Journal of Theoretical and Applied Information Technology
31st December 2020. Vol.98. No 24
© 2005 – ongoing JATIT & LLS
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

EEG BASED BCI FOR ALS USING COMPLEX WAVELETS AND MULTI-LAYERED NEURAL NETWORKS

[1]TEJASWINI. C, [2]SREERAMA REDDY G. M, [3]CYRIL PRASANNA RAJ. P

[1]Associate Professor, Department of ECE, M.S. Engineering College, Bangalore, India.

[2]Principal, C Byregowda Institute of Technology, Kolar, India.

[3]Senior Member, IEEE, Bangalore, India.

[1]tejuomshankar@gmail.com, [2]sreeramareddy99@gmail.com, [3]cyrilyahoo@gmail.com

ABSTRACT

Amyotrophic Lateral Sclerosis (ALS) is a neuro regenerative disorder causing motor neuron loss, muscle paralysis and respiratory failure progressively. Use of Brain Computer Interface (BCI) technology to record the brain functions in ALS patients and generate responses accurately to either actuate gadgets or information to care takers is a challenging task that needs to be accurate and reliable. Over the last few years several methods or techniques have been developed considering signal processing methods for EEG signal analysis and neural networks for classification of EEG features. Wavelet based methods for EEG signal analysis has demonstrated limitations as they are shift variant. In analysis of ALS EEG signals there is a need for shift invariant signal processing algorithms. In this paper, Dual Tree Complex Wavelet Transform (DTCWT) is used for extraction of features from the complex sub bands considering Power Spectral Density (PSD), Cross Power Spectral Density Estimation (CPSD) and Shannon Entropy. These features are classified into normal and abnormal EEG data. The multi-level DTCWT algorithm and multi-layered neural network structure presented in this work is modelled in MATLAB and is evaluated for its performances for feature extraction and classification. Results of classifier considering energy features from all five EEG bands have demonstrated 100% classification accuracy as compared with other methods. The classified EEG data from ALS patients can be further considered for interpretation of information and is used for all BCI applications.

Keywords: *Brain Computer Interface, Amytrophic Lateral Sclerosis, Dual Tree Complex Wavelet Transform, Discrete Wavelet Transform, Neural network.*

1. INTRODUCTION

Brain Computer Interface (BCI) technology uses brain signals to drive assistive devices or external devices directly without participation of spinal cord or the periphery motor system. Brain signals such as spike trains, Extracellular Local Potentials (LFP), Electrocorticograms (ECoG), Electroencephalogram (EEG), Event-Related Potentials (ERP), real-time functional Magnetic Resonance Imaging (MRI) and Near Infrared Spectroscopy (NIRS) are used as inputs to BCI system for control of assistive devices. Patients those who are diagnosed with Motor Neuron Disease (MND) or patients with traumatic brain damage or patients with Locked-In Syndrome (LIS) need these assistive devices in regular basis for both rehabilitation and for carrying out daily routine activities. Non-invasive technologies such as fMRI provide higher spatial resolution for BCI, EEG based BCI have become popular due to the advantages of measuring of neuron activity directly for real time use[1]. EEG electrodes placed on the scalp measures the brain activity of electric current caused by synaptic excitation of dendrites. EEG based BCI have been demonstrated for controlling of assistive devices and for rehabilitation of disabled [2]. The process of interpretation of EEG signals based on body movement, biomechanics and cognitive activity is a challenging activity [3]. Over the last few years different decoding method, signal processing methods for feature detection and classification methods for differentiating between EEG features have been published [4]. The classification algorithms classify the features and use of these features for further processing such as controlling of Neuro prosthetic arm is a challenge as the signal-to-noise ratio (SNR) is very low. Source localization methods with data selection have demonstrated to be aiding BCI process [5]. Machine learning algorithms combined with deep learning have also been reported for improving EEG based BCI [6]. Adaptive classifiers and decoding methods have also been reported to

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

address the non-stationary behaviour of EEG signals for BCI [7]. Customization of signal processing algorithms based on the needs of neurological disorders is required. Identifying suitable biomarkers to interpret the EEG signals for BCI is one essential requirement and the progression of disease using EEG biomarker is another challenge that need to be addressed [8]. Amyotrophic Lateral Sclerosis (ALS) is a rare disease that progressively damages motor neurons of the brain and the spinal cord sending signals to the muscle that controls breathing, movements and memory. Understanding neurophysiology in ALS patients or stroke patients is for development of customized signal processing algorithms for BCI is an important factor. The non-stationary behaviour of recorded EEG signals form ALS or stroke patients is addressed using improved methods based on Dual Tree Complex Wavelet Transforms that have the advantages of shift invariance and provide phase information as well. In this work, signal processing algorithms for feature extraction from EEG signals from ALS patients are extracted using DTCWT and classification is carried out using neural network methods. DTCWT based signal decomposition generates two sub bands that are real and complex. Information from these two sub bands need to be processed without redundancy and the significant features that contribute to ALS signal interpretation need to be processed by classifier module. Neural network classifiers performance is based on training the network with suitable input features and multiple data sets. Complexity of fully connected neural network model limits its use for real time applications where the response need to be within few seconds from the time signal capture occurs. With DTCWT generating complex features from both sub bands it is required to develop a suitable neural network model that can be robust in accurate classification and also be faster in data processing. In this work, new algorithm is proposed based on DTCWT and fully connected neural network model for EEG signal processing.

2. EEG-BASED BRAIN-COMPUTER INTERFACE

Progressive motor neuron degeneration in ALS patients leads to quadriplegic and anarthric state ultimately leading to locked-in syndrome (LIS). Once ALS patient reach LIS they become completely dependent on others for every activity and basic daily needs. Once a patient is diagnosed with ALS and as the age progresses it is required to provide assistive devices at the initial stages of ALS so that as the disease progresses the assistive device starts learning the requirements of the patient as well as with proper feedback the progression in ALS can be retarded. In the recent years there is lot of study on developing BCI technology to overcome the challenges in rehabilitation methods of helping patients with ALS in restoring normal motor functions. With adaptive control and therapeutic interventions BCI systems can improve quality of life and restore motor recovery in severe impairment patients [9]. BCI based devices are significantly used in gaming, control of military equipment and biofeedback systems. However, there is still lot of research required in development of assistive devices based on BCI technology for rehabilitation of people suffering from Multiple Sclerosis (MS) ALS, and Parkinson's disease. Use of adaptive control mechanisms in BCI technology is towards rehabilitation of Patients with Disabilities (PWD) so that they can control and interact with environment. In therapeutic intervention based BCI technology restoring of impaired muscle functions or motor functions is carried out through brain guided Functional Electrical Stimulation (FES) [10]. Figure 1 presents the EEG based assistive device for flow diagram with techniques used for signal analysis. The EEG signal captured is filtered and features are extracted. The features are classified according to emotional and non-emotional groups.

Hardware devices are interfaced to generate corresponding control signals to activate external devices or for feedback into the brain system. Very recently, ALS patients or patients with serious spinal cord injury have been able to communicate with external devices with commercially developed BCI system with Internet or Thing (IOT) interface [11]. Event Related Potentials (ERP) that reflects the neural processing for a specific stimuli captured from the EEG signal is widely used for BCI. ERP that occurs between 300 ms to 500 ms or generally term as P300 is considered as a pattern in the EEG when the patient focusses on a particular pattern considered as stimuli [12]. Signal processing techniques are used to extract this P300 feature or pattern from the EEG signal recorded from ALS patients. Another factor of measurement is the coefficient of determination represented as r^2 (in statistics) is considered as a feature computed by processing EEG signals. Mark et al. [13], in their work have considered r^2 as the metric for predicting BCI performances (considering two

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

different instants of EEG recording) for ALS patients.

