Epileptic seizure endorsement technique using DWT power spectrum

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Abstract: EEG signals play significant role in the study of mental disorders. Epilepsy is one of the major mental disorder and need significant technological support in the treatment. A method proposed here is an endorsement technique for epileptic seizures using electroencephalogram (EEG) signals captured using non-invasive method. The method uses power spectrum density and discrete wavelet transformation (DWT). The impact of power spectral analysis along with the usage of EEG characteristics in endorsement of epilepsy is addressed here. A publicly available EEG epileptic dataset is processed using FIR filters along with DWT. The power spectrum density and its average were compared with specific spectrum to get the results and were compared against the standard EEG signal frequency range. It is found that the usage of DWT is more accurate and reliable to process and classify the EEG data for epilepsy endorsement.
Keywords: Electroencephalogram, Brain, Signal Analysis, Power spectrum, DWT.

1 Introduction

The area of EEG signal processing is now grabbing the interest of many researchers to contribute towards the achievement of accurate analysis and classification on epilepsy [2,17]. The clinical signs and EEG patterns of epilepsy depends on the type of subjects' reaction. The cases like, head injury, cerebrum tumors, strokes and brain diseases are known as epileptogenesis. Hereditary changes can also be linked with such cases. EEG is one of the ways for recording brain electrical activity from the top of the skin on the head. The signals captured are the waveforms and they reflect the electrical activity of the outer layer of the cerebrum. The captured signals' intensity indicates the small EEG activity and is commonly measured in microvolts (μV). Delta, Theta, Alpha and Beta waves are the categories into which the human EEG wave frequencies[1] are divided. A delta wave has a frequency less than or equal to 3 Hz and has the property of highest amplitude. The observation in this wave is prepotent rhythm in young babies up to one year and the sleeping stages of 3 and 4[1,2]. This occurrence may be observed focally in case of "sub cortical lesions", "in general distribution with diffuse lesions", "metabolic encephalopathy hydrocephalus or deep midline lesions" and most prominent posterior in children, and frontally in adults[1,2].

The slow activity frequency range is from 3.5 Hz to 7.5 Hz in case of theta waves[1,2]. This can be considered as abnormal for adults in awake state but in case of children up to 13 years it is quite normal. It will be in general seen as an indication of focal subcortical wounds; it can likewise be seen in summarized scattering in diffuse messes up, for instance, metabolic encephalopathy or a couple of events of hydrocephalus[1,2]. The frequency range from 7.5 Hz to 13 Hz is termed as alpha wave; its place is on backside of the head on each side and is found higher to accept on the predominant side. On the other hand, a beta wave indicates "quick" action, has a frequency range of at least 14 Hz, and is generally seen on the two sides of the brain in even dissemination and is frontally most apparent[1,2]. It is emphasized by narcotic sleep-inducing drugs particularly the “benzodiazepines and the barbiturates”. It might be missing or decreased in areas of cortical harm, is typically considered as normal rhythm, and is the prevailing beat in patients who are alert or restless or have their eyes open[1,2]. The emphasizing characteristics of EEG waves are majorly considered in medical treatment of mentally disordered patients. Epilepsy is a mental disorder and based on the properties of human EEG waves, the medical practitioners can treat this disorder effectively. The technological support in epileptic seizure endorsement for medical practitioner will be a synergetic inclusion.

The methodology for epileptic seizure endorsement is proposed here using EEG wave patterns. Four EEG wave patterns, namely Delta, Theta, Alpha and Beta waves, were studied. The publicly available EEG data [32] which has been captured with sampling rate of 128 Hz is tested for the said purpose. However, the acquisition system with the spectral bandwidth of 0.5 Hz to 85 Hz was set[32]. Therefore, 40 Hz low pass filter is introduced first. The EEG data is collected on ten epileptic subjects in order to reassert each subject as epileptic[32]. The usage of a finite linear impulse filter (FIR) filter with DWT led to an effective classification and recognition. This article is organized as – introduction of related work in the next section, the adopted methodology is described afterwards, then a discussion on the obtained results, and finally the conclusions are pointed out.

