# Subband Correlation For EEG Data in the Dual Tree Complex Wavelet Transform Domain For the Detection of Epilepsy and Seizure

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***Abstract*—In this paper, a comprehensive analysis of electroencephalogram (EEG) signals is carried out in the dual tree complex wavelet transform domain using a publicly available EEG database. It is shown that maximum cross-correlation among the sub-bands along with the absolute values of the corresponding correlation coefficient and co-variance can be effective in distinguishing EEG signals such as seizure and non-seizure. Thus, these quantities may be used to characterize EEG signals to realize the underlying diverse process of EEG recordings and help the researchers in developing improved classifiers for the detection of epilepsy and seizure.**

***Index Terms*—Electroencephalogram(EEG), Seizure, Dual Tree Complex Wavelet Transform(DT-CWT), Correlation.**

## I. Introduction

Seizure a transient occurrence that arises due to the abnormal and excessive neuronal activity in the brain. It causes a neurological disorder of the brain named epilepsy. Around 1% of the world's population (more than 50 million) is affected by epilepsy [1]. Traditional method of seizure detection involves long-term visual observation of EEG records, which is a time-consuming and laborious job. Besides, it is prone to error because of its subjective nature. Another aspect of seizure detection is that about 25% of the patients do not respond well to the medications and/or suffer from side effects. These epilepsy patients may require resective surgery such as temporal lobectomy, where a section of the temporal lobe is identified as the focal point for seizure and removed. However, such surgeries are not risk free especially in the case of multi-focal epilepsy and may affect one's mental abilities; and in some cases, the seizure may not go away. Implantable closed-loop neuro-stimulators such as the RNS(responsive neuro-stimulator) can provide an alternative solution [1]. Here, as the seizure is detected, it is aborted by triggering appropriate stimulation to the epileptogenic zone to suppress the neuronal discharge. Such devices obviously would require automatic detection of seizure events. Moreover, automatic detection may relieve the neurologists off the time-consuming job of observing EEG records and reduce misinterpretation since it is not subjective.

A number of algorithms have been introduced in the literature for automatic detection of seizures [2] - [9]. A major part of a detection algorithm is the extraction of the appropriate features to discriminate the EEG signals. The detection process is carried out by extracting the features from an EEG signal and classified into the appropriate categories such as ictal(seizure) and non-ictal(non-seizure). The underlying diverse process of brain dynamics and associated major neuronal activities are represented in frequency sub-bands more precisely as compared to the original EEG [6]. For this reason, the time-frequency-based features have been shown to be highly promising in the detection of seizure and epilepsy [2]- [8].

The objective of this paper is to analyze the EEG signals in the dual tree complex wavelet transform (DT-CWT) domain and develop features for discriminating EEG signals to detect seizure and non-seizure. This transform has been chosen because of its offering a better time-frequency representation of a signal as compared to discrete wavelet transform (DWT) which is widely employed for the time-frequency representation of various types of signals. However, to the best of our knowledge, limited research has been reported in the literature by using DT-CWT for processing of biological signals such as EEG, EMG or ECG [8], [10]. In [8], higher order moments and model parameters in the DT-CWT sub-bands are shown to be effective to discriminate the EEG data. The target of this paper is to study the inter-sub-band correlation among the DT-CWT sub-bands of EEG data. The motivation comes from the inter-sub-band correlation that exists in other non-stationary signals such as image processing and speech recognition [11], [12]. Analysis of the EEG recordings in the related sub-bands signal of DT-CWT domain could help researchers in developing improved algorithms for seizure detection and provide with effective features that may result in understanding the epilepsy-related neural activities.