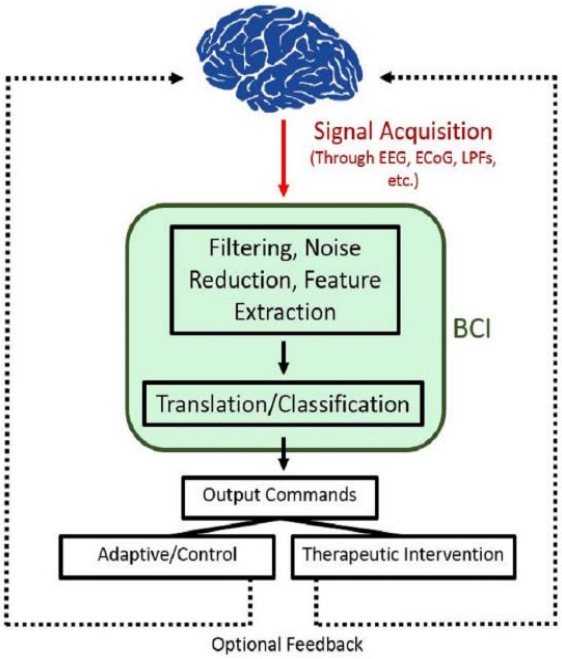


Figure 1: Data Flow Diagram In BCI Based Assistive Devices

The work carried out by Li et al., [14] have presented hybrid methods for understanding mental status of ALS patients in terms of stress and fatigue. Stress is quantified by computing stress index which is measured by considering Shannon's Entropy that represents the energy distribution from EEG power due to stress [15].

Correlation between EEG rhythms and entropy is considered for characterizing mental stress [16]. Monitoring changes in EEG pattern in the alpha band is also studied as one of the stress measuring methods or fatigue considering EEG signals [17]. Shannon Entropy and Kullback Leibler measurements have been considered as a measure for fatigue identification in EEG signals [18]. Spataro et al., in 2015 have reported studies on humanoid robots for assisting ALS patients as a feasible solution [19]. EEG signal processing plays an important role in BCI based assistive device design for ALS patients. With focus on design and development of reliable and cost effective assistive devices, signal processing techniques that provide the basic information on EEG signal characteristics are supposed to be accurate and robust. The basic steps in general EEG signal processing are: The EEG signal from electrodes placed on the scalp is taken as the input into the pre-processing module. Pre-processing reduces the noise and removes the artifacts from input EEG. Feature extraction processes generate the distinct characteristics of ALS patients. Different techniques such as Wavelet transform Fourier Transform, Auto Regression, Time and Frequency Domain Analysis (TFD) etc. can be used. The extracted features from EEG are classified using classifier algorithms such as neural network approaches. A detailed study and comparison on performance of different techniques such as Time and Frequency Domains (TFD), Fast Fourier Transform (FFT), Eigen vector methods (EM), Wavelet Transform (WT) and Auto Regression mode (AR) are presented [20]. Yunfeng Wu *et.* al [21], present the Fisher Linear Discriminant Analysis (FLDA) and the Least Squares Support Vector Machines (LS_SVM) for classification of ALS EEG signals. Both the methods were evaluated using cross validation method and compared the performance to obtain the better method for pattern classification. They have concluded that LS_SVM with sigmoid kernels generated output with an accuracy of 89.66% with an area of 0.9629 under operating curve. Stafford Michahial *et.* al [22], suggest the Discrete Wavelet Transform (DWT) for characteristic extraction of EEG signals.

In this paper describes the derivation of characteristics and further pattern classification of EEG waves that belongs to paralyzed ALS patients, in order to develop BCI applications. Limitations of DWT such as shift variance, limited directional patterns and phase information are addressed with DTCWT [23]. In EEG signal processing in particular for ALS EEG signal analysis the EEG signals captured are non-stationary. ALS patients may need proper assistance and response from both gadgets and care takers. EEG signals captured at different intervals of time need to provide the same information and any changes in signal features will lead to false response. One of the primary aim of this work is to use the complex wavelet sub bands that provide information on both magnitude and phase to identify the signal entropy every time accurately. The complex wavelets will generate

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

large number of sub bands and hence will have redundant information that will improve complexity in feature classification. The neural network algorithm needs to be designed to process the non-redundant features and perform classification accurately. Most of the literature work report on use of entropy features for signal classification. It is required to capture more than one feature from every band of EEG data recorded from every electrode and perform classification. Improving classification accuracy and reducing computation complexity for real time use for BCI applications is the primary focus of this paper. Design of suitable feature extraction algorithm based on DTCWT and corresponding classification methods based on neural network approaches is carried out in this work for processing EEG signals from ALS patients for BCI applications. Evaluation the proposed algorithm is carried out by considering 200 different data sets that are available online. Each of the data is labelled and the response for each of the signals recorded from ALS patients is addressed. The ALS signals are grouped into normal and abnormal signals and are labelled for identification. For evaluation of the developed algorithms 20% of the EEG signals are reserved and the remaining 80% of the signals are used for training. Among the EEG signals considered for training 60% of them are abnormal and 40% of them are normal. The training algorithm considers these signals and the network is trained to achieve 100% classification. The network is designed to process the features that are extracted from DTCWT sub bands. For evaluation of the trained network, the data sets that are not part of the training are used of which 15% of them are normal and remaining 85% are abnormal. The classification accuracy is computed for all the data sets and compared with the existing algorithm. Based on the accuracy achieved it is required to justify the improvement in data processing techniques proposed in this work.

3. FEATURE EXTRACTION AND BIOMARKER DETECTION

EEG signal processing requires suitable data sets that are obtained from reliable sources that are recommended for evaluation of algorithms for BCI applications. The data sets are labelled and stored in order differentiating between normal and abnormal. Pre-processing is carried out on every EEG data considering every signal recorded from the EEG electrode. Pre-processing of EEG data remove artefacts and noise that are captured while signal recording. From the pre-processed data the most relevant EEG signal captured from the electrodes are selected for analysis. DTCWT and neural network based algorithms are developed in MATLAB for ALS signal classification as normal and abnormal. By classifying the signals into normal and abnormal, the normal signals are considered for further processing and interpretation. Evaluation of the algorithm is carried out by identifying classification accuracy.

3.1 Development of Algorithm

EEG signals from 8 ALS participants asked to focus on 36 different characters are recorded at the Neuroelectrical imaging and BCI laboratory, IRCCS foundation Santa Lucia, Rome, Italy is downloaded from bnci-horizon-2020.eu for analysis. The EEG data set represents evoked potentials recorded using BCI2000 by Farwell and Donchin [24] to differentiate between 36 characters. Scalp EEG recorded using MOBILAB from channels Fz, Cz, Pz, Oz, P4, PO7 and PO8 with sampling frequency of 256 Hz and band pass filtering with bandwidth of 0.1 Hz to 30 Hz. Participants seated were allowed to face computer screen were flashed with the 36 characters and subsequent eye movement were recorded. The flowchart for feature extraction and feature classification for the standard data sets is presented in Figure 2.

The input data is pre-processed to remove artifacts by filtering the raw data using moving average filter (MAV) of order 10 and the filtered data is interpolated by a factor of 5 to improve the number of samples. The advantage of using order 10 MAV and 5-point
interpolation will compensate loss of information due to filtering. Interpolated EEG data is decomposed using DTCWT with 9-stage decomposition algorithm. From the decomposed EEG data, the sub bands capturing EEG data above

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

64 Hz are discarded and the EEG data within the band of interest are considered for further processing. Discarding the sub bands outside 64Hz results in denoising process and the EEG data within the band of interest is processed by inverse DTCWT to reconstruct EEG data. The de-noised EEG data is further processed by the FFT module to generate five sub bands and Power Spectral Density (PSD) of each of these sub bands is computed. From the PSD computed using three different methods, neural network (NN) model is trained to classify EEG data and 2/3rd rule is adopted to generate the final output classifying the EEG data. La-grange's Eq. (1) is used for the interpolation of 5-point sequence.

$$y = \frac{(x-x_1)(x-x_2)\dots(x-x_5)}{(x_0-x_1)(x_0-x_2)\dots(x_0-x_5)}y_0 + \frac{(x-x_1)(x-x_2)\dots(x-x_5)}{(x_1-x_0)(x_1-x_2)\dots(x_1-x_5)}y_1 + \dots + \frac{(x-x_0)(x-x_1)\dots(x-x_5)}{(x_5-x_0)(x_5-x_1)\dots(x_5-x_4)}y_5 \quad (1)$$

Where, x_1 to x_n are the known data points. Figure 3 presents the 6-level DTCWT decomposition algorithm. 10-tap Qshift filters represented as {H0, H1, G0 and G1} are used for signal decomposition. Decomposition of signals considering both real and imaginary bands are considered to generate real and imaginary sub bands that are symmetrical for denoising process.