2. Related work

Many research communities are now attracted towards Brain-Computer Interface (BCI). BCI acts like a channel from the brain to external equipment. The BCI treats the foreign device as a body part and also helps in achieving comprehensive brain mapping. The BCI involves research, augmenting, mapping, rectifying, and/or restoring sensory, experimentation, and cognitive functions. Artificial intelligence, machine learning, and data science are contributing in the arena of BCI; however, the work done in this area is still wide open for research.

The BCI has been presented as one of the major contributors in the area of medical and non-medical applications [16, 17]. There are many challenges and difficulties in utilizing brain signals [2, 17]. For example, in the study of acts of hand movement or various finger movements, EEG signals have to be properly amplified and filtered [3]. Further to add more about BCI, the study of amyotrophic lateral sclerosis (ALS) patients with the use of a P300 [8] speller BCI was also found effective [4][5]. For stroke motor recovery, BMI-based techniques are found useful and effective by many researchers. The physiological signals of the body and hemodynamic responses of the brain are combined with the brain-body machine interface to improvise the detection of intention to move in healthy participants[7]. Moreover, studies examining whether NIRS-based BBMI systems boost reliability in determining stroke patients' intention to move are still missing, and the effectiveness of NIRS-based BBMI in restoring motor function in patients with stroke is still unknown[7].

It is possible to design a prosthetic limb for amputees that allows them to behave like that of a normal person, with the arm actuated by system instructions derived from brain signals. Amputees who have lost appendages and whose brains work normally will use such a device [9]. Rarely occurs the front-parietal and parieto-occipital networks primarily encode information on target and cursor positions and speeds, which are carried by EEG [10]. Attempts to raise the arm and head by people with spinal cord injuries (SCI) leave decodable neural correlates. An analysis of hand open, palmar grip, lateral grip, supination, and pronation in ten people with cervical SCI was carried out[10]. The same approach was tested on a person with cervical SCI as a proof-of-concept for classifying movement attempts online in a closed-loop, and a moderate classification output of 68.4 percent was achieved concerning palmar grasp vs hand open (chance level of 50 percent)[11]. When used as part of an intracortical brain-computer interface (iBCI) in a closed-loop, offline decoders configured to reconstruct expected movements from neural recordings often struggle to achieve optimal online performance [12]. It was the first asynchronous high-speed BCI to distinguish between deliberate regulation (IC) and non-control (NC), with just 0.075 erroneous classifications per minute [13]. Using a matrix-keyboard of 32 targets, the asynchronous speller obtained an average information transmission rate (ITR) of 122.7 bits per minute.

EEG-based lie detectors became common over polygraphs as a result of human actions cannot influence them. varied studies conducted "Guilty data Test" or "Concealed data Test" by making a mock crime state of affairs to spot potential changes within the brain [14]. This work enclosed a simulated crime state of affairs EEG acquisition tool for ten participants. The wavelet approach created most of the themes to perform higher for EEG data. A comparison between the bottom classifiers and therefore the ensemble structure was given with the over-performing ensemble approach across the fundamental classifiers. The additional projected framework was compared with some existing approaches, achieving the most accuracy of 92.4% [14].

A 13-layer deep convolutional neural network (DCNN) rule was accustomed to find traditional, preictal, and seizure categories [20]. This DCNN technique had AN accuracy, specificity, and sensitivity of 88.67%, 90.00%, and 95.00%, severally. Complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) for convulsion identification has eliminated the concern of medical professionals and expedite encephalopathy analysis and diagnosing [21]. The Bayesian error and non-parametric chance distribution estimation have created an effect to work out the importance of every feature extracted [22]. Moreover, a redundancy analysis was done with correlation-based feature choice. The features: variance, energy, nonlinear energy, and technologist entropy were ready to capture the seizures considerably.

