EEG SIGNAL FEATURE EXTRACTION USING DTCWT FOR NORMAL AND ABNORMAL SUBJECT

Mangala Gowri S G A[1], Dr.Cyril Prasanna Raj P B[2]
[1] *Research Scholar, M.S.Engineering College,Visvesvaraya Technological University,Department of Electronics and Communication, Karnataka,Bangalore,India*
[2] *Dean of Research and Development, Visvesvaraya Technological University, Department of Electronics and Communication, Karnataka, Bangalore, India*
(E-mail: mangalag21@gmail.com)

Abstract— Brain Computer Interface (BCI) provides the communication between the human and the system by using Brain signals. Electroencephalogram (EEG) signals are often used for BCI purpose since it is implemented as a non-invasive sytem.In this paper, the EEG Signal Feature Extraction using Dual Tree Complex Wavelet Transform (DTCWT) is been proposed considering two different Emotional states. Feature extraction is performed by extracting energy levels for Real and Imaginary coefficients for all the EEG Bands for both Normal and Abnormal Subjects.

Keywords—Dual Tree Complex Wavelet Transform (DTCWT), Electroencephalography (EEG), Feature Extraction, Energy Levels, Emotions

I. INTRODUCTION

Electroencephalogram(EEG) is a valuable measure of the brain's electrical function and generated by the cerebral cortex's nerve cells **[1].**Due to the complex interconnections between billions of neurons, the recorded EEG signals are complex, non-linear, non-stationary and random in nature **[2]**.These days signal analyzing and processing techniques have been investigated for different EEG signal classification. There are three different stages of EEG signal processing techniques, they are, pre-processing, Feature Extraction and Classification. There are several methods which are applied for EEG Feature extraction. In this work Dual Tree Complex Wavelet Transform (DTCWT) has been proposed as a feature extraction method. DTCWT is an enhancement to the discrete wavelet transform (DWT).It is a shift invariant and directionally selects two and higher dimensions[**3**]**.**It achieves a redundancy factor of 2^d for d-dimensional signals, which is lower than the undecimated DWT.The multidimensional (M-D) Dual-tree complex Wavelet Transform is non separable but is based on a computationally efficient, separable filter bank (FB).The DTCWT of a sign, x(n) is executed utilizing two fundamentally inspected DWT's as a part of parallel on the same information.DTCWT coefficients are non-swaying with an almost move invariant greatness and altogether lessened associating with more directionalities when contrasted with the DWT.Thus is it more efficient in time frequency localization of EEG signal. Similar to the positive or negative post-filtering of real subband signals, the idea behind dual tree approach is quite simple [**4**].A survey of recent studies on the feature extraction methods on Dual tree Complex Wavelet Transform (DTCWT) proposed by different authors have been discussed and the comparisons of DTCWT with DWT have been illustrated from the previous literature.Kingsbury.N[**4**] according to the author, DWT is very sensitive in the translation, it is very less effective in the domain of statistical signal processing. To address the, shift-variance problem a new method is employed by considering two DWT's, one of DWT gives the real part of the transformed co-efficients and the other one gives the imaginary part. By combining the co-efficients of two DWT's into complex-valued co-efficients, a new transform is obtained by the name Dual Tree Complex Wavelet Transform(DTCWT).This new transform has some, characteristic properties including near shift-invariance, better directional selectivity, which is very important in signal processing.Musa et.al [**5**][**6**], in this study first the features of EEG data are extracted using a dual-tree complex wavelet transformation at different levels of granularity to obtain size reduction and statistical features are extracted. Five statistical features are extracted from new dataset with reduced size and are classified with the help of Complex valued neural networks (CVANNs) using DTCWT in the classification of EEG data. The proposed method is tested using a benchmark of EEG dataset, and high accuracy rates are obtained. The stated results show that the proposed method can be used to design an accurate classification system for epilepsy diagnosis.R.Y.Yu [**7**], proposed that DWT is not able to cancel the aliasing, thus resulting in unclearly separated sub-bands. The dual-tree complex wavelet transform (DTCWT) was first introduced by Kingsbury, and he proposed to extract the signal component related to sensory motor rhythms.Piyush Swami [**8**], focused on the development of a robust automated system for classification against low levels of supervised training. The EEG signals were decomposed into time-frequency sub-bands till sixth level using dual-tree complex wavelet transform