## II. Description of the EEG Database

In this Section, a brief description of the database [13], [14] is provided for the convenience of the readers. The database has been widely used in the literature of EEG (See references [2], [3], [5] and the references therein) and has a considerable volume of data that is necessary to provide the statistical significance of the discriminating features. This EEG database consists of five sets of grouped data namely A, B, C, D and E, each containing 100 EEG segments, thus total 500 single-channel EEG segments of 23.6-seconds duration each. The standard 10-20 electrode placement scheme is used to collect the scalp EEG data for Set A and Set B from five healthy volunteers in awake and relaxed state, with their eyes open and closed, respectively. The signals in the Sets C, D and E are collected during presurgical diagnosis from five patients, who gained complete control of seizures after resection. These resected sites are thus diagnosed as epileptogenic zone. EEG data in Sets C and D are obtained from the electrodes placed in the hippocampal formation of the opposite hemisphere and epileptogenic zone, respectively. In this connection, it may be mentioned that there are four lobes in the brain, among which the temporal one is considered to be highly responsible for having the epileptogenic zones, the focal points of seizure, such as hippocampus and amygdala. Data in Set E are collected from these electrodes as well as those implanted in temporal and basal regions of the neocortex. Thus, signals in Sets C and D correspond to seizure-free epochs and signals in Set E correspond to seizure attacks. The intra-cranial electrodes containing pathological activity are not considered in these sets. All of the signals are recorded in digital format at a sampling rate of 173.61Hz. The corresponding bandwidth is 86.8 Hz and the sample length of each segment is 173.61 $\times$ 23.6 $\approx$ 4097.

## III. Dual Tree Complex Wavelet Transform (DT-CWT)

The DT-CWT (Dual Tree Complex Wavelet Transform) contains two critically sampled DWT trees (Fig. 1). The first tree gives the real part of the complex coefficients whereas the second gives the imaginary parts. The DT-CWT decomposes a signal in terms of a scaling function $\phi(t)$ and dilations of a mother wavelet function $\psi(t)$ [15]. These functions are complex, where the real and imaginary parts are given by

$$\psi_r(t) = \sqrt{2}\sum_n h_1(n)\phi_r(2t-n) \tag{1}$$

$$\psi_i(t) = \sqrt{2}\sum_n g_1(n)\phi_i(2t-n) \tag{2}$$

$$\phi_r(t) = \sqrt{2}\sum_n h_0(n)\psi_r(2t-n) \tag{3}$$

$$\phi_i(t) = \sqrt{2}\sum_n g_0(n)\psi_i(2t-n) \tag{4}$$

where, $h_0$ and $g_0$ represent the low-pass filters for the real tree, whereas $h_1$ and $g_1$ represent the high pass filters. The synthesis filters are the transpose of these analysis filters. In this paper, the Farras wavelets [16] are employed for performing DT-CWT decomposition. In comparison to the traditional time-frequency representation such as the DWT and stationary wavelet transform, the DT-CWT offers a number of advantages that include shift-invariance with a modest increase in the computational complexity, better directionality and improved representations of singularities such as jumps or spikes.It may be noted that the traditional complex wavelet transform also offers these advantages, but has the limitation of perfect reconstruction beyond level 1. On the contrary, the DT-CWT has the perfect reconstruction property for higher number of levels.

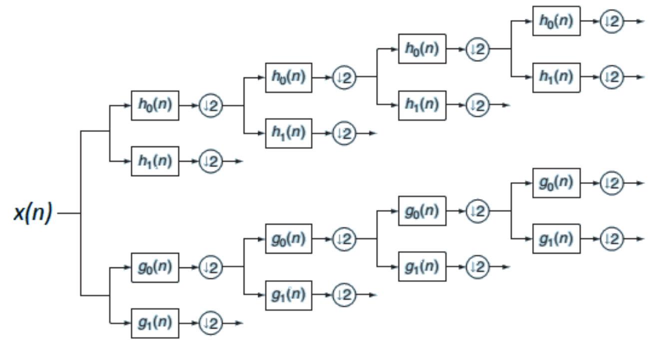


Fig. 1. 1-D Dual Tree Complex Wavelet Transformation [15]

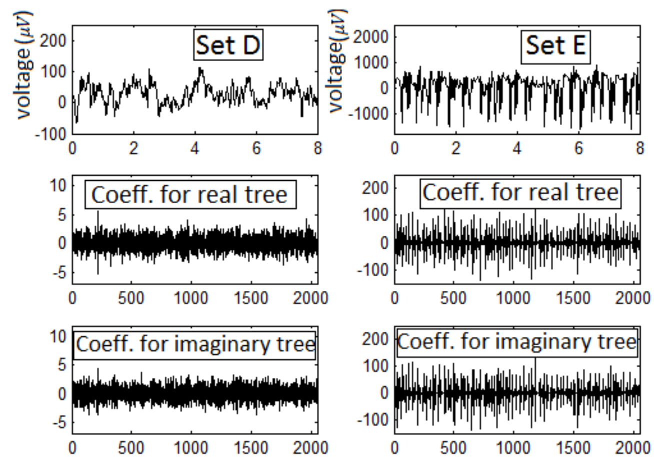


Fig. 2. Sample EEG Signals and the corresponding DT-CWT coefficients

Fig. 2 shows the plots of sample EEG segments for eight seconds from the datasets D (top left) and E (top right) in the first row and the plots of the corresponding first level DT-CWT real and imaginary coefficients, respectively in the second and the third rows.

