Effect of Tuning TQWT Parameters on Epileptic Seizure Detection from EEG Signals

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***Abstract*— In this paper, we study the effect of tuning the tunable-Q wavelet transform (TQWT) parameters on analyzing the Electroencephalogram (EEG) signals used for detecting epileptic seizure. Publicly available Bonn University database is used in this study, fifteen different combinations were examined. TQWT is used to decompose each EEG signal into a valuable set of band limited signals (sub-bands), the value of the Q parameter is tuned from one to four and the number of sub-bands (J) from six to twenty two. Two statistical features were extracted from the sub-bands having the highest percentage of total signal energy. K-nearest neighbor (K-NN) was used for classifying the EEG signals into either seizure or seizure-free. Our results clarify that, increasing the value of Q enhance the classification accuracy and best results were achieved at Q equals two.**

Electroencephalogram (EEG), Epileptic seizure, Tunable-Q wavelet transform (TQWT), Q Parameter, K-nearest neighbor (K-NN).

I. Introduction

Epilepsy is a neurological disorder of the brain that can be detected from Electroencephalogram (EEG) signals. Numerous signal processing techniques have been widely studied during the last two decades for EEG signal analysis and processing with the intension to automatic diagnosis of epilepsy.

Several seizure detection techniques use time-domain and frequency-domain features to detect epileptic seizure from EEG signals. V. Srinivasan et al. [1] extracted both time-domain and frequency-domain features from EEG signals and performed classification using artificial neural networks (ANN). K.Polat et al. [2], and R. Hussein et al. [30] used fast fourier transform (FFT) for feature extraction.

Due to the noise sensitivity of FFT and the non-stationary behavior of the EEG signals, a great deal of interest has been devoted to analyze EEG signals using time - frequency techniques. L. Duque-munoz et al. [3] used short time fourier transform (STFT), while M.K.Kiymik et. al [4] performed a comparison between STFT and wavelet transform (WLT) methods in determining epileptic seizure activity from EEG signals. Discrete Wavelet Transform (DWT) was used for analyzing EEG signals [5] - [11], [22], while L.Guo et al. [12] used multiwavelet transform. L. S. Vidyaratne et al. [13] proposed a real time ecliptic seizure detection using a fast wavelet decomposition method known as harmonic wavelet packet transform (HWPT), and T. Gandhi et al. [14] offered a comparative study of wavelet families for EEG signal classification.

Ivan W. Selesnick [15] [16] offered a wavelet transform with tunable Q which can be used to enhance sparse signal representation. S. Patidar et al. [17] detected epileptic seizure using Kraskov entropy on TQWT of EEG signals, and A. Bhattacharyya et al. [18] analyzed focal EEG signals using multivariate sub-band fuzzy entropy based on TQWT.

In this work, our objective is to study the effect of tuning the Q parameter of the TQWT on the accuracy of the epileptic seizure detection. First, TQWT is used to decompose the EEG signals into a set of band limited signals (sub-bands), with tuning the Q parameter from one to four and the number of sub-bands (J) from six to twenty two. Then, each sub-band energy as a percentage of the total signal energy is calculated. Two statistical features namely; average power (AVP), and standard deviation (SD) were extracted from sub-bands having the highest percentage of total signal energy. Extracted feature vectors are classified into either seizure and seizure-free signals using K-nearest neighbor (K-NN) classifier.

The rest of this paper is organized as follows: in section II Bonn University database is described. Section III, explains the basic principles of tunable Q wavelet transform. Section IV, is devoted to the proposed methodology. Results and discussion are presented in section V. Conclusions are drawn in section VI.

II. EEG Data Segmentation

The publicly available database from Bonn University ,Germany, consists of five EEG data sets from A - E [19]. Sets A and B are recorded from relaxed healthy volunteers with their eyes open in set A and closed in set B. Set C is recorded from hippocampal formation of opposite hemisphere of brain. Set D recorded from epileptogenic zone. Set C and D were recorded during seizure free intervals. Set E was recorded during the occurrence of epilepsy within an epileptogenic zone.

III. Tunable Q Wavelet Transform

The TQWT is a special type of discrete-time wavelet transform (DWT). In TQWT input parameters namely, the Q-factor (Q), the number of sub-bands (J), and the redundancy or the over sampling rate (r) can be tuned according to the oscillatory behavior of the signal to which it is applied [15]. TQWT has found a wide range of applications in biomedical signal analysis [17] [18] [23] [24] due to it's ability to tune it's parameters to match the oscillatory behavior of the EEG signals, resulting in better discrimination between two classes of signals.