(DTCWT).The features like Energy, Standard deviation, Root-Mean-Square, Shannon Entropy, mean values and maximum peaks were calculated using detailed and last approximation co-efficients. Syed Khairul Bashar et. al **[9**] developed a BCI system for identifying imagery hand movements by automatically extracting suitable features from EEG signals in the dual tree complex wavelet transform (DTCWT) domain carried out by taking feedback from C3 and C4 channel while making Cz the reference which was decomposed into three levels.EEG signals have been successfully classified by extracting features like variance and Shannon entropy of EEG signals in the dual tree complex wavelet transform domain. In In Anindya Bijoy Das et. al [**10**] shows that the values of the statistical moments computed for the dual tree complex wavelet transform (DTCWT) sub bands provide a significant level of discrimination of various classes of EEG signals, such as seizure and non-seizure. The author in Guangyi Chen [**11**] performed the Electroencephalography (EEG) seizure detection method by using the dual-tree complex wavelet (DTCWT) Fourier features. These Feature extraction methods outperform a number of existing methods published in the literature. But the objective of our work is to extract Real and Imaginary Energy Levels of normal and abnormal subjects and understand the behavior of EEG sub-bands by implementing Double Tree Complex Wavelet Transform (DTCWT).

II. DUAL TREE COMPLEX WAVELET TRANSFORM (DTCWT)

An analytic wavelet transform was first introduced by Kingsbury in 1998 **[12][13].**The DTCWT uses analytic filters to perform the wavelet analysis.DTCWT has a more complex structure compared to standard DWT,The dual tree CWT employs two real DWT's the first DWT gives the real part of the transform and is called the real tree while the second DWT gives the imaginary part called the imaginary tree that work parallel to each other, shown in Figure 1.One of these trees is called the real tree, whereas the other is called the imaginary tree.DTCWT uses a pair of filters for mother wavelet function $\psi(t)$ and scaling function $\phi(t)$ .Let the filters $h_0(n)$, $h_1(n)$ denote the low-pass and high-pass filter pair for the upper FB, and let $g_0(n)$, $g_1(n)$ denote the low-pass/high-pass filter pair for the lower FB**[12]**[**14].**Wavelet function and scaling functions are calculated by the equations

$$\boldsymbol{\psi_h}\ \mathbf{(t)} = \sqrt{2}\sum_n \mathbf{h_n}\, \boldsymbol{\varphi_h}\ \mathbf{(2t-n)} \qquad \mathbf{(1)}$$

$$\boldsymbol{\emptyset_h}\ \mathbf{(t)} = \sqrt{2}\sum_n \mathbf{h_0}\,\mathbf{(n)}\, \boldsymbol{\varphi_h}\mathbf{(2t-n)} \qquad \mathbf{(2)}$$

The two real wavelet transforms uses two different sets of filters, with each satisfying the Perfect Reconstruction (PR) conditions. The two sets of filters are jointly designed so that the overall transform is approximately analytic. The two real wavelets are associated with each of the two real wavelet transforms are denoted as $\psi_h(t)$ and $\psi_g(t)$.The PR conditions is given by the equation(3) **[3]**

$$\boldsymbol{\psi}\mathbf{(t)} = \boldsymbol{\psi_h}\mathbf{(t\ )} + \mathbf{j}\boldsymbol{\psi_g}\mathbf{(t)} \qquad \mathbf{(3)}$$

and the filters are designed so that the complex wavelet is approximately analytic.