## IV. Analysis of EEG in DT-CWT domain

The highest frequency component of an EEG segment of the database being used in this paper is 86.8 Hz, whereas the frequency range of an EEG signal spans over 0 to 60 Hz. The frequencies greater than 60 Hz may be considered as noise [6] and that is why a 6th order Butter-worth filter is employed to remove the frequencies beyond 60 Hz.

For the analysis, first the band-limited signals are subjected to a 4 level DT-CWT decomposition. The EEG signal, X (0-60 Hz), will be decomposed into its higher resolution components m1 (30-60 Hz) and lower resolution components, n1 (0-30 Hz) after the first level of decomposition. In the second level, the n1 component is then decomposed into higher resolution components, m2 (15-30 Hz) and lower resolution components, n2 (0-15 Hz). Thus, the components obtained after four levels of decomposition, are- (i) m1 (30-60 Hz), (ii) m2 (15-30 Hz),

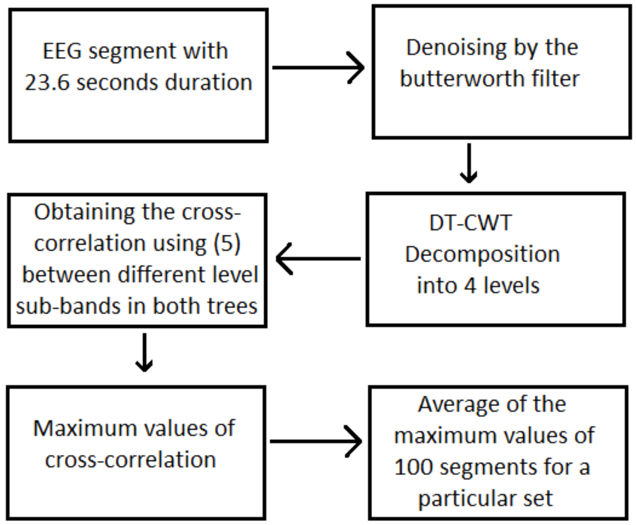


Fig. 3. Flow Chart for the Working Procedure to Find the Maximum Cross-correlation among the Sub-bands in Real and Imaginary Trees

(iii) m3 (8-15 Hz), (iv) m4 (4-8 Hz) and (v) n4 (0-4 Hz). Reconstructions of these five components using the inverse DT-CWT approximately correspond to the five physiological EEG sub-bands delta, theta, alpha, beta, and gamma respectively [6]. Since, each DT-CWT coefficient has two parts, real and imaginary, the 4-level decomposition yields ten sub-bands in total (five for real and five for imaginary). In order to understand the underlying diverse process of an EEG signal, it might be more useful to analyze it in the frequency domain (as in the DT-CWT sub-bands) as compared to the band-limited ones [6]. In this paper, first the EEG signals are analyzed in the DT-CWT domain using the inter-sub-band correlation and finally in terms of correlation coefficient and co-variance. The purpose of this analysis is the characterization of the sub-bands of EEG signals in form of those parameters and thus shows their ability to describe the diverse processes underlying the EEG signals and discriminate those signals. Cross-correlation vector(**R**) between two vectors (**x** and **y**) with length N is expressed as-

$$R_{xy}(m) = \begin{cases} \sum_{n=0}^{N-m-1} x_{n+m} y_m^*, & \text{if } m \geq 0 \\ R_{xy}^*(-m), & \text{if } m < 0 \end{cases} \tag{5}$$

The cross-correlation vectors are obtained using (5) and then, the maximum cross-correlation among the DT-CWT sub-bands in the real and imaginary tree is calculated for all the 100 data-sets from each of the five sets as described in Fig. 3 and their respective averages are shown in tables I and II. Note that the correlation between the sub-bands are indicated as mentioned earlier; . For instance, max23 means the maximum correlation between sub-bands m2(15-30 Hz) and m3 (8-15 Hz) or max15 means the the maximum correlation between sub-bands m1(30-60 Hz) and n4 (0-4 Hz) for any tree.