The baseline technique of classifying all epochs as traditional was shown AN improvement of 4.77 – 13.51% in terms of the Bayesian error. The empirical mode decomposition (EMD) and a multilayer perceptron neural network (MLPNN) were accustomed to decompose a time phase graphical record into intrinsic mode functions (IMFs) on that autoregressive (AR) parameters were extracted, combined, and fed to the MLPNN classifier [23]. AN experiment doles out on an in public offered dataset[31][32], comprising traditional, interictal, and ictic graphical record signals achieved a classification accuracy of up to ninety-eight. smoothened pseudo-Wigner-Ville distribution gave 98.9% of accuracy [24]. AN adaptive multi-parent crossover Genetic rule was used for optimizing the options utilized in classifying epileptic seizures [25]. Weighted Permutation Entropy and a Support Vector Machine classifier model were accustomed to enhance the sensitivity and exactness of the detection method [26].

The matrix determinant of graphical record as a big feature for recognition of epileptic seizures classified mistreatment support vector machine (SVM), K-nearest neighbor (K-NN) [30], multilayer perceptron (MLP) classifiers with 10-fold cross-validation was proposed[27]. The results disclosed classification accuracies of 99.45% employing a dataset from the University of urban center and of 97.56% mistreatment the RMCH dataset once classifying between the traditional and epileptic graphical record. The signals were rotten into time-frequency sub-bands until sixth-level mistreatment dual-tree advanced ripple rework (DTCWT) [28]. Tunable-Q ripple rework (TQWT) was projected and twenty-five frequency coefficients sub-bands were calculated by mistreatment TQWT within the pre-processing [29]. Interaction with the physical world a Human-in-the-loop cyber-physical systems (HiLCPSs) are introduced. Human cognitive activity can be measured using a HiLCPS through body and brain sensors. [34]. The more accurate prediction along with low cost can be done with Human-in-the-loop by the integration of experience and knowledge. A survey shows[35] works on human-in-the-loop from a data perspective and classify them into three categories with a progressive relationship: (1) “the work of improving model performance from data processing”, (2) “the work of improving model performance through interventional model training”, and (3) “the design of the system independent human-in-the-loop”[35]. Artificial Intelligence(AI) is playing a major role to add more strength to the medical field. AI has a potential unique offer towards the best opportunities in improving medical practice. The argument in technological solutions should include integration of three conditions: (1) “they serve human ends”; (2) “they respect personal identity”; and (3) “they promote human interaction”. [36]. The field of soft wearable robotics is just beginning and will evolve based on a better understanding of the underlying fundamental science of soft robotics and the human-machine interaction[37].

Further, the methodologies custom-made within the survey found strengthening the method of graphical record signal analysis and classification; but, a combination of power spectrum density and DWT can contribute additional towards increasing the potency of convulsion detection. Therefore, the methodology projected during this article is a cooperative inclusion in graphical record signal analysis and classification for the epileptic disorder.

3. Methodology

The importance of EEG signal processing can be seen in various medical and non-medical applications. The methodology proposed here is a set of different influential stages that plays a significant impact on the outcome. It is composed of dataset acquisition, filtering, feature extraction, classification, and recognition. The dataset [32] used in the proposed method was captured by using a 16-channel EEG cap aiming to reassert the subject under study is in an epileptic state. To begin with, the process EEG signal acquisition [32] of 10 subjects is done, channel selection is done to extract the signals of interest. Features are extracted using DWT to excerpt the attributes to be used in the classification. Feature extraction is done with the help of DWT because of its effectiveness compared to other methods in terms of accuracy of extraction features to ensure the effectiveness in the following steps, this had been proved in several previous studies such as [38,39]. The strength of power spectrum can be seen through the characteristics of hypnotic agent, which were discovered by raw EEG power spectral analysis; these