$\psi_g(t)$ is designed approximately as the Hilbert transform of $\psi_h(t\ )$ where $\psi_g(t\ ) \approx H\{\psi_h(t\ )\}$.The dual-tree CWT is not a critically sampled transform, it is two times expansive in 1-Dimensional because the total output data rate is exactly twice the input data rate. The inverse of the dual-tree CWT is as simple as the forward transform. To invert the transform, the real part and the imaginary part are each inverted and the inverse of each of the two real DWTs are used to obtain two real signals. These two real signals are then averaged to obtain the final output. The original signal x(n)can be recovered from either the real part or the imaginary part. The inverse dual-tree Complex wavelet transform do not capture all the advantages as an analytic wavelet transform offers. If the two real DWTs are represented by the square matrices $\mathbf{F}_h$ and $\mathbf{F}_g$, then the dual-tree CWT can be represented by the rectangular matrix **[12]**as in equation (4),

$$\mathbf{F} = \begin{bmatrix} F_h \\ F_g \end{bmatrix} \qquad \mathbf{(4)}$$

If the vector **x** represents a real signal, then $\mathbf{w}_h = \mathbf{F}_h\mathbf{x}$ represents the real part and $w_g = F_g x$ represents the imaginary part of the DTCWT.The complex coefficients are given by equation (5),

$$w_h + jw_g. \qquad \mathbf{(5)}$$

fg A (left) inverse of **F** is then given by equation **(6),**

$$F^{-1} = \frac{1}{2}\,[\mathbf{F}_h^{-1}\mathbf{F}_g^{-1}] \qquad \mathbf{(6)}$$

It can be verified as in equation (7),

$$\mathbf{F^{-1} * F} = \frac{1}{2}\,[\mathbf{F}_h^{-1}\ \ \mathbf{F}_g^{-1}] * \begin{bmatrix} F_h \\ F_g \end{bmatrix} = \frac{1}{2}\,[\mathbf{I} + \mathbf{I}] = \mathbf{I} \qquad \mathbf{(7)}$$

The factor of one half between the forward and inverse transforms is given by equation (8)

$$\mathbf{F:} = \frac{1}{\sqrt{2}}\begin{bmatrix} F_h \\ F_g \end{bmatrix}, \mathbf{F^{-1}:} = \frac{1}{\sqrt{2}}\,[\mathbf{F}_h^{-1}\ \ \mathbf{F}_g^{-1}] \qquad \mathbf{(8)}$$

The dual-tree complex DWT of a signal $x(n)$ is implemented using two critically-sampled DWTs in parallel on the same data as shown in Figure 1.The input signal x(n) is decomposed to four sub bands at level-1 by the tree-a and tree-b filter banks that consists of low pass and high pass filters. The low pass filtered output of tree-a and tree-b are further decomposed into level-2 sub bands by the second stage filter banks. The first stage filter coefficients represented by {H0a, H1a, H0b and H1b} are different from second stage filter coefficients represented by {H00a, H01a, H00b, H01b}.After decomposition, from the acquired EEG signal, the EEG Bands namely, Gamma Beta, Alpha, Theta and Delta, the extracted

EEG Bands are decomposed giving rise to real and imaginary co-efficients, and the energy of the wavelet co-efficients is performed further each EEG Bands.

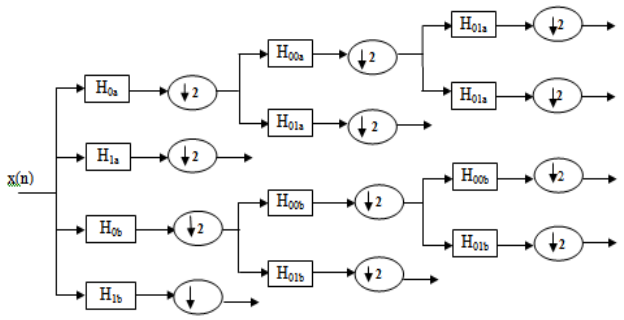

Figure 1: Three level DTCWT decomposition structure

III. FEATURE EXTRACTION USING DTCWT

The EEG electrodes capture real time data which is in the format of .xls format is loaded to the MATLAB workspace which is converted to .csv format. From all the electrodes stored in .xls data format represents the voltage levels in micro volts. From the EEG data available, onlyt the most suitable electrodes that are selected for emotion analysis are considered for wavelet decomposition. Selection of electrodes are presented in previous chapter. The electrodes for which DTCWT is computed are {FP2-F4, F4-C4, P4-O2, FP1-F3, F3-C3, P3-O1**}**.For the EEG data acquired from six electrodes is transformed into wavelet domain by performing DTCWT that generates both real and imaginary bands. From the DTCWT bands, energy levels are computed and from the energy levels obtained are the most distinct energy levels are considered for further classification into normal and abnormal EEG data.Further the energy of the co-efficients has been found from the EEG Bands. The original signal of normal and abnormal subject is shown in Figure 2 and Figure 3.

