CHAPTER 3

3 Removal of Ocular artifacts from Single channel EEG signal using DTCWT with Quantum inspired Adaptive Threshold

3.1 Introduction

The electrical signals originated from the brain are called electroencephalogram (EEG) signals and can be recorded by placing electrodes over the scalp using the standard international 10-20 system. In practice, while acquiring EEG, biopotential signals with no cerebral origin often contaminate electrical signals of the brain. These contaminating biopotentials are mainly produced by eye blinks and movements, popularly referred as Ocular artifacts (OAs). OAs have larger amplitudes (in the order of mV) compared to that of EEG (amplitude in the order of uV). In many brain-computer interfaces (BCIs) applications, EEG signal of the subject is measured, and features are extracted to control the external devices. Thus, removal of OAs from the EEG signals plays a vital role in order to enhance the performance of the BCI system [202]. To reduce the EOG artifacts, one possible solution is directing the subject not to make eye blink and movement during the experiment. However, such instructions may not be practical in most cases. Hence the elimination of OA's is an essential step in EEG signal analysis.

It is notable that thresholding plays a vital role in all the wavelet de-noising techniques discussed in section 2.3.1 of chapter 2. To enhance the wavelet shrinkage's performance, thresholding rules can be explored further. Quantum-inspired de-noising algorithm proposed by P. Wang et al. [203] shows effective and enhanced performance than conventionally used techniques like soft threshold and hard threshold.

This work suggests the use of dual-tree complex wavelet transform for the decomposition of EEG in wavelet domain and quantum-inspired adaptive threshold algorithm for suppression of ocular artifacts. The proposed algorithm is capable of altering the value of threshold and eliminating the eyeblink wavelet coefficients. The present work is organized as follows. Section 3.2 explains the Dual-Tree Complex Wavelet Transform and Quantum-inspired adaptive threshold algorithm. Steps followed to suppress OAs are elaborated in section 3.3. Results are further discussed in section 3.4. Finally, the conclusion has been drawn in section 3.5.

3.2 Materials and methods

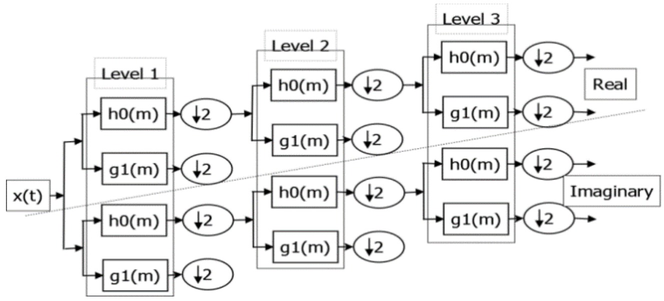
3.2.1 Dual-Tree Complex Wavelet Transform (DTCWT)

DTCWT is an improvement of the DWT. It computes the signal x(n) using two real DWTs in parallel to evaluate the real part and imaginary part of the transform. In the DTCWT structure, two different real filters for each DWT are designed in a specific way that the sub-bands of upper DWT and lower DWT are interpreted as real part and imaginary part of the transform, respectively, as shown in Figure 3.1.

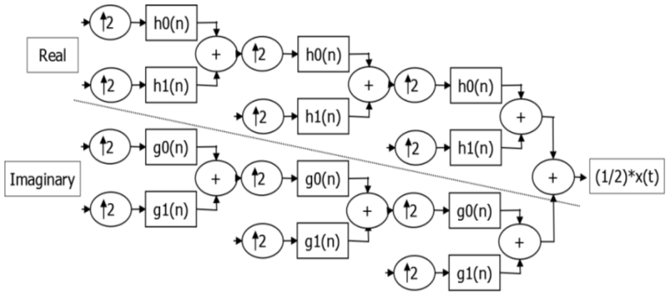
The expression of dual-tree complex wavelet transform can be written as

$$\emptyset(t) = \emptyset_h(t)+\emptyset_g(t) \tag{3.1}$$

Where, $\emptyset_h(t)$ and $\emptyset_g(t)$ denote the two real wavelets, also $\emptyset_h(t)$ and $\emptyset_g(t)$ must be a Hilbert transform pair.