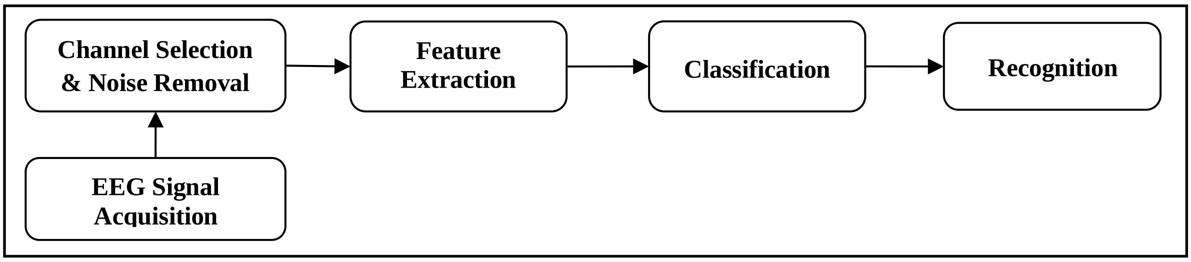


Fig. 1 Brain EEG signal processing and analysis.

characteristics are related to the mechanism of the agent. When inducing propofol sedation, beta oscillation is normal, and slow-delta oscillation occurs during the loss of consciousness. Since its mode of action is similar to propofol's, midazolam's EEG pattern is similar to propofol's, and beta oscillation is common when sedation is induced. The oscillations of ketamine, beta, and gamma can be seen in the 25-32 Hz band. Slow oscillation of the delta and spindles is a characteristic of dexmedetomidine[17]. Hence DWT power spectrum will add more strength in EEG data processing.

Basically the two level DWT is used here to extract features and these features are taken in the form of LL, LH, HL, HH band coefficients. From these features, the classification and recognition are done

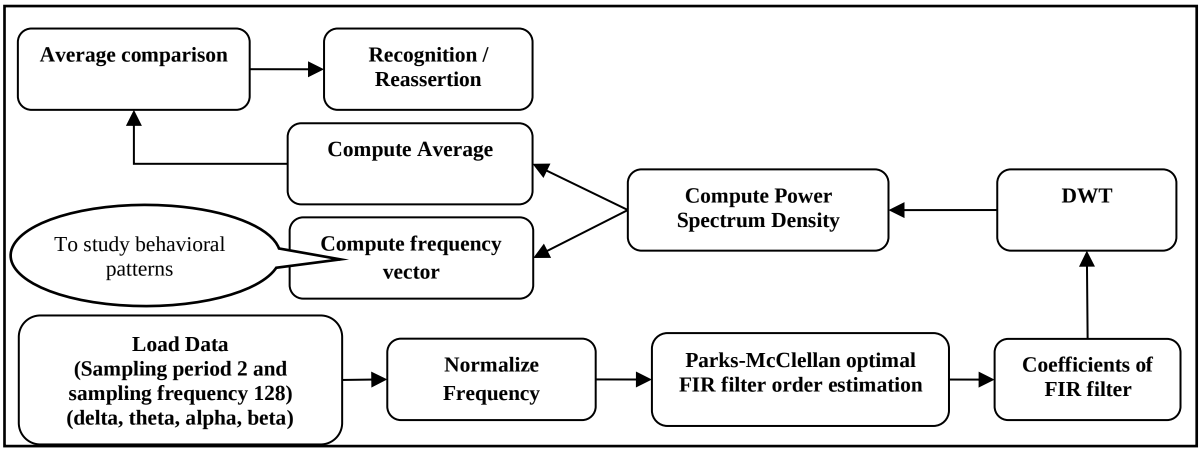


Fig. 2 Detailed methodology for brain EEG signal processing and analysis.

with respect to power spectrum. The propounded methodology of Fig.1 shows the brain EEG signal processing and classification.

