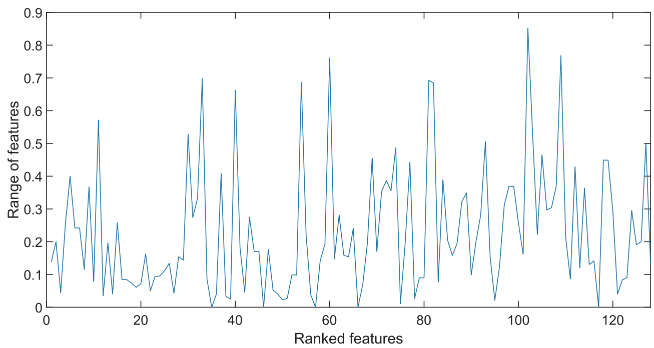


Fig. 6. A graphical example of the reduced features.

Table 1
The defined cases for experiments.

Number	Case	Classes
1	A-E	Classification A and E clusters.
2	A-D	Classification A and D clusters.
3	B-E	Classification B and E clusters.
4	D-E	Classification D and E clusters.
5	C-E	Classification C and E clusters.
6	A-D-E	Classification A, D and E clusters.
7	A-B-C-D-E	Classification A, B, C, D and E clusters.

represents weights of the 6656 features, $feat_{min}$ and $feat_{max}$ are minimum and maximum values of the feature set respectively.

After the weight generation, the most significant k features are selected. In this study, we selected 128, 256, 512 and 1024 features. Algorithm 4 explains the used NCA based feature selection procedure.

Algorithm 4. The NCA based feature selection procedure.

Input: Feature set ($feat$) with a size of 6656
Output: Selected features ($feat^S$) with sizes of k
1: Use Eq. (9) generates weights (w) with sizes of 6656
2: $[a, b] = sort(w, descending)$; // Sorting weights. a and b arrays store weights and indices of the weights by descending.
3: **for** i = 1 to k **do**
4: $feat^S(i) = feat(b(i))$;
5: **end for i**

A graphical example of the reduced features is shown in Fig. 6.

Fig. 6 shows selected 128 most distinctive feature of a sample EEG signal by using the proposed method.

Classification

In order to classify the selected features, we used kNN [50,51] classifier. kNN is one of the commonly used classifiers in the literature. It has many variations. By using variable k values and distance metrics, variable kNN classifiers are presented in the literature. In this study, k was chosen as 1 and we used city block (Manhattan) distance metrics. Mathematical notation of the Manhattan distance is shown as Eq. (11) [52].

$$M(x, y) = |x - y| \tag{11}$$

where $M(.,.)$ expresses Manhattan distance and x, y are its input parameters. To obtain train and test results, 10-fold cross validation is selected.

kNN is one of the commonly used conventional classifiers in the literature. It has basic mathematical background and low computational complexity. Therefore, implementation of the kNN is easy and it

Table 2
Accuracy, recall, precision and F-Measure values of the proposed method.