High values of Q is suitable for analyzing signals with oscillatory nature, while lower values of Q is suitable for signals that are non-oscillatory in nature [15] [16]. Increasing the number of sub-bands (J) along with increasing the value of Q-factor helps in achieving better resolution in both the high and low frequency regions of the considered signal.

The TQWT is built by using two channel filter bank operations a low-pass filter $F_0(\omega)$ with scaling factor α and high-pass filter $F_1(\omega)$ with scaling factor β. The TQWT expressions as described by Ivan W. Selesnick [15] are:

$$F_0(\omega) = \begin{cases} 1 & , \quad |\omega| < (1-\beta)\pi \\ \theta(\frac{\omega+(\beta-1)\pi}{\alpha+\beta-1}) & , \quad (1-\beta)\pi \leq |\omega| < \alpha\pi \\ 0 & , \quad \alpha\pi \leq |\omega| \leq \pi \end{cases} \tag{1}$$

$$F_1(\omega) = \begin{cases} 0 & , \quad |\omega| < (1-\beta)\pi \\ \theta(\frac{\alpha\pi-\omega}{\alpha+\beta-1}) & , \quad (1-\beta)\pi \leq |\omega| < \alpha\pi \\ 1 & , \quad \alpha\pi \leq |\omega| \leq \pi \end{cases} \tag{2}$$

Where $\theta(\omega)\ \big(= 0.5(1+\cos(\omega))\sqrt{(2-\cos(\omega))},\ \ |\omega| \leq \pi\ \big)$ is the Daubechies filter frequency response. Low-pass and high-pass scaling factors are chosen to satisfy the conditions:

$$0 < \alpha < 1; \qquad 0 < \beta \leq 1; \qquad \alpha+\beta > 1 \tag{3}$$

TQWT parameters, quality factor Q, redundancy R and maximum number of sub-bands J_{max} is defined in terms of α and β as [15]:

$$r = \frac{\beta}{1-\alpha}; \qquad Q = \frac{2-\beta}{\beta}; \qquad J_{max} = \frac{\log(\beta N/8)}{\log(1/\alpha)} \tag{4}$$

The specified Q-factor should be chosen such that, $Q \geq 1$, and the over-sampling rate r must be greater than one. Detailed mathematical explanation of TQWT can be found in [15] [16].

IV. Methodology

In this work, TQWT is used to decompose the EEG signals into a set of band limited signals (sub-bands). Four values of Q and J parameters were chosen such that, $\{Q, J\} = \{1,6\}, \{2,10\}, \{3,16\}, \{4,22\}$ respectively. Each sub-band energy as a percentage of the total signal energy is calculated (as shown in Figs.1, 2) and energy (ENG) is given by:

$$E(D_j) = \sum_{i=1}^{N} |D_{ij}|^2, \tag{5}$$

Features are extracted from the most distinctive sub-bands only. It's clear from Figs. 1, 2 that most of the EEG signal energy is concentrated in a limited number of sub-bands (the highest order sub-bands). Two statistical features namely, average power (AVP), and standard deviation (SD) were extracted from Sub-bands having the highest percentage of total signal

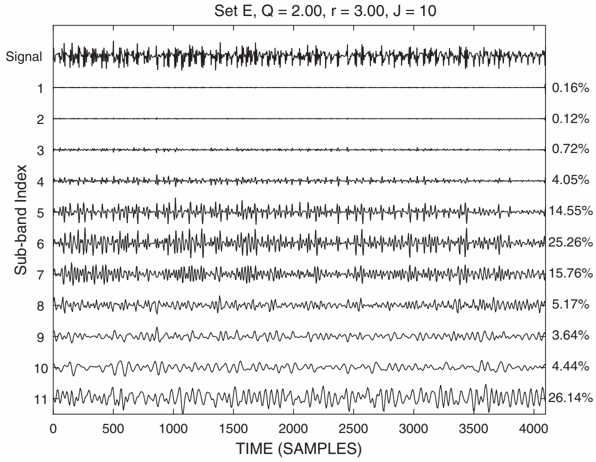

Fig. 1. TQWT decomposition for a signal from set E (seizure EEG signal) with the energy of each sub-band displayed as a percentage of total signal energy. Q=2, r=3, $J = 10$.