(a)



(b)

Figure 3.1 (a) Analysis Filter bank of DTCWT and (b) Synthesis Filter bank of DTCWT.

3.2.2 Thresholding

In de-noising of the signals, thresholding plays a vital role. Wavelet transform has multi resolution property that decomposes the contaminated signals into low frequency and high-frequency sub-bands. Noise components are present in the wavelet coefficients. If we eliminate the noise components from the wavelet coefficient by comparing each coefficient with a threshold value, the original signal can be recovered. The model of contaminated EEG signal is written as

$$y(n) = x(n) + p \times d(n) \tag{3.2}$$

where, $y(n)$is Contaminated EEG, $x(n)$ is EEG Signal, $d(n)$ is EOG Signal, and p is the scaling factor. De-noising is generally defined as recovery of unknown clean data from the contaminated signal. In [204,205] Donoho defined term "denoise" as the optimization of the mean-squared error.

The two main thresholding methods in wavelet domain are soft threshold and hard threshold. Soft threshold is defined as

$$\eta_s(\omega, T) = \begin{cases} \omega - T & \omega \geq T \\ 0 & |\omega| < T \\ \omega + T & \omega \leq -T \end{cases} \tag{3.3}$$

Hard threshold is defined as

$$\eta_s(\omega, T) = \begin{cases} \omega, & |\omega| \geq T \\ 0, & |\omega| < T \end{cases} \tag{3.4}$$

Where T is the threshold value, and ω is the wavelet coefficient.

In hard threshold scheme, all the wavelet coefficients with values greater than the given threshold T are chosen, and others are set to zero. However, soft threshold shrinks the wavelet coefficients by T towards zero. Estimation of threshold value is an important step in the elimination of OAs from noisy EEG. In this work, we have used an adaptive threshold proposed by Zikov et al. [206]. In this method, Wavelet coefficients for each band k with decomposition below 16 Hz have been selected, and then estimated the maximum value M_K of the selected coefficients. To make this threshold adaptive and to perform the algorithm to work in real-time, we have calculated M_K for every second. The threshold T_k can be expressed as

$$T_k = mean(M_K) + 2.std(M_K) \quad (3.5)$$

Where functions $mean(.)$ and $std(.)$ computes the mean and standard deviation, respectively.

3.2.3 Quantum inspired adaptive threshold (QAT)

According to quantum theory of information, each wavelet coefficient of the contaminated signal is in the superposition state of noise and signal.

$$\left|\omega_{i,j} >= s|0 > + n|1 > \quad (3.6)$$

This equation is in Dirac notation. Quantum state $|0 >$ represents signal state whereas $|1 >$ represents noise state. Also, s and n are the probability amplitudes of the two quantum states$|0 >$ and$|1 >$, respectively. However, $\left|\omega_{i,j} >\right.$ is the quantum state that varies according to the change in s and n. It may be assigned either to signal state '0' or to the noise state '1' accordingly.

The formulas for estimation of *n* and *s* are

$$n = k(\omega) \text{ and } s = 1 - k(\omega) \quad (3.7)$$

Where, $k(\omega)$ is a distribution function estimated by,

$$k(\omega) = \frac{1}{1 + \exp - \left(\left(|\omega_{i,j}| - T_k \right) \big/ B \right)} \quad (3.8)$$

In the above expression, B represents a constant positive number. $\omega_{i,j}$ is the wavelet coefficient and T_k is the threshold defined in Equation (3.5).

Once the values of s and n are calculated, state of the wavelet coefficient needs to be measured. According to quantum theory, until the nonstationary state is measured, it wouldn't be assigned to one of the states. To measure wavelet coefficient quantum state$\left|\omega_{i,j}\right.>$, a variable number *R* is generated for each measurement, which is uniformly distributed in the range [0,1]. If the estimated value of *R* falls in the range [0,s], then $\left|\omega_{i,j}\right.>$ is in the signal state, and if *R* projects in the range [s,1], then $\left|\omega_{i,j}\right.>$ is in the noise state. Hence the wavelet coefficients of the noise state are removed by setting them to zero.