The original EEG signal and the reconstructed signal after denoising using complex wavelets using 6-level decomposition is shown in Figure 4. Figure 4(a) is the interpolated EEG data and Figure 4(b) presents the five sub bands and the reconstructed data.

The de-noised signal using DTCWT is further processed by FFT module for PSD estimation. For comparison of performance improvement, PSD estimation is carried out by computing FFT of de-noised EEG signal carried out using both DTCWT and DWT. Table 1 presents the PSD of EEG signal computing using DWT and Table 2 presents the PSD computed using DTCWT. EEG signals recorded from ALS patients while carrying out training is considered as subjects and while ALS patients are in relaxed position is considered as normal. The PSD levels of normal subjects in the delta band between 4125 units to 37609 units which is highest among all bands. The PSD levels are lower in the theta band for normal subjects. Comparing the PSD levels of normal and subjects, PSD levels in both alpha and theta bands are lowest compared with all other bands (Figure 5). Alpha band represent the relaxed state and theta band represents activity state. The non-stationary behaviour of EEG data during experimentation is not captured using DWT and hence lower PSD levels are obtained. Comparing the PSD levels using DTCWT processing as shown in Table 2 and Figure 6, the activity in both alpha and theta bands are captured and hence the PSD levels are higher as compared with PSD levels computed using DWT. The feature extraction using DWT is providing significant variation in Delta band activity in Subjects when compared with Normal group with variation to an extent of 95%.

Table 1: PSD Estimation Of Features Using DWT Denoising And FFT

Sl. no	Normal					Subjects				
	Gamma	Beta	Alpha	Theta	Delta	Gamma	Beta	Alpha	Theta	Delta
1	894.71	2216.83	289.09	1259.02	147.40	4786.67	429.83	190.18	0.70	44.17
2	1144.22	1154.56	310.48	4607.69	10537.19	2091.24	3758.81	258.28	1726.84	553.85
3	614.30	8067.55	2939.49	100.96	1111.22	3211.87	1097.48	341.50	95.81	1829.39
4	1153.83	759.54	869.26	28.18	7790.03	1352.70	437.20	128.90	476.23	3347.72
5	422.43	231.84	212.52	127.35	6918.24	2248.56	76.49	110.54	8.15	454.11
6	404.63	1393.13	328.34	6.09	4124.70	1851.32	1035.05	536.64	13.87	112.85
7	3245.60	870.82	14.59	3425.35	37608.23	691.75	1088.55	148.19	429.12	337.57
8	7429.50	3771.58	103.23	166.77	14063.83	1431.52	2932.24	46.38	32.41	1314.29

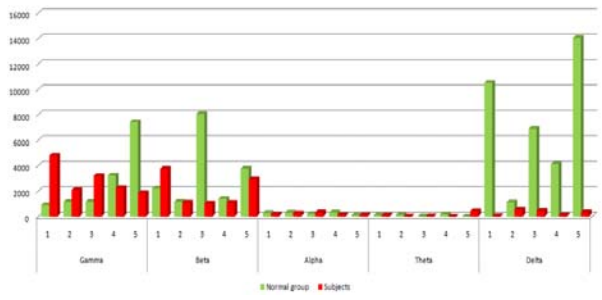


Figure 5: Graph Showing PSD Estimated For Features Using DWT And FFT

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 2: PSD Values Of Features By Using DTCWT Method

Sl. no	Normal					Subjects				
	Gamma	Beta	Alpha	Theta	Delta	Gamma	Beta	Alpha	Theta	Delta
1	371.80	1084.83	632.27	368.61	604.22	1994.59	241.08	116.25	3.07	11.09
2	932.12	1421.20	472.54	2155.4	13124.4	1615.91	1335.8	1335.7	325.91	358.2
3	630.71	9417.21	1839.8	7.57	663.08	1752.72	2434.1	67.73	1122.2	8.32
4	1530.63	744.02	1055.0	2544.6	405.36	1503.22	1162.9	132.77	875.10	577.3
5	314.78	152.72	369.13	161.98	1806.70	1437.18	261.18	366.76	493.30	456.8
6	734.60	924.28	241.04	112.43	1778.88	1167.24	522.83	188.72	174.10	56.98
7	1370.21	897.52	3353.0	507.85	2045.90	782.87	542.47	45.38	879.84	301.9
8	4666.34	1294.28	464.71	660.19	19895.6	1325.01	2736.5	84.02	145.86	393.9

Comparing the activity in terms of PSD between normal and subject in all five bands considering all eight EEG data sets, it is found that there is significant variation in PSD levels between normal and subjects. The variation in the gamma band is not very distinct and is less than 21% difference. The PSD level variation in beta band is more than 67% and the variation in alpha, theta and delta bands are more than 85%. Comparing the PSD variations in the alpha and theta band computed using DTCWT is higher and distinct as compared with PSD levels computed using DWT. Considering PSD levels as biomarkers in beta, alpha, theta and delta bands to distinguish between normal and subjects it is required to perform classification of EEG signals to develop a generalized method.

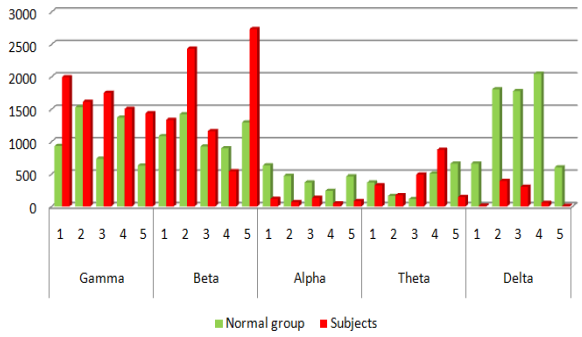


Figure 6: Graph Showing Average Of PSD Values Estimated Using DTCWT Method

Figure 6 presents PSD characteristic plot estimated for five people from Normal and Subjects. Delta band activity in Subjects is relatively higher when compared to Normal group. The average percentage of decrement in Delta band activity is 55%-90%.

The Cross Power Spectral Density Estimation (CPSD) of EEG signals has been estimated by taking two central brain signals from each person. The CPSD of eight people belonging to each group is presented in Table 3 and the corresponding bar chart is presented in Figure 7. CPSD activity computed on both normal and subjects are very significant in delta band as compared with all other bands. The average percentage variation of Delta band activity is observed between 90%-95%.

Table 3: CPSD Estimation Of Features

Sl. no	Normal					Subjects				
	Gamma	Beta	Alpha	Theta	Delta	Gamma	Beta	Alpha	Theta	Delta
1	0.01	0.51	0.19	0.50	42.47	0.01	2.91	0.08	0.13	0.37
2	0.01	0.76	0.44	0.90	74.88	0.01	3.04	0.10	0.08	0.14
3	0.01	2.36	0.65	0.46	143.64	0.01	1.84	0.49	0.68	20.49
4	0.01	0.79	0.57	1.12	303.42	0.01	1.41	0.45	0.98	5.36
5	0.01	0.44	0.43	0.64	196.53	0.01	0.94	0.17	0.40	1.47
6	0.01	0.67	0.08	0.28	26.90	0.01	0.99	0.15	0.47	0.43
7	0.01	1.19	0.33	0.56	96.00	0.02	2.75	0.21	0.78	2.14
8	0.03	2.83	2.46	1.97	217.34	0.01	2.02	0.12	0.11	0.85

Computing CPSD significantly reduces the intensity levels in all other bands compared with delta band. The activity levels in beta, alpha, theta and delta bands are higher as compared with delta bands and hence the CPSD levels are considered as biomarkers.