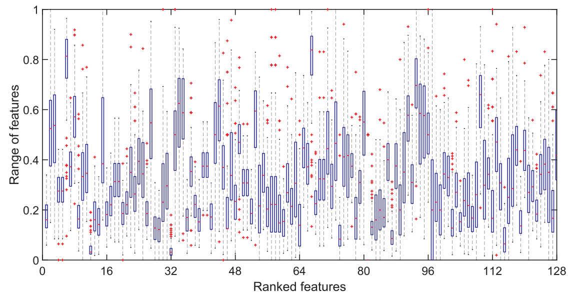
Case	*Acc*	*recall*	*precision*	*F1*	Features
A-E	99.5%	99.5%	99.5%	99.5%	128
	99.5%	99.5%	99.5%	99.5%	256
	99.5%	99.5%	99.5%	99.5%	512
	99.5%	99.5%	99.5%	99.5%	1024
A-D	100.0%	100.0%	100.0%	100.0%	128
	100.0%	100.0%	100.0%	100.0%	256
	100.0%	100.0%	100.0%	100.0%	512
	100.0%	100.0%	100.0%	100.0%	1024
B-E	100.0%	100.0%	100.0%	100.0%	128
	100.0%	100.0%	100.0%	100.0%	256
	100.0%	100.0%	100.0%	100.0%	512
	100.0%	100.0%	100.0%	100.0%	1024
D-E	100.0%	100.0%	100.0%	100.0%	128
	100.0%	100.0%	100.0%	100.0%	256
	100.0%	100.0%	100.0%	100.0%	512
	100.0%	100.0%	100.0%	100.0%	1024
C-E	100.0%	100.0%	100.0%	100.0%	128
	100.0%	100.0%	100.0%	100.0%	256
	100.0%	100.0%	100.0%	100.0%	512
	100.0%	100.0%	100.0%	100.0%	1024
A-D-E	99.67%	99.67%	99.67%	99.67%	128
	99.67%	99.67%	99.67%	99.67%	256
	99.67%	99.67%	99.67%	99.67%	512
	99.67%	99.67%	99.67%	99.67%	1024
A-B-C-D-E	98.00%	98.00%	98.00%	98.00%	128
	97.40%	97.40%	97.43	97.41%	256
	97.80%	97.80%	97.83%	97.82%	512
	98.40%	98.40%	98.22%	98.31%	1024

Table 3
Confusion matrix of the A-B-C-D-E classes using 1024 most discriminative features.

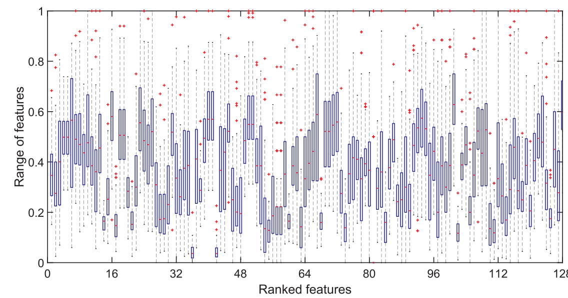
	Predicted classes					
True classes	A	B	C	D	E	Average
A	100	0	0	0	0	100.0%
B	2	98	0	0	0	98.0%
C	0	0	97	3	0	97.0%
D	0	0	2	98	0	98.0%
E	0	0	1	0	99	99.0%
Average	98.04%	100.0%	97.0%	97.03%	100.0%	98.41%

Table 4
Computational complexity calculation of the proposed method.

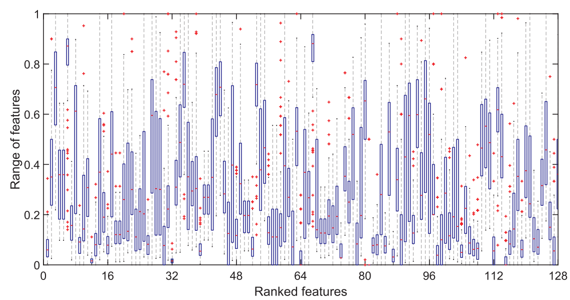
Phase	Big O notation
Pre-processing	$O(n^2)$
Feature extraction	$O(26n)$
Feature concatenation	$O(6656)$
Feature selection	$O(k)$
Classification	$O(10k)$
Total	$O(n^2 + 26n + 11k + 6656)$



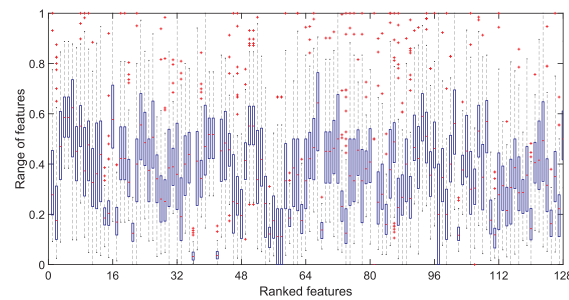
(a) Statistical attributes of the reduced features of class A.