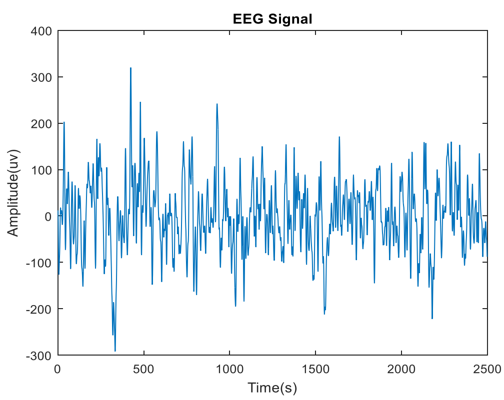

Figure 2: Original signal of Normal Subject

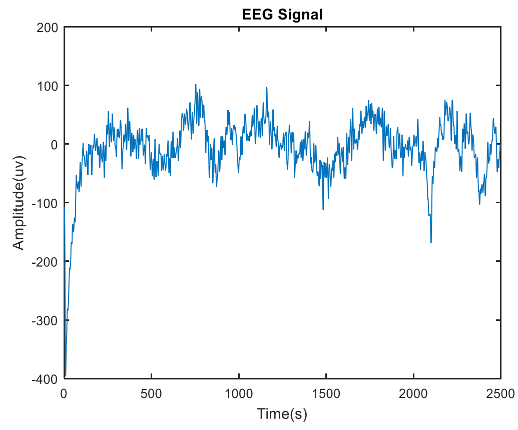

Figure 3: Original signal of Abnormal Subject

IV. RESULTS AND DISCUSSION

The energy Levels of Normal and Abnormal subjects are tabulated by considering the electrodes FP2-F4, F4-C4, P4-O2 which is illustrated in Table 1 and FP1-F3, F3-C3 and P3-O1 is shown in Table 2 of real co-efficients.

TABLE 1: ENERGY LEVELS OF REAL CO-EFFICIENTS OF FP2-F4, F4-C4 AND P4-O2 ELECTRODES

Scalp Electrodes	Real energy levels	
	Normal Subject	*Abnormal subject*
FP2-F4	21.5666	7.1624
	0.0607	0.0445
	0.4506	0.2599
	3.135	1.4121
	8.6771	2.5512
	26.8587	19.3837
	37.317	43.801
F4-C4	18.8359	4.901
	0.0593	0.0578
	0.4674	0.3231
	3.1186	1.5846
	8.718	3.0178
	27.9392	10.6158
	21.4287	29.8215
P4-O2	19.7139	5.9652
	0.0671	0.0556
	0.5299	0.3556
	3.0201	2.0605
	8.7825	3.1349
	29.7972	18.0883
	28.4651	24.2599

TABLE 2: ENERGY LEVELS OF REAL CO-EFFICIENTS OF FP1-F3, F3-C3 AND P3-O1 ELECTRODES

Scalp Electrodes	Real energy levels	
	Normal Subject	*Abnormal subject*
FP1-F3	15.0236	4.9581
	0.0725	0.0526
	0.62	0.2405
	3.7027	1.1193
	7.9474	2.1918
	27.5813	10.6661
	33.402	27.8192
F3-C3	15.7133	8.2786
	0.0745	0.0721
	0.4549	0.7171
	2.9013	1.4103
	8.2897	3.9485
	18.5907	18.2052
	30.0405	40.8423
P3-O1	15.3936	8.2905
	0.0588	0.063
	0.4295	0.3914
	3.117	2.0273
	9.5029	3.244
	22.5404	18.0062
	26.4975	29.6594