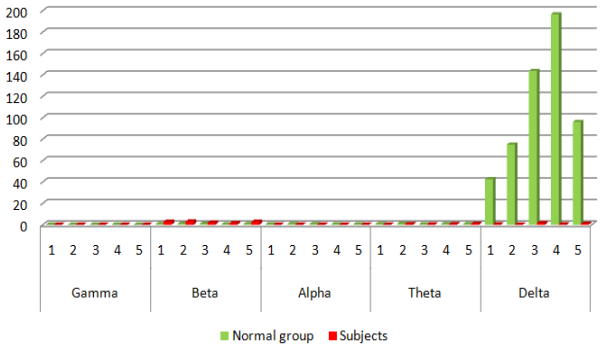


Figure 7: Graph Showing Average Of CPSD Values

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

PSD estimation using Maximum Entropy Method by processing the de-noised EEG data using DTCWT is tabulated in Table 4 and the corresponding bar graph comparing PSD levels in normal and subjects is presented in Figure 8. Comparing the PSD levels in the delta band between normal and subjects there is a maximum variation of 98% (considering 6th test case) and minimum variation of 41% (considering 7th test case). Similarly considering the theta band the maximum and minimum variation is 97% and 33% respectively. In the alpha band the variation between normal and subject is 87% and 4%. Considering all the three bands of delta, theta and alpha PSD levels computed using MEM method as biomarkers classification algorithms can be designed.

Table 4: PSD Estimation Of Features Using MEM

Sl. no	Normal					Subjects				
	Gamma	Beta	Alpha	Theta	Delta	Gamma	Beta	Alpha	Theta	Delta
1	7.85	39.51	14.70	26.36	767.39	29.62	65.59	5.81	6.16	15.30
2	19.18	36.79	22.89	36.03	1807.75	30.23	57.90	24.09	5.90	395.16
3	17.67	113.68	46.69	34.47	571.61	23.56	70.37	25.46	19.38	29.07
4	9.52	48.03	28.32	157.4	1122.92	20.18	57.31	28.41	70.75	732.23
5	9.83	43.15	16.05	16.39	1172.64	22.56	36.11	24.04	27.10	582.02
6	16.36	27.09	9.10	5.39	2533.49	18.39	36.32	13.96	174.1	30.98
7	33.32	61.07	19.05	17.86	238.75	82.98	85.48	27.61	33.05	402.61
8	42.78	135.09	64.66	52.72	2121.68	19.76	43.61	7.85	11.43	296.16

The PSD levels computed in the delta band for both normal and subject compared with PSD levels computed using CPSD method there is significant difference in intensity levels.

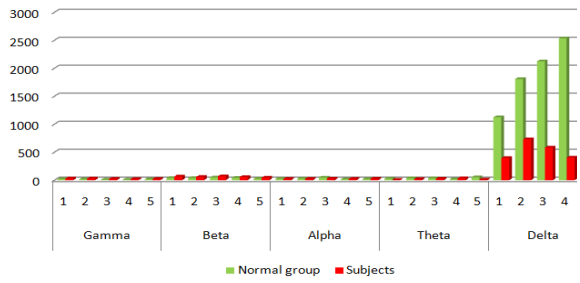


Figure 8: Graph Showing The Average Of PSD Estimated Using MEM

Shannon entropy method is also used to compute energy levels of the EEG signals and is considered as biomarker for ALS analysis. The average values of entropy for the feature sets have been calculated and the corresponding bar graph is presented in Figure 9.

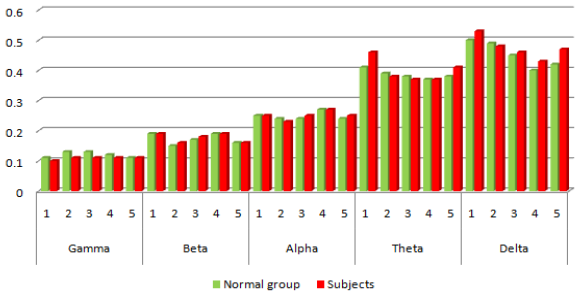


Figure 9: Graph showing the Shannon entropy estimation of features

Considering Shannon method for energy computation and the bar graph analysis it is found that the energy levels between normal and subjects in all five bands are not very distinct and hence of all the four energy levels only three of them are considered as biomarkers for signal classification.

4. Neural Network Classifier

Feedforward neural network (FFNN) algorithm with more than two layers is used for classification. The
input data to the FFNN is from three data: PSD, CPSD and MEM. Each of the data consists of 5 energy levels and the input layer to the FFNN is set to five. The output to be generated by the FFNN is set to 2 considering redundancy and hence the output layer is designed with two neurons. The number of hidden layers is selected to be 3 with each layer having different number of neurons. The FFNN structure selected is shown in Figure 10. Each of the input data set corresponds to the feature set that generates biomarker for ALS classification. Each of the feature sets is normalized and given as the input to FFNN. The target output for normal subject is set to [0.2 0.2] and for subject the target is set to [0.8 0.8] and is shown in Figure 11. The PSD levels obtained are arranged in 5 x 1 column data as input layer to the FFNN and the target is set to 0.8 or 0.2. FFNN network is set with 1000

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

epochs and MSE is set to 10^{-7}. Two levels of targets are used to increase consistency and efficiency of algorithm. For the first NN created, PSD values of feature sets correspond to Normal group and Subjects have been used and it is shown in Figure 12(a). The input matrices are of dimension 5-by-32. Similarly, for the second pattern classifier has been created using CPSD estimation values as the input matrix and this is shown in Figure 12(b). The third NN has been created using PSD estimation using MEM as the input matrix and it is shown in Figure 12(c). The FFNN is trained for the known data sets and the network parameters are observed for MSE, gradient and regression matrix. Based on the training performances the number of neurons in the hidden layers is set to obtain accurate classification of data sets.

The outputs for the FFNN trained is obtained and presented in Figure 13, outputs obtained demonstrate the classification as ALS and non-ALS based on outputs generated 0.2 or 0.8.

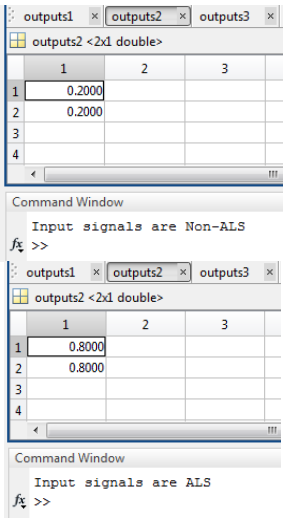
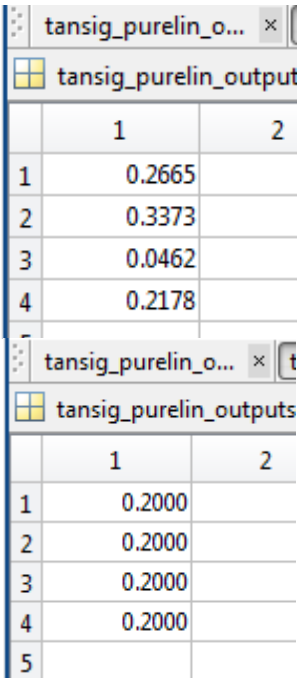


Figure 13: Output Of The DTCWT Based Algorithm For Classification Of ALS, When Input Signals Are: (A) Normal Or Non-ALS. (B) ALS

5. COMPARISON OF DTCWT ALGORITHM WITH DWT

The results are consistent while using DTCWT and the results are not consistent with DWT algorithm. The training of neural network with tansig-purelin transformations and by using PSD estimations of the feature sets obtained from DWT and DTCWT based algorithms are shown in Figure 14. The target output is 0.2 and it has been achieved using DTCWT algorithm.