From tables I and II, it is seen that the values for maximum

TABLE I
VALUES OF MAXIMUM CROSS-CORRELATION AMONG VARIOUS DT-CWT SUB-BANDS FOR THE REAL TREE

| Sub-bands | Set A | Set B | Set C | Set D | Set E |
|---|---|---|---|---|---|
| max12 | 5.98e+3 | 1.03e+4 | 3.04e+3 | 4.54e+3 | 2.18e+5 |
| max13 | 1.03e+4 | 2.49e+4 | 5.94e+3 | 1.15e+4 | 5.49e+5 |
| max14 | 8.81e+3 | 1.88e+4 | 8.79e+3 | 1.60e+4 | 5.12e+5 |
| max15 | 1.11e+4 | 1.78e+4 | 1.62e+4 | 2.84e+4 | 5.84e+5 |
| max23 | 5.07e+4 | 1.43e+5 | 2.14e+4 | 4.51e+4 | 3.02e+6 |
| max24 | 3.79e+4 | 6.98e+4 | 3.18e+4 | 6.57e+4 | 2.98e+6 |
| max25 | 4.34e+4 | 6.97e+4 | 4.61e+4 | 9.47e+4 | 3.15e+6 |
| max34 | 9.18e+4 | 2.76e+5 | 7.87e+4 | 1.85e+5 | 1.06e+7 |
| max35 | 1.33e+5 | 2.70e+5 | 1.38e+5 | 3.39e+5 | 1.06e+7 |
| max45 | 1.96e+5 | 4.20e+5 | 3.22e+5 | 7.25e+5 | 1.93e+7 |

TABLE II
VALUES OF MAXIMUM CROSS-CORRELATION AMONG VARIOUS DT-CWT SUB-BANDS FOR THE IMAGINARY TREE

| Signals | Set A | Set B | Set C | Set D | Set E |
|---|---|---|---|---|---|
| max12 | 5.90e+3 | 1.04e+4 | 2.93e+3 | 4.63e+3 | 2.30e+5 |
| max13 | 1.00e+4 | 2.68e+4 | 6.13e+3 | 1.16e+4 | 5.53e+5 |
| max14 | 9.02e+3 | 1.90e+4 | 8.34e+3 | 1.77e+4 | 5.02e+5 |
| max15 | 1.10e+4 | 1.76e+4 | 1.61e+4 | 3.04e+4 | 5.93e+5 |
| max23 | 5.03e+4 | 1.47e+5 | 2.26e+4 | 4.44e+4 | 2.91e+6 |
| max24 | 3.85e+4 | 6.70e+4 | 3.11e+4 | 7.54e+4 | 2.92e+6 |
| max25 | 4.42e+4 | 6.82e+4 | 4.50e+4 | 9.24e+4 | 3.27e+6 |
| max34 | 9.19e+4 | 2.72e+5 | 8.13e+4 | 2.04e+5 | 1.02e+7 |
| max35 | 1.29e+5 | 2.73e+5 | 1.37e+5 | 2.96e+5 | 1.07e+7 |
| max45 | 2.05e+5 | 4.21e+5 | 2.95e+5 | 7.98e+5 | 1.94e+7 |

correlation are significantly different among the five cases. In all the cases, the values of maximum cross-correlation is highest in Set E (seizure cases). Between the healthy cases (Set A and Set B) and between the inter-ictal cases (Set C and Set D), the values for Set A and Set C are always lower than those for Set B and Set D respectively. However, the significance is further confirmed from the box plots and p-values of the ANOVA analysis for the various sub-bands. Two sample box plots, based on the maximum cross-correlation between the m1 and m2 sub-bands in real and imaginary trees respectively, are shown in Figs. 4 and 5 which show that it can distinguish the seizure data from the non-seizure ones.

The p-values obtained from the anova analysis are given in table III. The p-values are quite small for all the sub-bands; indicating their ability to discriminate the different sets of EEG data.