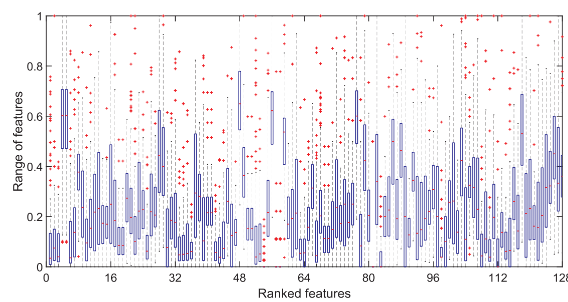
(c) Statistical attributes of the reduced features of class C.



(b) Statistical attributes of the reduced features of class B.



(d) Statistical attributes of the reduced features of class D.



(e) Statistical attributes of the reduced features of class E.

Fig.7. Statistical analysis of the proposed TQWT-QSP based feature extraction network.

has short execution time. Methods developed using kNN can be used for further validation using bigger datasets. kNN is also used to show strength of the proposed TQWT-QSP based multileveled feature extraction network.

Experimental results

To test the performance of the proposed method, EEG signal dataset of Bonn University [53] was used. This dataset consists of five classes of EEG and each class has 100 samples. These classes are called as A, B, C, D and E. A and B classes belong to healthy people and they were recorded when people's eyes were open and closed respectively. C, D and E classes express epilepsy patients' EEG signals. EEG signals of the classes C, D and E were recorded before epileptic seizure, epileptic zone and during epileptic seizure respectively. Seven cases were used to calculate numerical results by using A, B, C, D and E classes. These cases were listed in Table 1.

The proposed method was implemented by using a personal computer (PC). The attributes of the used PC are given as follows. The used PC has 8 GB main memory and i5-8250 microprocessor with 1.60 GHz. The operating system of the PC is Windows 10 professional. The proposed method and tests were implemented by using MATLAB 2019a.

To evaluate classification capability of the proposed method, widely used performance metrics were used. In the classification methods, accuracy, recall, precision and F-Measure are widely used. The mathematical notations of these performance metrics are shown in Eqs. (12)–(15) [20]

$$Acc = \frac{tp + tn}{tp + tn + fp + fn} \tag{12}$$

$$recall = \frac{tp}{tp + fn} \tag{13}$$

$$precision = \frac{tp}{fp + tp} \tag{14}$$

$$F1 = 2 \times \frac{precision x recall}{precision + recall} \tag{15}$$

where tp is true positive, tn represents true negative, fp describes false positive, fn is false negative, Acc represents accuracy and $F1$ expresses F-measure.

In order to obtain these numerical results, 1NN classifier with Manhattan distance was used. In the tests, 10-fold cross validation was chosen. The calculated best scores of the proposed TQWT-QSP based method were listed in Table 2 according to the defined cases and feature sizes.

As seen from Table 2, the proposed method achieved 98.40% classification accuracy for 5 clusters classification. In order to better understand performance of the proposed TQWT-QSP based method, confusion matrix of this result is given as below.

As seen from the confusion matrix (Table 3), the best accuracy rate was calculated as 100.0% for A class and the worst classification rate

Table 5
Comparison results for A-E, A-D, B-E, D-E, C-E and A-D-E cases.