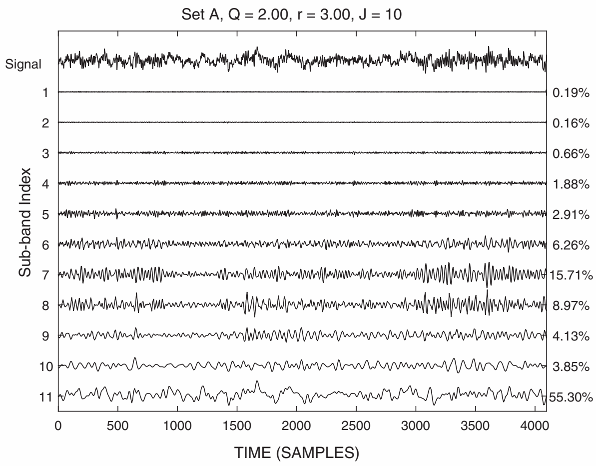

Fig. 2. TQWT decomposition for a signal from set A (seizure-free EEG signal) with the energy of each sub-band displayed as a percentage of total signal energy. Q=2, r=3, $J = 10$.

energy along with the approximation level.
Average power (AVP):

$$AVP(D_j) = \frac{1}{N}\sum_{i=1}^{N} |D_{ij}|^2, \tag{6}$$

Standard deviation (SD):

$$SD(D_j) = \frac{1}{N-1}\sum_{i=1}^{N} (D_{ij}-\mu)^2, \tag{7}$$

Where:
D_{ij}: is the i^{th} sample in the J^{th} sub-band.
N: number of samples in the j^{th} sub-band.
μ: mean of the sub-band.

For classification the extracted features were fed to K-nearest neighbor (K-NN) classifier. The KNN classifier is a relatively simple non linear classifier, that can detect linear or non-linear distributed data, and works robustly for larger training sets

[20]. Unlike many other classification techniques KNN does not make any assumptions on the underlying data distribution, and all the training data is needed during the testing phase. KNN classifier has been used in many applications in the field of statistical pattern recognition, data mining, and image processing, and in 2006 KNN classifier was chosen as one of the top 10 data mining algorithms [21].

The performance of the classifier was determined using three scale parameters:
Accuracy (ACC):

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{8}$$

Sensitivity ($SENS$) or true positive rate (TPR):

$$SENS = TPR = \frac{TP}{TP + FN} \times 100 \tag{9}$$

Specificity ($SPEC$) or true negative rate (TNR)

$$SPEC = TNR = \frac{TN}{TN + FP} \times 100 \tag{10}$$

Where TP, TN, FP, and FN are the numbers of true positives, true negatives, false positives, and false negatives respectively.

V. Results and Discussion

In this study, publicly available Bonn University database is used [19]. Fifteen different classification combinations (Sets A, B, C, and D versus Set E) were examined in order to identify epileptic from non-epileptic EEG signals. Researchers examined different combinations from the data sets achieving accuracy range from 95% to 100% for two-class combinations [25]-[29], from 96.1% to 99% for three class combinations [10] [28] [29], from 95.1% to 98.8% for four-class combinations [10] [27] [29], and from 95.8% to 97.1% for five class combination [10].

In this work, the proposed scheme aims to investigate the effect of tuning the Q and J parameters of the TQWT on the accuracy of the epileptic seizure detection. Four different combinations of Q and J were used namely, $\{Q, J\} = \{1, 6\}, \{2, 10\}, \{3, 16\}, \{4, 22\}$ respectively. The value of the TQWT r-parameter was set equal to three throughout this analysis to ensure that the wavelets are well localized [15].

Initially, EEG signals were decomposed using TQWT into a useful set of wavelet coefficients known as sub-bands. Figs.1, and 2 shows a seizure (set E) and seizure-free (set A) EEG signals obtained by applying TQWT (Q=2, r=3, J=10), energy in each sub-band as a percentage of total signal energy is also displayed. In Fig. 3, energy distribution from seizure and seizure-free EEG signals sets A, B, C, D, and E is shown. It's clear that most of the signal energy is concentrated in a limited number of sub-bands along with the approximation level, features are extracted only from those distinctive sub-bands. EEG signals were decomposed and four different combinations of Q