(a) (b)

Figure 14: Result Of NN For Normal EEG Signal Using: (a) DWT And (b) DTCWT

Using DTCWT algorithm, perfect reconstruction can be achieved from wavelet coefficients than from the DWT algorithm. Using DWT, it cannot be achieve beyond level1. After training the neural network, the best performance validation rate, network training state and the training error are estimated from the plots as depicted in following figures. Figure 15 reflects the best validation performance curves with MSE for an NN that obtained minimum gradient at epoch 20. The curves in Figure 16 show the estimation of training states at epoch 20. Errors after NN training are plotted as histogram in Figure 17.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

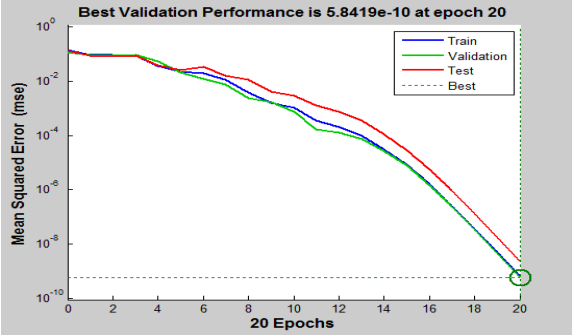


Figure 15: Best Validation Performance Curve For An NN After Training

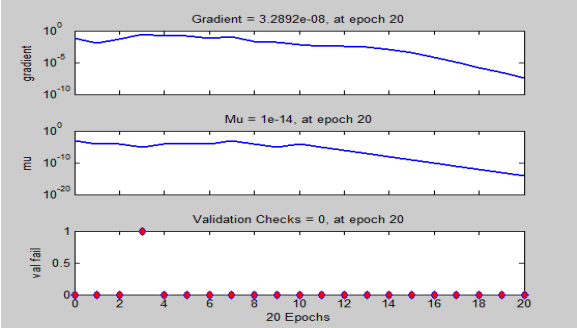


Figure 16: Plots For The Estimation Of Training States

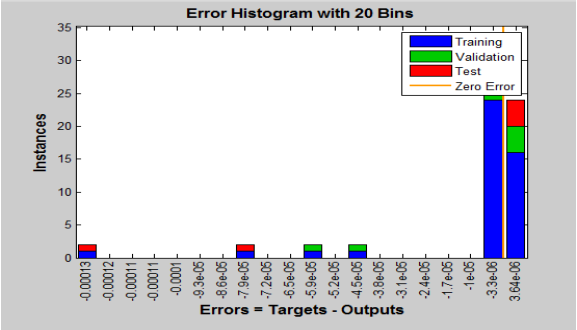


Figure 17: Histogram Showing NN Training Errors

The weights and biases of each network are obtained after training in MATLAB. The developed algorithm demonstrates improvement in classification accuracy and achieves 100% accuracy for all the data sets considered. The processing speed of the proposed algorithm is optimized and a trade-off is achieved between speed and accuracy. Redundant features captured from both the real and imaginary sub bands are selected to improve processing speed. Features from multiple levels considering all the EEG bands provide additional information for accurate classification. Considering PSD, CPSD and Shannon entropy features and training the neural network model improves the performance of the proposed model. It is required to evaluate the performance of the proposed algorithm considering ALS signals with multiple motor neuron movements. Artefacts due to recording, muscle movement and eye movement need to be identified and removed prior to classification.

6. CONCLUSION

The proposed method based on DTCWT based algorithm is a novel algorithm for the consistent detection and classification of Amyotrophic Lateral Sclerosis at the earliest. From the analysis of proposed method it has been found that the PSD at Delta band is comparatively very less in ALS patients. The reduced activity of the Delta band reflects the structural and functional alterations occurred in the neural network of the affected person due to ALS. The average decrement in Delta band activity of an affected person is approximately 60-90%. The maximum computation time for the proposed algorithm is approximately 9.5 seconds. Therefore, PSD estimation of EEG signals based on DTCWT algorithm, especially that of the Delta band generates the potential biomarker and the proposed method can be used as the best algorithm for easiest and earliest detection and classification of ALS. The comparative study of DTCWT with DWT reveals that DTCWT is the efficient method that produces consistent result for biomarker detection as well as for classification of ALS_EEG, even when multi-level decomposition using DWT also provides biomarkers to some extent. 100% accuracy is achieved for the verification of the suggested algorithm with test datasets.

REFRENCES:

[1] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain computer interfaces, a review," Sensors, vol. 12, No. 2, 2012, pp. 1211-1279.

[2] J. Meng, S. Zhang, A. Bekyo, J. Olsoe, B. Baxter, and B. He, "Noninvasive Electroencephalogram Based Control of a Robotic Arm for Reach and Grasp Tasks," Scientific Reports, vol. 6, 2016, pp. 38565,

[3] J. L. Contreras-Vidal, A. Presacco, H. Agashe, and A. Paek, "Restoration of Whole Body Movement: Toward a Noninvasive Brain-Machine Interface System," Pulse, IEEE, vol. 3, No. 1, 2012, pp. 34-37.

[4] A. Bashashati, M. Fatourechi, R. K. Ward, and G. E. Birch, "A survey of signal processing algorithms in brain-computer interfaces based on electrical brain signals," (in eng), J Neural Eng, vol. 4, No. 2, Jun 2007, pp. R32-57.

[5] N. Tomida, T. Tanaka, S. Ono, M. Yamagishi, and H. Higashi, "Active data selection for motor imagery EEG classification," IEEE Transactions on Biomedical Engineering, vol. 62, No. 2, 2015, pp. 458-467.

[6] I. Sturm, S. Lapuschkin, W. Samek, and K.-R. Müller, "Interpretable deep neural networks for single-trial eeg classification," Journal of Neuroscience Methods, vol. 274, 2016, pp. 141-145.

[7] S. Perdikis, R. Leeb, and J. d R Millán, "Context-aware adaptive spelling in motor imagery BCI," Journal of neural engineering, vol. 13, No. 3, 2016, p. 036018.

[8] Nowicka N, Juranek J, Juranek JK &Wojtkiewicz J Risk Factors and Emerging Therapies in Amyotrophic Lateral Sclerosis. International Journal of Molecular science, Vol. 20, No. 11, 2019, 2616, doi: 10.3390/ijms20112616.

[9] J. J. Daly and J. R. Wolpaw, Brain Computer interfaces in neurological rehabilitation, The Lancet Neurology, Volume 7, No. 11, (2008), pp.1032-1043.

[10] W. P. Teo , E. Chew . "Is motor-imagery brain-computer interface feasible in stroke rehabilitation?", PM R. Vol. 6, no. 8, 2014 pp.723-728. doi: 10.1016/j.pmrj.2014.01.006.

engagement in P300-BCI," in Proc. 6th Int. IEEE/EMBS Conf. Neural Eng. (NER), Nov. 2013, pp. 1066–1069.

[17] S. K. Lal, A. Craig, P. Boord, L. Kirkup, and H. Nguyen, "Development of an algorithm for an EEG-based driver fatigue countermeasure", Journal of safety research, vol. 34, No. 3, 2003, pp. 321–328.

[18] C. Papadelis Z. Chen, C. Kourtidou-Papadeli, P. D. Bamidis, I. Chouvarda, E. Bekiaris, N. Maglaveras, "Monitoring sleepiness with on-

[11] Xiang Zhang, Lina Yao, Shuai Zhang, Salil Kanhere, Michael Sheng, Yunhao Liu, "Internet of Things Meets Brain-Computer Interface: A Unified Deep Learning Framework for Enabling Human-Thing Cognitive Interactivity", IEEE Internet of Things Journal, Vol. 6, No. 2, 2018, pp.2084–2092.

[12] C. M. Karns and R. T. Knight, "Intermodal auditory, visual, and tactile attention modulates early stages of neural processing," Journal of Cognitive . Neuroscience, vol. 21, No. 4, 2009, pp. 669-683.

[13] J. N. Mak, D. J. McFarland, T. M. Vaughan, L. M. McCane, P. Z. Tsui, D. J. Zeitlin, E. W. Sellers and J.R. Wolpaw, "EEG correlates of P300-based brain–computer interface (BCI) performance in people with amyotrophic lateral sclerosis," J. Neural Eng., vol. 9, No. 2, 2012, p: 026014, doi: 10.1088/1741-2560/9/2/026014.