3.3 Application of DTCWT-QAT for removal of ocular artifacts from EEG

Ocular artifacts have frequencies up to 16 Hz and have significantly larger amplitudes than the raw EEG signal. Wavelet decomposition of contaminated EEG signal generates larger coefficients in the lower frequency band (0-16 Hz); this shows the presence of OAs. Applying an adaptive thresholding algorithm on these coefficients, in other words removing large OAs coefficients and then reconstructing the signal, will thus correct the EEG. In our work, we have decomposed the contaminated EEG signal using dual-tree complex wavelet transform (DTCWT) and therefore applied quantum information theory to eliminate OAs from the EEG signal. Major steps followed are as below

Step1 EEG signal is added with EOG signal to make contaminated EEG using Equation (3.2).

Step2 Calculate the input Signal to artifact (SAR) ratio using

$$SAR = \left(\frac{\sum_{n=0}^{N} x(n)^2}{p \times \sum_{n=0}^{N} d(n)^2} \right) \tag{3.9}$$

where, N represents the total number of samples.

Step3 Decompose the input signal y(n) using DTCWT

$$Y(n) = X(n) + D(n) \tag{3.10}$$

Where, $Y(n)$, $X(n)$ and $D(n)$ are DTCWT coefficients of $y(n)$, $x(n)$, and $d(n)$, respectively.

Also,
$$Y(n) = Y_r(n) + iY_i(n) \tag{3.11}$$

Where, $Y_r(n)$and $Y_i(n)$are real and imaginary coefficients of $Y(n)$.

Step4 Applying Quantum inspired adaptive threshold (QAT) algorithm.

Each wavelet coefficient with decomposition below 16 Hz of contaminated EEG signal may be assigned either to signal state or noise state according to quantum theory of information. Values of s and n are calculated using Equation (3.7) to every wavelet coefficient and measured the superposition state of each wavelet coefficient. The noise state is considered as artifact state and if the state is in noise state, set it to zero.

Step5 Now apply the inverse DTCWT to get the corrected EEG signal in the time domain. The reconstructed signal $\hat{x}(n)$ can be defined by

$$\hat{x}(n) = ddtreecfs(\hat{X}(n)) \tag{3.12}$$

Where function $ddtreecfs(.)$ computes the inverse DTCWT. $\hat{X}(n)$ are the wavelet coefficients after quantum thresholding.

3.4 Results and Discussion

3.4.1 EEG simulation

Clean EEG simulated signal is generated using NI LABVIEW 2015 Biosignal toolkit. The LABVIEW block diagram is shown in Figure 3.2. Then, the generated signal was being written to excel sheet and loaded on MATLAB for signal processing. We generated a contaminated EEG signal using Equation (3.1) by adding Eyeblink artifacts in the clean EEG. The simulated EEG signal, Eyeblink artifact, and contaminated EEG signal are shown in Figure 3.3. Thus applied the Quantum inspired adaptive wavelet threshold algorithm to remove the ocular artifacts from the contaminated EEG. Figure 3.4 shows the comparison among clean EEG, Contaminated EEG, and the DTCWT-QAT extracted EEG signal. Figure 3.4 depicts that eyeblinks have been successfully eliminated without losing the raw EEG signal information.

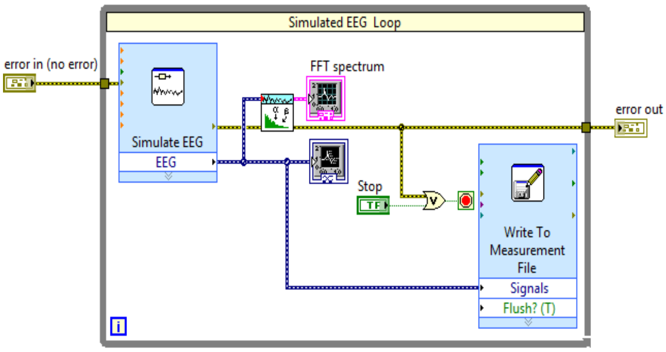


Figure 3.2 Labview Model for the generation of synthetic clean EEG signal.