Case	Method	Performance (Accuracy %)
A-E	Nicolaou and Georgiou. (2012) [26]	93.42
	Zhu et al. (2014) [54]	99
	Kaya et al. (2014) [19]	99.5
	Husain et al. (2014) [55]	99.8
	Ghayab et al. (2016) [56]	99.9
	Kaya (2015) [57]	100
	Fathima et al. (2011) [58]	99.75
	Guo et al. (2010) [59]	99.85
	Nigam and Graupe (2004) [60]	97.2
	Srinivasan et al. (2005) [52]	99.6
	Orhan et al. (2011) [21]	100
	Kaya and Ertuğrul (2018) [20]	100
	Siuly et al. (2018) [61]	99.5
	The proposed TQWT-QSP + 1NN	99.5
A-D	Kaya et al. (2014) [19]	99.5
	Kaya and Ertuğrul (2018) [20]	100
	The proposed TQWT-QSP + 1NN	100
B-E	Kaya (2015) [57]	96
	Kaya and Ertuğrul (2018) [20]	97.5
	Siuly et al. (2011) [62]	93.6
	Supriya et al. (2016) [63]	95
	Zhu et al. (2014) [54]	97
	Siuly et al. (2018) [61]	99
	The proposed TQWT-QSP + 1NN	100
D-E	Zhu et al. (2014) [54]	93
	Kumar et al. (2014) [64]	93
	Nicolaou and Georgiou (2012) [26]	83.13
	Kaya and Ertuğrul (2018) [20]	94.5
	Siuly et al. (2018) [61]	97.5
	The proposed TQWT-QSP + 1NN	99.5
C-E	Zhu et al. (2014) [54]	98
	Supriya et al. (2016) [63]	94.5
	Kaya and Ertuğrul (2018) [20]	97.5
	Siuly et al. (2018) [61]	98.5
	The proposed TQWT-QSP + 1NN	100
A-D-E	Kaya et al. (2014) [19]	95.67
	Kaya and Ertuğrul (2018) [20]	95.7
	The proposed TQWT-QSP + 1NN	99.67

Table 6
Comparatively results for A-B-C-D-E classes.

Method	Success rate (%)	Feature dimension
1D-LBP [19]	66.0	256
1D-TP Lower Features [20]	79.0	256
1D-TP Upper Features [20]	77.6	256
1D-TP Combined Features [20]	79.8	512
1D- CNN [32]	88.7	1000
LSP + SVM [66]	93.0	256
Proposed TQWT-QSP + 1NN	98.0	128
Proposed TQWT-QSP + 1NN	97.4	256
Proposed TQWT-QSP + 1NN	97.8	512
Proposed TQWT-QSP + 1NN	98.4	1024

was calculated as 97.0% for C class.

Computational complexity of the proposed method was also calculated in this paper. Big O notation was used to calculate computational complexity of the proposed method. The computational complexity of each phases are listed in Table 4.

Table 4 clearly show the computational complexity of the proposed method and it is calculated as $O(n^2)$.

Discussions

A multilevel TQWT and QSP based feature extraction network is presented in this paper. By using TQWT, different 25 sub-bands are calculated. QSP is also utilized as feature extractor. QSP extracts 256 features from each sub-bands and raw EEG signal. These features are concatenated and 6656 features are finally obtained. A NCA-based method is utilized as feature selection. The main objective of the proposed method is to extract distinctive features from EEG signals by using lightweight and cognitive method with high performance. This method achieved 100.0% success rate in three cases (see Tables 2 and 3). The proposed TQWT-QSP based method distinctively extracts feature from the EEG signal. Therefore, the proposed method has very high success rate. In order to show success of the proposed method, the statistical analysis of extracted features is shown in Fig. 7 using boxplot analysis.

In Fig. 7, blue boxes represent range of features and red stars are upper and lower bound values. It clearly shows the statistical attributes of features and it is demonstrated that the proposed method extracts separate features. In order to show the effectiveness of extracted features, 1NN classifier is used. Seven cases were defined to calculate success rates and comparison results. The proposed method also achieved 100% success rate for three cases which were A-D, B-E, and C-E.

In order to examine the efficiency of the proposed method, it was compared with the previously presented EEG classification methods and results are listed in Table 5.

As seen in Table 5, the proposed method achieved high EEG signal classification capability. Most of the EEG classification methods failed to give results for all of the five classes. Only two or three classes have been worked on in most of the studies. Therefore, other methods were simulated by us.

The proposed TQWT-QSP is a textural feature extraction method similar to 1D-LBP and 1D-TP. 1D-LBP and 1D-TP were previously used for EEG classification [19,20,65]. Therefore, this method was also compared with 1D-LBP and 1D-TP for all of the five classes and the results are given Table 6 [66]. 1NN classifier was used to measure the classification abilities of features of these methods, because the best results were obtained using 1NN with Manhattan distance.