[14] Yuanqing Li, Jiahui Pan, Yanbin He, Fei W ang, Steven Laureys, Qiuyou Xie , Ronghao Yu, "Detecting number processing and mental calculation in patients with disorders of consciousness using a hybrid brain-computer interface system," BMC Neurol., vol. 1 No. 1, 2015 , p. 1.

[15] N. Sulaiman, Mohd Nasir Taib, Sahrim Lias, Zunairah Murat , Siti Armiza Mohd Aris, Mahfuzah Mustafa, Nazre abdul rashid, "Development of EEG-based stress index", International Conference on Biomedical Engineering (ICoBE), Penang, Feb. 2012, pp. 461–466.

[16] Y. Liu, H. Ayaz, B. Onaral, P. A. Shewokis, "EEG band powers for characterizing user

board electrophysiological recordings for preventing sleep-deprived traffic accidents," Clin. Neurophysiol., vol. 118, No. 9, 2007 , pp. 1906–1922.

- [19] R. Spataro, R. Sorbello,, S. Tramonte, G. Tumminello, M. Giardina, A. Chella, V. La Bella, "Reaching and grasping a glass of water by locked-in ALS patients through a BCI-controlled humanoid robot," *J. Neurol. Sci.*, vol. 357, Mar. 2015, pp. e48–e49.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[20] Amjed S. Al-Fahoum and Ausilah A. Al-Fraihat, "Methods of EEG Signal Features Extraction Using Linear Analysis in Frequency and Time-Frequency Domains", Hindawi Publishing Corporation, 2014, pp. 1-7.

[21] Yunfeng Wu and Sridhar Krishnan, "Computer-Aided Analysis of Gait Rhythm Fluctuations in Amyotrophic Lateral Sclerosis", Medical and Biological Engineering, Vol 47, No. 11, 2009, pp. 1165-1171.

[22] Stafford Michahial, R.Ranjith Kumar, Hemath Kumar P. and Puneeth Kumar A., Speech Synthesizer and Feature Extraction Using DWT With Classification by Euclidian Distance and Neural Network of EEG Signals, International Journal of Advanced Research in Computer and Communication Engineering, Vol. 1, No. 4, June 2012, pp. 2278-1021.

[23] Nick Kingsbury, "The Dual Tree Complex Wavelet Transform: A New Technique for Shift Invariance and Directional Filters", Proceedings of the IEEE Digital Signal Processing Workshop,1998.

[24] L. A. Farwell E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing eventrelated brain potentials" Electroencephalography and Clinical Neurophysiology, vol. 70, No. 6, 1988, pp. 510–523.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