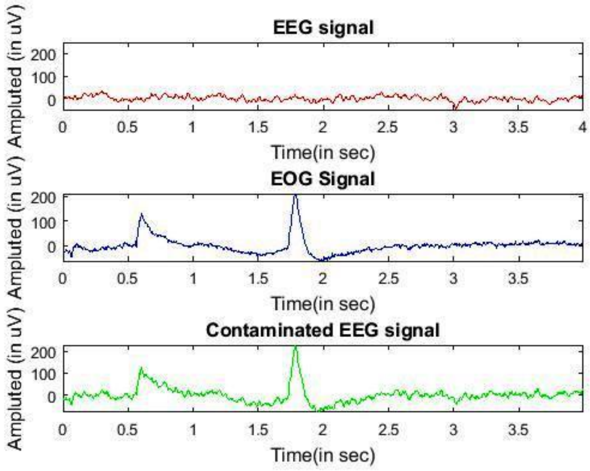


Figure 3.3 The clean EEG signal (upper graph). EOG signal (middle graph) and Contaminated EEG signal (lower graph).

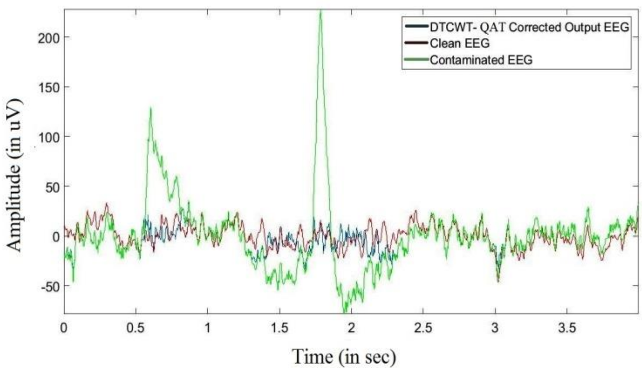


Figure 3.4 Comparison of Clean EEG, Contaminated EEG, and DTCWT-QAT corrected EEG.

For comparative study, we have performed some of the existing wavelet thresholding techniques popularly used for OAs removal. We have also drawn a comparison between DTCWT and DWT in terms of Relative Root Mean Square Error (RRMSE). We decomposed the contaminated EEG using DWT and applied soft threshold, hard threshold, and Quantum inspired adaptive threshold for removal of OAs. In DWT, Daubechies5 wavelet function was used with seven decomposition levels. The wavelet coefficients of the added artifact signal (EOG) are eliminated by applying the hard threshold, soft threshold, and Quantum inspired adaptive threshold on the decomposition levels below 16 Hz. After thresholding, inverse DWT was performed; thus, we get the corrected EEG signal.

To evaluate the comparative study of all these techniques, we have calculated the Relative Root Mean Square Error (RRMSE). The formula for the calculation of RRMSE is

$$RRMSE=\frac{\sqrt{\frac{1}{N}\sum_{n=0}^{N}(\hat{x}(n)-x(n))^2}}{\frac{1}{N}\sum_{n=0}^{N}x(n)^2}\times 100 \tag{3.13}$$

The RRMSE is calculated in percentage. The accuracy of any model is considered as good if the value of RRMSE is low. The curves of RRMSE at different input SAR for various artifact removal techniques are shown in Figure 3.5. The overall performance of DTCWT-QAT is quite good.