TABLE III
P-VALUES OBTAINED FROM ANOVA ANALYSIS

| Sub-bands | Real Tree | Imaginary Tree |
|---|---|---|
| max12 | 1.6032e-33 | 5.3044e-31 |
| max13 | 1.1028e-34 | 1.4242e-33 |
| max14 | 4.5976e-59 | 3.1863e-59 |
| max15 | 5.0757e-55 | 1.7006e-47 |
| max23 | 1.3124e-40 | 8.4070e-42 |
| max24 | 2.5822e-60 | 4.1958e-65 |
| max25 | 1.6665e-54 | 2.4660e-53 |
| max34 | 2.1846e-56 | 5.7755e-56 |
| max35 | 5.0592e-63 | 6.6394e-65 |
| max45 | 3.0380e-51 | 9.5026e-53 |

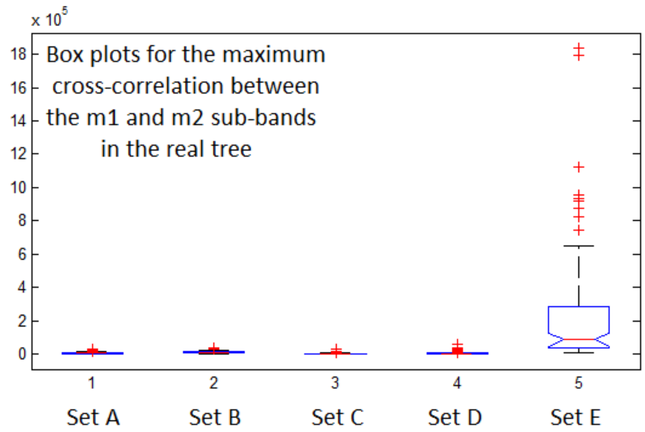


Fig. 4. Box plot among the Five Sets based on the maximum cross-correlation between the m1 and m2 sub-bands in the real tree

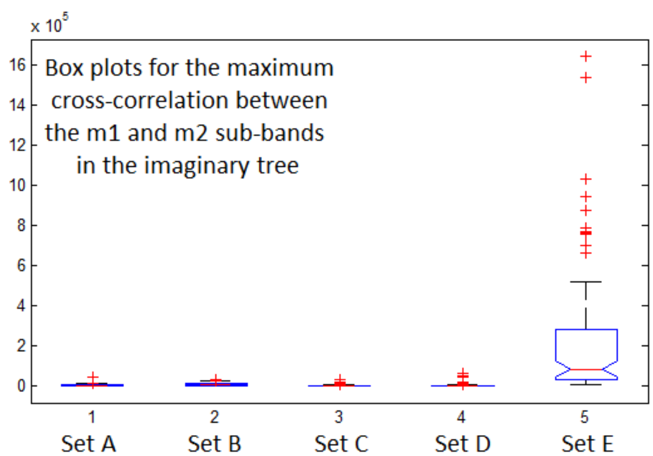


Fig. 5. Box plot among the Five Sets based on the maximum cross-correlation between the m1 and m2 sub-bands in the imaginary tree

After realizing the significance of the sub-band correlation in both of the real and imaginary trees, it may seem to be relevant to study whether the sub-band correlation between the trees is effective enough to discriminate among various types of EEG recordings. Thus, for all the five Sets, the maximum cross-correlation between the real and imaginary sub-bands are calculated for all the 500 data-sets using (5) and the average value of the 100 data-sets, from each of the five Sets, are calculated. After that, to have a better understanding of the underlying significance, two more correlation features named as covariance (Cov) and correlation coefficient (CC) are calculated for all the five sub-bands from the real and imaginary trees for all the five Sets. These two features are expressed as-

$$Cov(x,y) = E(xy) - E(x) \times E(y) \tag{6}$$

$$CC(x,y) = \frac{Cov(x,y)}{\sigma_x \times \sigma_y} \tag{7}$$

where E(k) and $\sigma_k$ are the expected value and the standard deviation, respectively, for vector **k**. However, for an unbiased