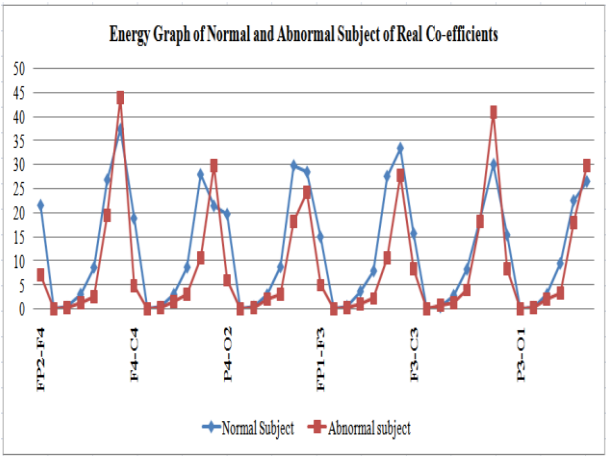

Figure 4: Energy Graph of Normal and Abnormal Subject of Real Co-efficients

From the energy graph shown in Figure 4, the energy features of real co-efficients representing electrodes FP2-F4, F3-C3,F4-C4 and P3-O1 are having higher energy levels which is observed for Abnormal Subjects, compared to P4-O2, FP1-F3 which are having higher levels for Normal Subjects. Thus the electrodes are distinct from and can be used to distinguish between Normal and Abnormal Subjects.

The energy Levels of Normal and Abnormal subjects are tabulated by considering the electrodes FP2-F4, F4-C4, P4-O2 which is illustrated in Table 3 and FP1-F3, F3-C3 and P3-O1 is shown in Table 4 of imaginary co-efficients

TABLE 3: ENERGY LEVELS OF IMAGINARY CO-EFFICIENTS OF FP1-F3, F3-C3 AND P3-O1 ELECTRODES

Scalp Electrodes	Imaginary energy levels	
	Normal Subject	*Abnormal Subject*
FP2-F4	19.3812	5.3743
	0.0594	0.0376
	0.5106	0.2881
	3.3146	1.4784
	9.0815	3.0225
	29.5411	15.8708
	37.3578	45.5455
F4-C4	16.9605	5.4047
	0.0576	0.0424
	0.4619	0.2973
	3.3539	1.6216
	8.4005	2.79
	32.8351	10.4889
	20.5233	29.841
P4-O2	17.9895	6.2177
	0.0651	0.0507
	0.4974	0.3946
	3.3283	1.9995
	8.8375	3.3931
	29.737	15.2423
	30.6918	25.5545

TABLE 4: ENERGY LEVELS OF IMAGINARY CO-EFFICIENTS OF FP1-F3, F3-C3 AND P3-O1 ELECTRODES

Scalp Electrodes	Imaginary energy levels	
	Normal Subject	*Abnormal Subject*
FP1-F3	14.3061	4.4635
	0.0715	0.0359
	0.618	0.2427
	3.5645	1.1519
	7.9206	1.972
	28.4261	13.3088
	34.9919	27.2092
F3-C3	16.5571	8.7883
	0.0582	0.105
	0.421	0.362
	3.0056	2.048
	7.3465	3.0986
	22.4873	20.164
	28.9793	40.062
P3-O1	15.8684	8.2581
	0.0585	0.059
	0.4675	0.384
	3.2968	1.9475
	8.8339	3.5777
	22.1288	19.5706
	27.8377	28.4414

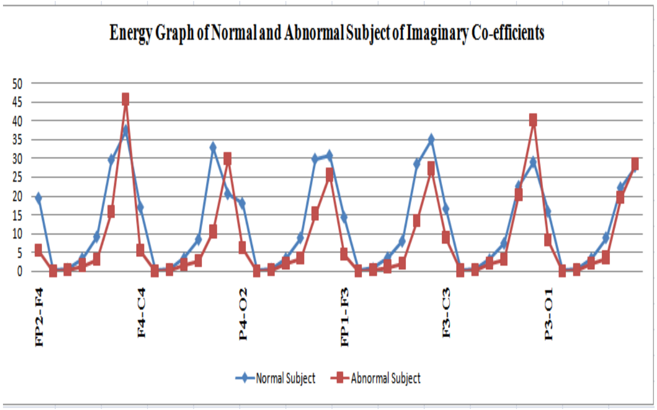

Figure 5: Energy Graph of Normal and Abnormal Subject of Imaginary Co-efficients

Considering the imaginary energy features of all six electrodes the comparison of normal and abnormal subjects are presented in Figure 5. From the comparison graphs of imaginary features of FP2-F4, F3-C3 and P3-O1 are having higher energy levels which is observed in abnormal subject compared to F4-C4, P4-O2 and F3-C3. Thus remaining electrodes are distinct from abnormal and can be distinguished from normal subjects.