In the literature, the classification rates of A, B, C, D and E were not given in most of the EEG classification studies because the some previously presented methods failed to achieve high success rates for five classes of epilepsy classification in the Bonn dataset. To show the distinctiveness of our features, classification results for five classes were listed in Table 6. The best accuracy value of the proposed method was calculated as 98.4% for all of the five classes by using 10-fold cross validation. The proposed TQWT-QSP has higher classification accuracy than other state-of-the-art methods. In addition, 5.4% higher success rate was calculated than the best of the others. The computational complexity of the proposed method is calculated as $O(n^2)$.

Advantages of the proposed method are listed below.

- The proposed method has a simple mathematical background. Therefore, the proposed method can be programmed simply by researchers.
- Discriminative features are extracted using the proposed method. Because, 1NN [67] is one of the simplest conventional classifiers and 98.4% classification rate was achieved by using 1NN.
- As known from the literature, TQWT [43,44] is one of the new generation wavelet transforms and have been used in signal processing and machine learning methods in the literature. Furthermore, the multilevel transformation based methods [68,69] have achieved high classification accuracies. In order to create a multilevel EEG classification method [70], TQWT is chosen and 25 TQWT coefficients are generated using 5 different Q values. Due to the positive effects of TQWT on feature extraction, a large feature set is extracted. By using this feature set, distinctive features are easily selected.
- The computational cost of the proposed method was calculated using Big O notation [71,72] and it was concluded that the proposed method has low computational complexity. It is clearly indicated that this method is a lightweight learning method.
- In some methods, metaheuristic optimization algorithms and

ensemble classifiers have been used to obtain high success rates. However, there is no ensemble and metaheuristic optimization technique in this study. Hence, the proposed method is a cognitive method.
- The proposed TQWT-QSP + 1NN [67] method has very high classification capability by using kNN. This situation clearly indicated that the proposed method can achieved high success rate in larger dataset by using deep classifiers.
- The proposed method is superior to 1D-CNN deep learning method (see Table 6).

The limitation of the proposed method is summarized as follows. Bonn [21]dataset was used to test the success of the proposed method. It is a small and homogenous dataset. However, this database has been widely used in the literature and the results of the previously presented methods were achieved basically for comparisons. Therefore, Bonn dataset is utilized as test suit in this paper.

Conclusions and future works

The main objective of this study is to propose a multilevel learning method to achieve high classification ability using EEG signals. This method consists of 5 phases and these are TQWT-based preprocessing, feature extraction with QSP, feature concatenation, feature selection and classification. 25 TQWT sub-bands were generated using 5 different Q factors of the TQWT. 6656 features are extracted from the original EEG signal and the generated 25 TQWT sub-bands. In order to improve the classification ability of the proposed method, NCA based feature selection method is used. In the classification phase, 1NN classifier was chosen. To test performance of this method and obtain comparative results, seven cases were defined. According to the results, the proposed method achieved 100% classification accuracy for three cases (see Table 2). The proposed method was also compared with other EEG classification methods and the comparisons proved the success of the proposed method (see Table 6). Especially, this method achieved 98.4% classification rate calculated for five classes. This result has approximately 5.4% higher success rate than the best of the other methods (see Table 6). Also, the proposed method has higher classification ability than 1D-CNN according to results (see Table 6). Computational complexity of the proposed TQWT-QSP based method was calculated as O (n2) (see Table 4). This result clearly indicates that the proposed method is a lightweight EEG classification method. According to the results, the proposed TQWT and QSP based method is a highly accurate, cognitive and lightweight EEG classification method.

This paper clearly demonstrates that this method can be utilized as a healthcare monitoring system for epilepsy patients in the future. A real-time application can be implemented to predict epilepsy seizures by using the proposed method. The proposed TQWT-QSP based method can be applied onto other types of signals. A deep learning method can also be proposed for 1D signals based on TQWT and QSP for large and heterogeneous EEG dataset in future works.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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