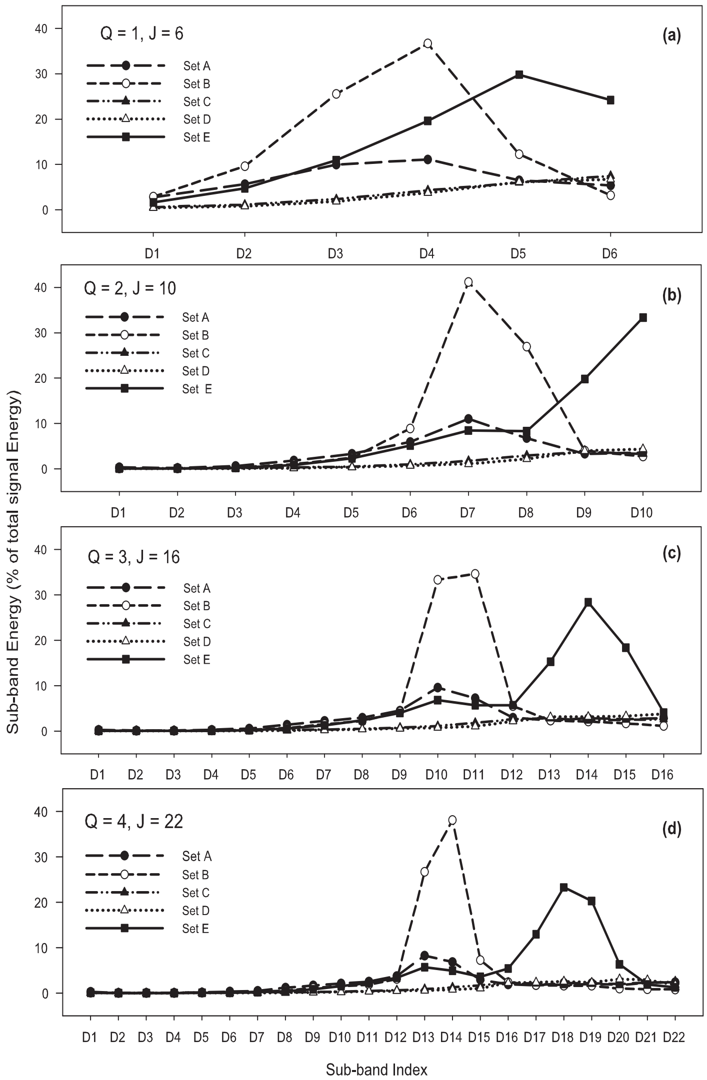

Fig. 3. Sub-band energy as a percentage of total energy at each decomposition level for signals from sets A, B, C, D, and E. (a) For Q=1; J=6, (b) For Q=2; J=10, (c) For Q=3; J=16, (d) For Q=4; J=22.

TABLE I

Sub-bands with the highest percentage of total signal energy.

	Sub-bands with highest energy
Q=1, J=6	D3 to D6 along with A6
Q=2, J=10	D5 to D10 along with A10
Q=3, J=16	D8 to D16 along with A16
Q=4, J=22	D11 to D22 along with A22

TABLE II

PERFORMANCE OF KNN CLASSIFIER FOR TWO AND THREE CLASS COMBINATIONS OF DATA SETS A TO D WITH E

Data Sets	**Q**	**AVP**			**SD**		
		ACC	SENS	SPEC	ACC	SENS	SPEC
A-E	1	99	98	100	99.5	99	100
	2	**99.5**	**99**	**100**	**99.5**	**99**	**100**
	3	99	98	100	98.5	97	100
	4	98.5	97	100	98	96	100
B-E	1	96.5	93	100	98	96	100
	2	**98.5**	**97**	**100**	**98.5**	**97**	**100**
	3	98	96	100	98	96	100
	4	98	96	100	97.5	95	100
C-E	1	96.5	94	99	96	95	97
	2	**98.5**	**97**	**100**	**98.5**	**97**	**100**
	3	98	96	100	98	96	100
	4	98	96	100	97	94	100
D-E	1	91.5	89	94	93.5	91	96
	2	**96**	**97**	**95**	**95.5**	**96**	**95**
	3	94	93	95	95	94	96
	4	95	95	95	95	94	96
AB-E	1	98	94	100	99	97	100
	2	**99.3**	**98**	**100**	**99**	**97**	**100**
	3	98.3	95	100	98.7	96	100
	4	98.3	95	100	98	94	100
AC-E	1	98.3	96	99.5	98.3	96	99.5
	2	**99.3**	**98**	**100**	**99.3**	**98**	**100**
	3	99	97	100	98.7	96	100
	4	98.7	96	100	98.3	95	100
AD-E	1	95.3	93	96.5	96.3	93	98
	2	**97**	**95**	**98**	**97.3**	**96**	**98**
	3	96.3	93	98	95.7	91	98
	4	96.3	93	98	95.5	92	97.5
BC-E	1	98	94	100	98.3	96	99.5
	2	**99**	**97**	**100**	**98.7**	**96**	**100**
	3	98.7	96	100	98.7	96	100
	4	98.3	95	100	98.7	96	100
BD-E	1	94.3	91	96	96	92	98
	2	**97.3**	**96**	**98**	**96.7**	**95**	**98**
	3	96.3	93	98	96.3	94	97.5
	4	96	93	97.5	95.3	91	97.5
CD-E	1	95.7	94	96.5	96.8	91	98
	2	**97.3**	**96**	**98**	**98**	**97**	**98.5**
	3	95.7	92	97.5	96.7	93	98.5
	4	96	92	98	94.7	89	97.5