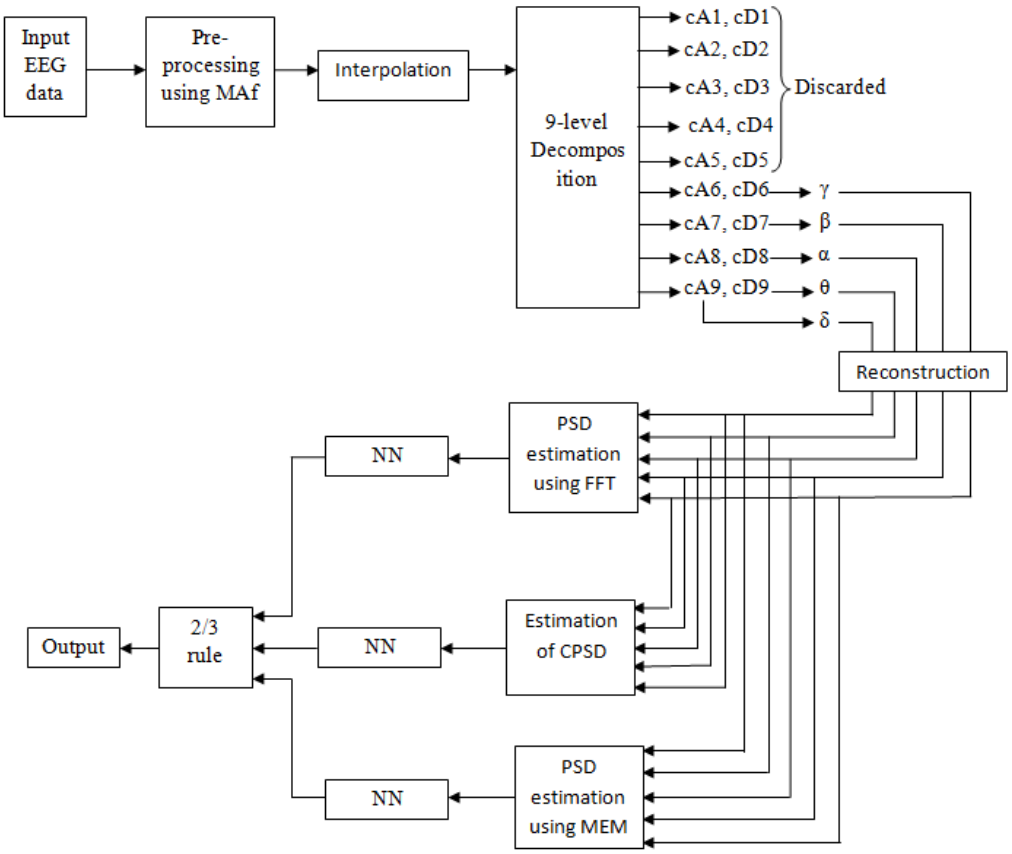


Figure 2: Proposed Algorithms For EEG Signal Processing Based On DTCWT

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

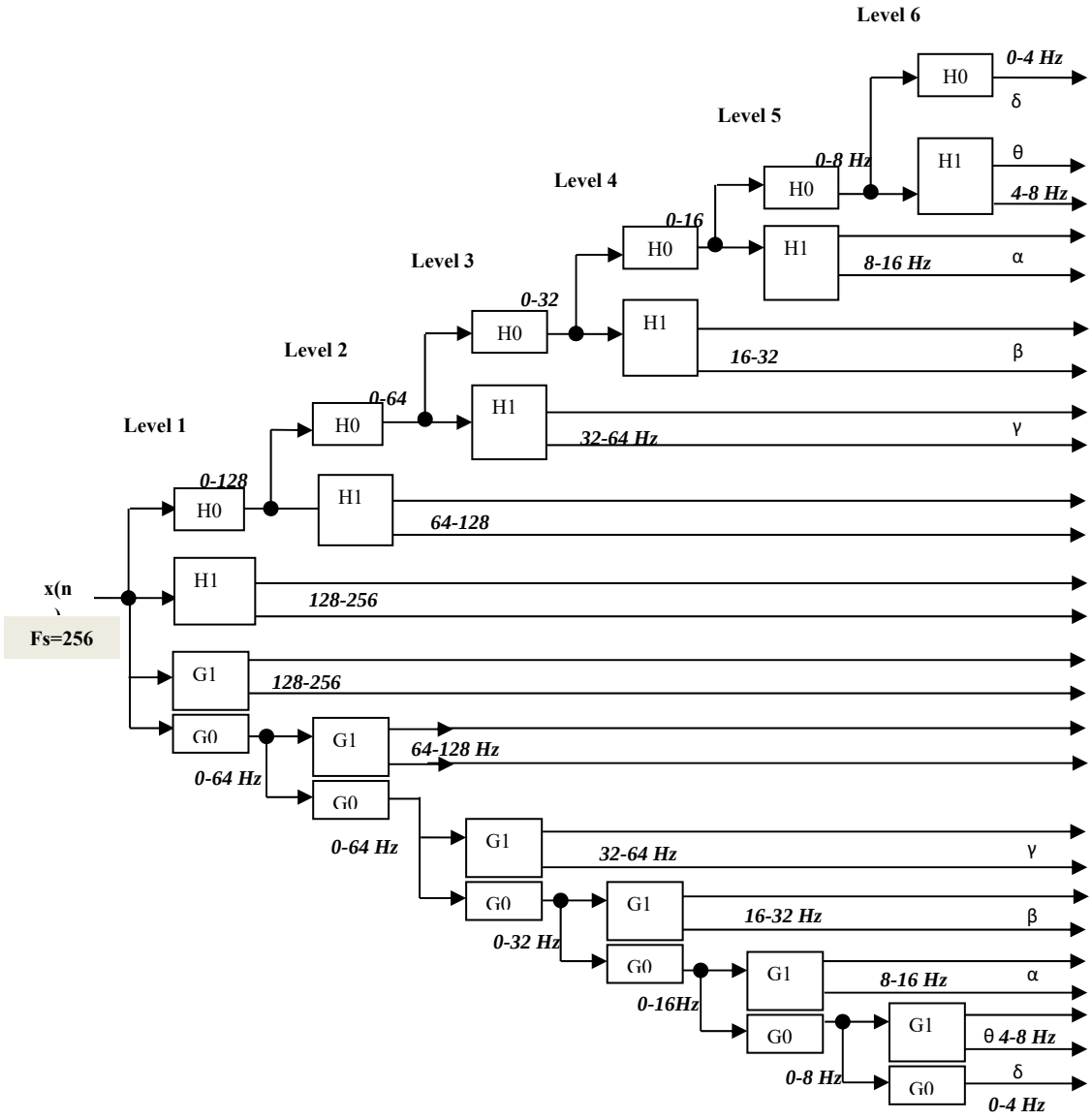
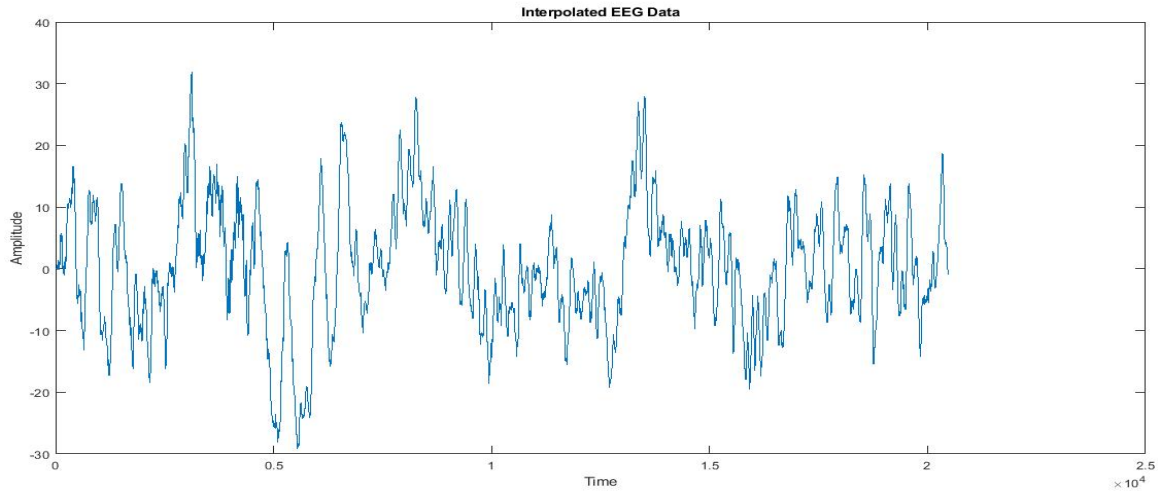
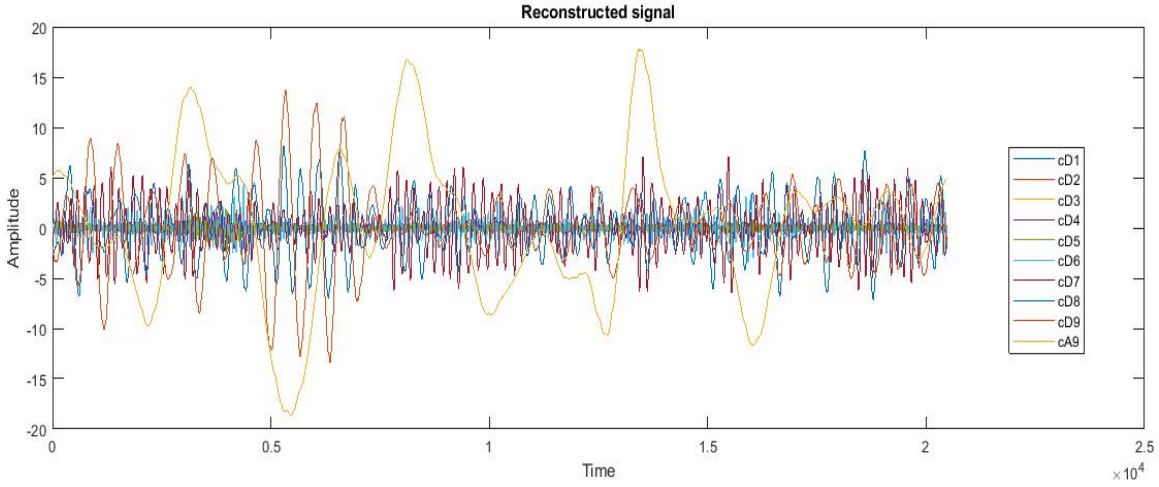


Figure 3: Symmetrical DTCWT Decomposition Algorithm

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195



(a)



(b)

Figure 4: Processing Using DTCWT (A) Original EEG Signal (B) Reconstructed EEG Signal

Journal of Theoretical and Applied Information Technology
31st December 2020. Vol.98. No 24
© 2005 – ongoing JATIT & LLS
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

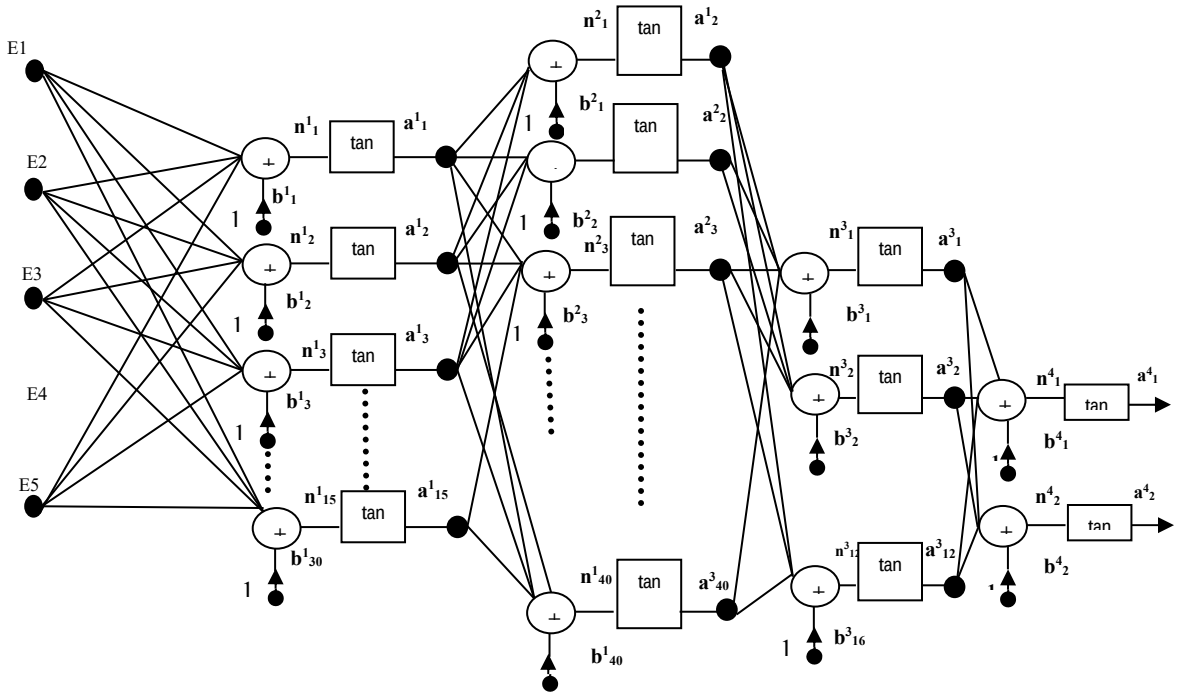


Figure 10: FFNN structure for classification

```
targets =  [0.2 0.2 0.2 0.2 0.2 0.2 0.2 0.2 0.8 0.8 0.8 0.8 0.8 0.8 0.8 0.8 0.2 0.2 0.2 0.2 0.2 0.2 0.2 0.2 0.8 0.8 0.8 0.8 0.8 0.8 0.8 0.8
            0.2 0.2 0.2 0.2 0.2 0.2 0.2 0.2 0.8 0.8 0.8 0.8 0.8 0.8 0.8 0.8 0.2 0.2 0.2 0.2 0.2 0.2 0.2 0.2 0.8 0.8 0.8 0.8 0.8 0.8 0.8 0.8];
```