V. CONCLUSION

From this work, the comparisons between Normal and Abnormal subject gives a good understanding of using Dual tree complex wavelet transform (DTCWT).The energy features extracted from real and Imaginary co-efficients of the two emotional states are distinguished which can be differentiated from the electrodes representing the higher energy levels. Thus in the future work , the energy values can be fed as a input for further feature classification using Artificial Neural Network (ANN).

REFERENCES

[1] K. Fu, J. Qu, Y. Chai, T. Zou, Hilbert marginal spectrum analysis for automatic seizure detection in EEG signals, Biomedical Signal Processing Control 179–185,Vol.18, 2015.

[2] U.R. Acharya, F. Molinari,S.V. Sree, S. Chattopadhyay, K.H. Ng, J.S. Suri,"Automated diagnosis of epileptic EEG using Entropies", Biomedical Signal Processing Control Vol.7,No. 4, pp.401–408,2012

[3] Selesnick Ivan W, Richard G. Baraniuk, and Nick C. Kingsbury "The dual-tree complex wavelet transforms." Signal Processing Magazine, IEEE 22, Vol. 6,pp. 123-151, 2005

[4]Kingsbury N,"Complex Wavelets for Shift Invariant Analysis and Filtering of Signals, Applied and Computational Harmonic Analysis" Vol.10, No. 3, pp.234-253, 2001.

[5] Musa Peker, BahaSen, and Dursun Delen,"A Novel Method for Automated Diagnosis of Epilepsy Using Complex-Valued Classifiers", IEEE Journal of Biomedical and Health Informatics,Vol. 20, No. 1, 2016

[6] G. Strang and T. Q. Nguyen,"Wavelets and Filter Banks", Wellesley, MA, USA: Wellesley-Cambridge, 1998.

[7]R.Y.Yu,"Theory of dual-tree complex wavelets",IEEE Transactions on Signal Processing, Vol. 56, no. 9, pp. 4263-4273, Sep 2008.

[8] Piyush Swami, Tapan K. Gandhi, Bijaya K. Panigrahi, Manjari Tripathi, Sneh Anand, "A novel robust diagnostic model to detect seizures in electroencephalography", Expert Systems with Applications, Vol.56, pp.116–130, 2016

[9] Syed Khairul Bashar, Mohammed Imamul Hassan Bhuiyan "Identification of Motor Imagery Movements from EEG Signals Using Automatically Selected Features in the Dual Tree Complex Wavelet Transform Domain", Universal Journal of Biomedical Engineering, Vol.3, No. 4, pp. 30-37, 2015

[10] Anindya Bijoy Das, Mohammed Imamul Hassan Bhuiyan and S. M. Shafiul Alam,"Statistical Parameters in the Dual Tree Complex Wavelet Transform Domain for the Detection of Epilepsy and Seizure", Proceedings of IEEE International Conference (EICT), pp.251-256, Khulna, Bangladesh, 2013.

[11] Guangyi Chen"Automatic EEG seizure detection using dual-tree complex wavelet-Fourier features, Expert Systems with Applications , 2391–2394,Concordia University, 41,2014,

[12] N.G. Kingsbury,"The dual-tree complex wavelet transform: A new technique for shift invariance and directional filters," in 8th IEEE DSP Proceedings Workshop, Utah, 86. 1998.

[13] N.G. Kingsbury,"Complex wavelets for shift invariant analysis and filtering of signals,"Appl. Computational. Harmon. Anal., Vol. 10, No. 3, pp. 234–253, May 2001

[14] M. H. M. Nerma, N. S. Kamel, and V. Jeoti, "Performance analysis of a novel OFDM system based on dual-tree complex wavelet transform," Ubiquitous Computational Communication. Journal, Vol. 4, No. 3, pp. 813–822, 2009.