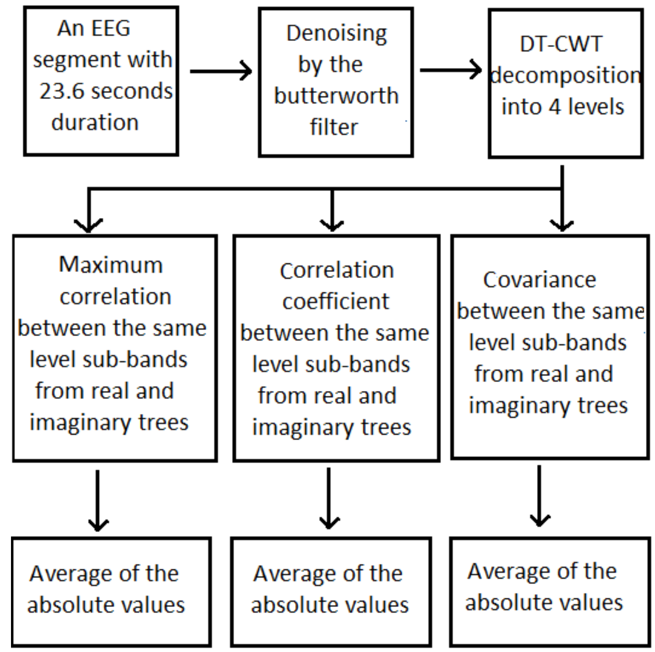


Fig. 6. Flow Chart for the Working Procedure to Find the Maximum Cross-correlation, Correlation Coefficient and Co-variance among the Sub-bands between Real and Imaginary Trees

estimation, (2) reduces to

$$Cov(x,y) = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y) \tag{8}$$

where $\mu_x$ and $\mu_y$ are the mean value of vector **x** and **y**. These two parameters, correlation coefficient and covariance, are calculated using (7) and (8) between the sub-bands for both of the trees for all the 500 recordings. The absolute values of correlation coefficient and covariance for all the five sets are calculated and their average values are obtained as described in Fig. 6. The average values of maximum cross-correlation, correlation coefficient and co-variance between the real and imaginary sub-bands are shown in tables IV, V and VI respectively. However, it should be noted that in these tables, the sub-bands are expressed as mentioned earlier. For instance, sub2 means the maximum cross-correlation between m2 sub-bands from the real and imaginary trees, or sub5 means the maximum cross-correlation between n4 sub-bands from the real and imaginary trees.

TABLE IV
VALUES OF MAXIMUM CORRELATION BETWEEN THE SUB-BANDS FROM THE TWO DT-CWT TREES FOR VARIOUS SETS OF EEG DATA

| Sub-bands | Set A | Set B | Set C | Set D | Set E |
|---|---|---|---|---|---|
| sub1 | 1.04e+4 | 1.87e+4 | 4.16e+3 | 5.45e+3 | 3.82e+5 |
| sub2 | 7.88e+4 | 9.76e+4 | 2.48e+4 | 3.45e+4 | 3.49e+6 |
| sub3 | 3.53e+5 | 1.59e+6 | 1.59e+5 | 3.03e+5 | 3.84e+7 |
| sub4 | 2.28e+5 | 1.00e+6 | 3.67e+5 | 9.21e+5 | 2.92e+7 |
| sub5 | 2.83e+6 | 3.71e+6 | 5.24e+6 | 1.18e+7 | 5.13e+7 |

TABLE V
ABSOLUTE VALUES OF CORRELATION COEFFICIENT BETWEEN THE SUB-BANDS FROM THE TWO TREES FOR VARIOUS SETS OF EEG DATA

| Signals | Set A | Set B | Set C | Set D | Set E |
|---|---|---|---|---|---|
| sub1 | 0.3020 | 0.3125 | 0.1591 | 0.1904 | 0.4764 |
| sub2 | 0.1608 | 0.1852 | 0.1386 | 0.1711 | 0.1939 |
| sub3 | 0.1874 | 0.1773 | 0.1821 | 0.1774 | 0.1797 |
| sub4 | 0.1019 | 0.1372 | 0.0819 | 0.0805 | 0.0940 |
| sub5 | 0.7162 | 0.6668 | 0.6858 | 0.6521 | 0.3985 |