Figure 11: Target Matrix For Nns Created

```
inputs1 = [0.018536076  0.046703391  0.031551495  0.076790519  0.015669678  0.03677405   0.068726197  0.234422819  0.100113811  0.081077549  0.087954994  0.075412617  0.072092782
           0.058522885  0.039200586  0.066453991  0.018536076  0.046703391  0.031551495  0.076790519  0.015669678  0.03677405   0.068726197  0.234422819  0.100113811  0.081077549
           0.087954994  0.075412617  0.072092782  0.058522885  0.039200586  0.066453991  0.05438013   0.071289467  0.473249295  0.037247594  0.007522913  0.046309273  0.044964047
           0.064909192  0.011964775  0.066998415  0.122210515  0.058307729  0.012975203  0.026128362  0.027115665  0.137411676  0.05438013   0.071289467  0.473249295  0.037247594
           0.007522913  0.046309273  0.044964047  0.064909192  0.011964775  0.066998415  0.122210515  0.058307729  0.012975203  0.026128362  0.027115665  0.137411676  0.031629916
           0.023600281  0.092333013  0.052883088  0.018401855  0.011962764  0.168401654  0.023206666  0.005689564  0.066994897  0.003250461  0.006520026  0.018282715  0.009332635
           0.002126926  0.004069361  0.031629916  0.023600281  0.092333013  0.052883088  0.018401855  0.011962764  0.168401654  0.023206666  0.005689564  0.066994897  0.003250461
           0.006520026  0.018282715  0.009332635  0.002126926  0.004069361  0.018375714  0.108197738  0.000226215  0.127763847  0.007988414  0.005497533  0.025375316  0.033033456
           0.016229183  0.056262241  0.043836992  0.024643887  0.008597687  0.044075272  0.007178061  0.018375714  0.108197738  0.000226215  0.127763847  0.007988414  0.005497533
           0.025375316  0.033033456  0.016229183  0.056262241  0.043836992  0.024643887  0.008597687  0.044075272  0.007178061  0.030219841  0.659611433  0.033178736  0.020223139
           0.090668572  0.089270059  0.102693168  1            0.000403166  0.017852906  0.000263918  0.028868079  0.022811544  0.02710058   0.015025215  0.019649557  0.030219841
           0.659611433  0.033178736  0.020223139  0.090668572  0.08927005   0. 02693168  1            0.000403166  0.017852906  0.000263918  0.028868079  0.022811544  0.002710058
           0.015025215  0.019649557 ];
```

(a)

© 2005 – ongoing JATIT & LLS
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

```
inputs2 = [0  0  0  0  0  0  0  6.59E-05  0  0  0  0  0  0  3.30E-05  0  0  0  0  0  0  0  0  6.59E-05  0  0  0  0  0  0  3.30E-05  0  0.001647935  0.002471903  0.007745295  0.002570779
0.001417224  0.002175274  0.003889127  0.009294354  0.009558024  0.009986487  0.00603144  0.004614218  0.003065159  0.003229953  0.009030685  0.006624699  0.001647935
0.00247190  0.007745295  0.002570779  0.001417224  0.002175274  0.003889127  0.009294354  0.009558024  0.009986487  0.006031443  0.004614218  0.003065159  0.003229953
0.009030685  0.006624699  0.000593257  0.001417224  0.002109357  0.001845687  0.001384266  0.000230711  0.001054678  0.008074882  0.000230711  0.000296628  0.001582018
0.001450183  0.000527339  0.000461422  0.000659174  0.000362546  0.000593257  0.001417224  0.002109357  0.001845687  0.001384266  0.000230711  0.001054678  0.008074882
0.000230711  0.000296628  0.001582018  0.001450183  0.000527339  0.000461422  0.000659174  0.000362546  0.001614976  0.002933325  0.00148314  0.003658416  0.002076398
0.000889885  0.001812729  0.006459906  0.000395504  0.00023071  0.002208233  0.003196994  0.001285389  0.0015161  0.00253782  0.000329587  0.001614976  0.002933325
0.001483142  0.003658416  0.002076398  0.000889885  0.001812729  0.006459906  0.000395504  0.000230711  0.002208233  0.003196994  0.001285389  0.0015161  0.00253782
0.000329587  0.139942652  0.246761807  0.473385848  1  0.647704426  0.08862595  0.316370588  0.716291487  0.001186513  0.000428463  0.067499423  0.017632906
0.00481197  0.001384266  0.007020204  0.002768531  0.139942652  0.246761807  0.473385848  1  0.647704426  0.08862595  0.316370588  0.716291487  0.01186513
0.000428463  0.06749942  0.017632906  0.004811971  0.001384266  0.007020204  0.002768531];
```

(b)

```
inputs3 = [0.000973063  0.005454689  0.004857403  0.001633638  0.00175626  0.004339227  0.011047822  0.014789763  0.009584273  0.009825561  0.007187216  0.005850243  0.006791662
0.005142202  0.030691033  0.005684111  0.000973063  0.005454689  0.004857403  0.001633638  0.00175626  0.004339227  0.011047822  0.014789763  0.009584273  0.009825561
0.007187216  0.005850243  0.006791662  0.005142202  0.030691033  0.005684111  0.013496302  0.012420395  0.04283454  0.016866421  0.014936118  0.008583521  0.022024445
0.05130335  0.023812349  0.020770539  0.025703097  0.020537162  0.012151418  0.012234484  0.031679918  0.015118073  0.013496302  0.012420395  0.04283454  0.016866421
0.014936118  0.008583521  0.022024445  0.05130335  0.023812349  0.020770539  0.025703097  0.020537162  0.012151418  0.012234484  0.031679918  0.015118073  0.003682607
0.006922195  0.016336379  0.009070053  0.004216605  0.001467505  0.005403267  0.023444484  0.000166133  0.007396859  0.007938768  0.009105652  0.007377082  0.003389898
0.008789209  0.000973063  0.003682607  0.006922195  0.016336379  0.009070053  0.004216605  0.001467505  0.005403267  0.023444484  0.000166133  0.007396859  0.007938768
0.009105652  0.007377082  0.003389898  0.008789209  0.000973063  0.008294767  0.012119774  0.01150271  0.060143982  0.004351094  0  0.004932558  0.01872157
0.000304577  0.000201733  0.0055338  0.025853408  0.008587477  0.066733911  0.010941023  0.002389146  0.008294767  0.012119774  0.01150271  0.060143982  0.004351094
0  0.004932558  0.01872157  0.000304577  0.000201733  0.0055338  0.025853408  0.008587477  0.066733911  0.010941023  0.002389146  0.301412128  0.712930659
0.223970571  0.442043432  0.461710375  1  0.092306475  0.837106918  0.00391994  0.154175072  0.009366718  0.28750445  0.228088288  0.010122226  0.157121949
0.115015229  0.301412128  0.712930659  0.22397057  1  0.442043432  0.461710375  1  0.092306475  0.837106918  0.00391994  0.154175072  0.009366718
0.28750445  0.228088288  0.010122226  0.157121949  0.115015229];
```

(c)

Figure 12: Input Matrices To Nns Created From: (a) PSD Estimated Using FFT (b) CPSD (c) PSD Estimate Using MEM