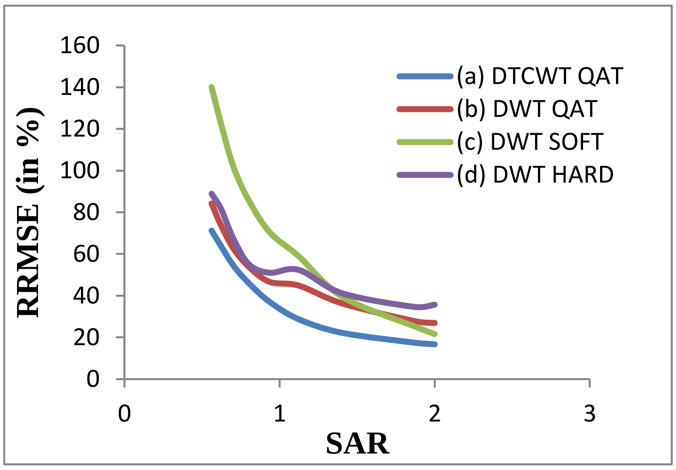


Figure 3.5 RRMSE curves for corrected EEG signal using (a) DTCWT-QAT (b) DWT-QAT (c) DWT soft threshold, and (d) DWT hard threshold.

3.5 Application to Real EEG data

For this work, the EEG dataset 2.1a from BCI Competition IV was used to be processed, which is available online at http://www.bbci.de/competition/iv/. The dataset consists of 22 channels of EEG recorded at a sampling frequency of 250 Hz with 3 EOG channels recorded simultaneously. A bandpass filter was applied to pre-process the EEG signal between 0.5 Hz to 100 Hz, and a notch filter was applied to eliminate line noise. The signal recording was performed by Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces), Graz University of Technology.

The EEG signal shown in Figure 3.6 is from channel location c3. Two eyeblinks can be observed at 0.6 sec and 1.8 sec. To remove these blinks, we applied DTCWT-QAT algorithm. Figure 3.7 shows the comparison between DTCWT-QT corrected signal and raw EEG signal. It can be observed that the eyeblinks have been removed successfully without altering the EEG signal information.

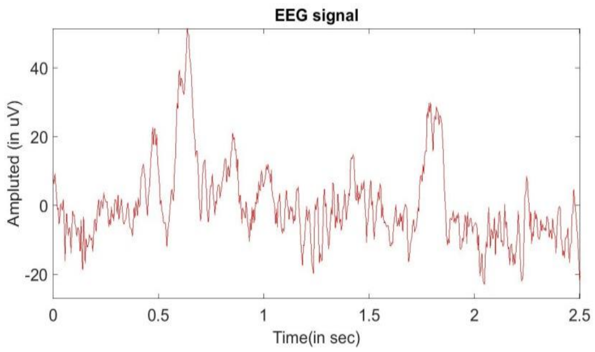


Figure 3.6 EEG signal from c3 Channel acquired while performing motor imaginary task with two eyeblinks at 0.6 sec and 1.8 sec.

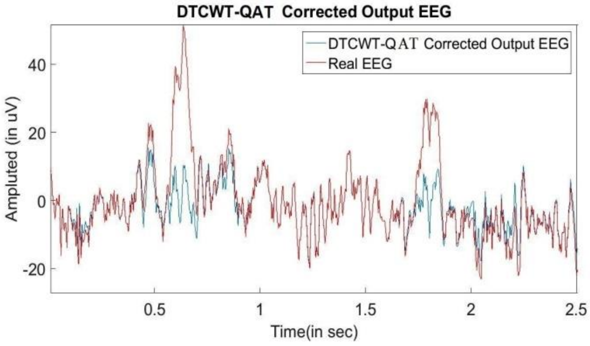


Figure 3.7 Comparison of real EEG signal from c3 Channel with eyeblink artifacts and DTCWT-QAT corrected EEG.

3.6 Conclusion

In this chapter, an effective adaptive threshold algorithm is proposed to address the issue of Ocular artifacts removal from the single-channel EEG signal. It is based on the quantum theory of information. We have used DTCWT for the decomposition of contaminated EEG. Unlike DWT, DTCWT is nearly shift-invariant and provides perfect reconstruction of the signal. Experiments are conducted to assess the performance of the proposed Quantum-inspired adaptive threshold algorithm in comparison with the soft threshold and hard threshold. It is shown that the RRMSE is reduced to a greater extent. Results obtained show that the proposed method suppresses the ocular artifacts successfully without affecting the EEG signal information.