and J parameters features were extracted from only the subbands having the highest percentage of total signal energy as shown in table (1).

Two statistical features namely, average power (AVP), and standard deviation (SD) were extracted. The generated feature vectors were fed to a KNN classifier. The classification performance was evaluated using three scale parameters: accuracy (ACC), sensitivity ($SENS$), and specificity ($SPEC$).

Table 2 and 3 shows the classifier performance when comparing set E versus 15 different combinations from sets A, B, C, D. Highest accuracy achieved (shown in bold) by KNN classifier for Q equals two.

TABLE III

PERFORMANCE OF KNN CLASSIFIER FOR FOUR AND FIVE CLASS COMBINATIONS OF DATA SETS A TO D WITH E

Data Sets	**Q**	**AVP**			**SD**		
		ACC	SENS	SPEC	ACC	SENS	SPEC
ABC -E	1	98.5	94	100	98.3	94	99.6
	2	**99**	**96**	**100**	**99.3**	**97**	**100**
	3	99	96	100	99	96	100
	4	98.8	95	100	99	96	100
ABD -E	1	95.8	88	98.3	96.8	92	98.3
	2	**97.8**	**96**	**98.6**	**97.5**	**96**	**98**
	3	97.3	94	98.3	96.8	92	98.3
	4	97.3	93	98.6	96.8	92	98.3
ACD -E	1	96.5	90	98.6	96.8	91	98.6
	2	**97.8**	**96**	**98.3**	**97.3**	**93**	**98.6**
	3	97.5	95	98.3	96.5	91	98.3
	4	96.3	89	98.6	96	88	98.6
BCD -E	1	96.8	92	98.3	96.5	90	98.6
	2	**97.5**	**95**	**98.6**	**97.3**	**93**	**98.6**
	3	97.5	94	98.3	97	93	98.3
	4	97.3	93	98.6	97	93	98.3
ABCD -E	1	97.4	91	99	97.6	92	99
	2	**98.2**	**94**	**99.25**	**98.2**	**95**	**99**
	3	97.6	91	99.25	97.8	93	99
	4	97.4	91	99	96.8	89	98.75

From table 2, and 3 we can see that the obtained results for combinations A-E, B-E, AC-E, C-E, and CD-E are combatable with that achieved by other researchers using DWT for feature extraction and KNN for classification [10]. Our results, using TQWT, shows a better performance for combinations D-E, AB-E, AD-E, BC-E, BD-E, ABC-E, ABD-E, BCD-E, ACD-E, ABCD-E at Q equals two. Our results clarify also that, increasing the value of Q enhance the system performance until it reaches it's best performance at Q equals two. After that increasing the value of Q will reduce the system performance.

VI. CONCLUSION

In this work, we explored the effect of tuning the TQWT parameters on the performance of epileptic seizure detection system which is used in classifying the EEG signals as seizure and seizure free signals. TQWT is an efficient tool for analyzing the non-linear and non-stationary nature of the EEG signals. The obtained results are comparable with that achieved by other researchers [10], [25]- [29]. Best performance was archived at Q equals two. In TQWT the variation of the Q parameter affect the computed features in different oscillatory levels. Selecting the proper value of Q improves the system accuracy until it reaches it's best performance, and then any further increase in the value of Q will reduce the system performance.

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