TABLE VI
ABSOLUTE VALUES OF CO-VARIANCE BETWEEN THE SUB-BANDS FROM THE TWO DT-CWT TREES FOR VARIOUS SETS OF EEG DATA

| Sub-bands | Set A | Set B | Set C | Set D | Set E |
|---|---|---|---|---|---|
| sub1 | 3.447 | 4.615 | 1.206 | 1.742 | 171.858 |
| sub2 | 32.894 | 66.517 | 10.826 | 21.177 | 2.09e+3 |
| sub3 | 279.520 | 1.14e+3 | 134.889 | 283.276 | 2.10e+4 |
| sub4 | 283.995 | 1.53e+3 | 285.084 | 630.550 | 2.72e+4 |
| sub5 | 5.22e+3 | 5.31e+3 | 1.27e+4 | 3.51e+4 | 1.44e+5 |

From tables IV, V and VI, the following observations can be made-

- It is seen that the values for maximum correlation from Set E are significantly larger for those from the other Sets like Sets A, B, C and D.
- The absolute values of correlation coefficient for the seizure cases (Set E) are significantly different from the values from the non-seizure cases (Sets A, B, C and D) in the m1 and n4 sub-bands. However, for the sub-bands m2, m3 and m4, the differences among the values are not significant which indicates their poor capability to discriminate the EEG data.
- The differences among the absolute values of covariance for different sets are significant enough to discriminate among the EEG data in all the sub-bands. The values are always highest for Set E, and lowest for Set C in the high frequency sub-bands (m1,m2 and m3) and for Set A in the low frequency sub-bands(m4 and n4).
- For correlation coefficient, it can be stated that, in sub-band m1, the values are significantly different for healthy cases (Sets A and B) from those from the inter-ictal cases (Sets C and D) and the ictal cases (Set E). But, in the other sub-bands, the values are not significantly different.
- For covariance, it is seen that in all the sub-bands, the differences among the values from Set A, B, C and D are significant which indicates that this parameter can distinguish these Sets in various sub-band levels.

However, the above observations are further confirmed from the ANOVA analysis for the various sub-bands. The p-values are given in table VII. The p-values are quite small almost for all the sub-bands for all three parameters indicating their capability to discriminate the different sets of EEG data. However, the p-values for correlation coefficient in the m2,m3 and m4 sub-band are not small enough to discriminate the EEG data.

The total analysis is carried out by calculating the cross-correlation vectors, correlation coefficient and co-variance

TABLE VII
P-VALUES FROM ANOVA ANALYSIS

| Sub-bands | Maximum Cross-correlation | Correlation Coefficient | Co-variance |
|---|---|---|---|
| sub1 | 9.0309e-34 | 2.0768e-72 | 1.6567e-30 |
| sub2 | 1.7509e-23 | 1.8573e-10 | 1.4218e-28 |
| sub3 | 2.7659e-27 | 0.6711 | 7.7635e-41 |
| sub4 | 1.2587e-42 | 1.7679e-11 | 2.5531e-42 |
| sub5 | 2.3436e-38 | 9.2657e-80 | 1.1744e-32 |

using (5), (7) and (8) between two of the DT-CWT sub-bands from the real and imaginary trees. Significance of the statistical analysis may be established from the following. First, there are 10 sub-bands for a 4 level decomposition which gives $10\times100$=1000 sub-bands for a given data-segment. As, five sets are used, there are total $1000\times5$ =5000 sub-bands. Secondly, the minimum and maximum length of a sub-band is 256 and 2048 respectively. Thus, the analysis of the EEG data in DT-CWT domain is comprehensive enough for the corresponding results being statistically significant.

## V. CONCLUSION

In this paper, an exhaustive analysis using the correlation among the DT-CWT sub-bands of EEG signals has been carried out. The maximum values of the cross-correlation between sub-bands of the same tree (real/imaginary) as well as that of the sub-bands at the same level in different trees (real and imaginary) has been shown to be able to discriminate the EEG data corresponding to healthy, inter-ictal (non-seizure) and ictal (seizure) signals. Moreover, the absolute values of correlation coefficient and co-variance among the sub-bands at the same level in different trees (real and imaginary) are shown to be effective to distinguish among the EEG signals in various levels. The discrimination using these parameters indicates a better representation of the underlying brain dynamics or processes at various sub-band levels. Thus, these parameters may also be used not only to discriminate but also to characterize the EEG signals. Overall, a number of statistical quantities have been shown to be able to discriminate the EEG data at sub-band levels which may be helpful for the researchers to develop efficient methods to classify EEG signals in order to detect epilepsy and seizure.

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