The patients' epilepsy reassertion process is shown in the block diagram of Fig.2 along with the EEG signal processing and analysis. Fig.3 shows the EEG data acquired from 10 subjects using a 16 channels EEG cap. A publicly available EEG data [32] is used; with the settings like - sampling frequency (SF), passband frequency (PBF) and ripples for both initializing and stop band frequency (SBF) for the signal frequencies of delta, alpha, beta and theta waveforms. The PBF and SBF normalization is done to measure the signal as usual, fixed, ease-to-use range as {[PBF. SBF] / Half of SF}. The frequency f is normalized to get f_n for the range [0 to 1] using frequency sampling:

$$f_n = {}^{f}/_{f_s} \tag{1}$$

However, in accordance with the Nyquist-Shannon theorem, the sampling frequency is usually to the minimal of twice the frequency f. Therefore, Eq. (1) is not more than 1/2. In order to get f_n between range [0, 1], Eq. (1) is multiplied with the factor of 2:

$$f_n = 2 \times {}^{f}/_{f_s} \tag{2}$$

The Parks–McClellan[33] algorithm works on iterative basis and is used for getting the most favorable Chebyshev Finite Incentive Response filter. The maximum filter coefficients were obtained by this algorithm, where optimal FIR filters were obtained using indirect approach. The main target of this algorithm is to reduce the error in the pass bands and stop bands with the help of Chebyshev approximation. The variation found in Remez exchange algorithm is termed as Parks–McClellan algorithm specially designed for FIR filters and considered as a standard way to design FIR filter. The Parks–McClellan algorithm can be described as:

Step.1 Guess the extreme positions that are equally spaced in the stop and pass bands

Step.2 Conduct interpolation of polynomial and re-assess the local extreme positions

Step.3 Extremes are changed to new positions and continue iteration until the extreme stops moving

Computing a discrete-time, direct-form FIR filter, with coefficients of numerator leads to filter the data with filter defined by a numerator coefficient vector. Applying DWT in order to extract LL, LH, HL and HH bands leads to get narrowed data called as feature extraction, which is useful in making the desired decision. The non-parametric estimation of the spectral power density of a broader sense uniform indiscriminate process is performed on LL, LH, HL and HH data. DWT is one of the finest transformation tools used to transform a given signal data into two-dimensional wavelets or applying the one-dimensional wavelet transformation along rows and columns of the data successively as separable two-dimensional transform.

In many cases, wavelets are used for signal data compression and signal data processing giving low computational complexity of separable transforms. Mathematically as a convolution operation, the wavelet transform passes the signal data through low and high pass filters. This transform will lead to data decomposition into LL, LH, HL, and HH frequency sub-bands, where L denote low-pass filtered bands and H denote high-pass filtered bands. The LL sub-band was obtained with the help of low-pass filters, filtered along with row and column-wise to get an approximated signal data. This approximation LL sub-band contains a very high quantity of information about the signal data under analysis; further obtained LL sub-band may be divided to get the most of the valuable quantity of information from the signal data. The components with high frequency can be found in other sub-bands, like LH, HL, and HH. These sub-bands may also be further divided to get four sub-bands and may be considered for utilization according to application. The decomposition of approximated data is done at each level, hence getting the pyramidal tree of four sub-bands. This particular two-level decomposition makes the wavelet disintegration by level two of the input signal data.

The DWT is taken to pair up the input to get a directory of 2n values to store and pass them using Haar wavelet. When it is repeated recursively, it is observed that the 2n-1 differences together with a final sum can be got by pairing the sums to prove the following scale. DWT decomposition splits the input signal in the form of higher-frequency and lower-frequency parts. To assess the high frequencies and low frequencies, the signal is passed through several high and low pass filters respectively, with different cutoff frequencies at various resolutions.

The DWT signal decomposition is done by spanning one-dimensional signal x[n] from 0 (zero) to π radians. First the signal x[n] is passed through the filters; high-pass g[n] along with a low-pass h[n].The Nyquist's theorem eliminates one half of the sampled signals, which possesses π/2 radians i.e highest frequency range. The subsampling of this signal is done by the factor 2 and discard each second sample. This is a kind of a higher-level decomposition of x[n] and is expressed in mathematical form as:

$$y_{high}[i] = \sum_n x[i] g[2i - n], \tag{3}$$

$$y_{low}[i] = \sum_n x[i]\, h[2i - n], \tag{4}$$

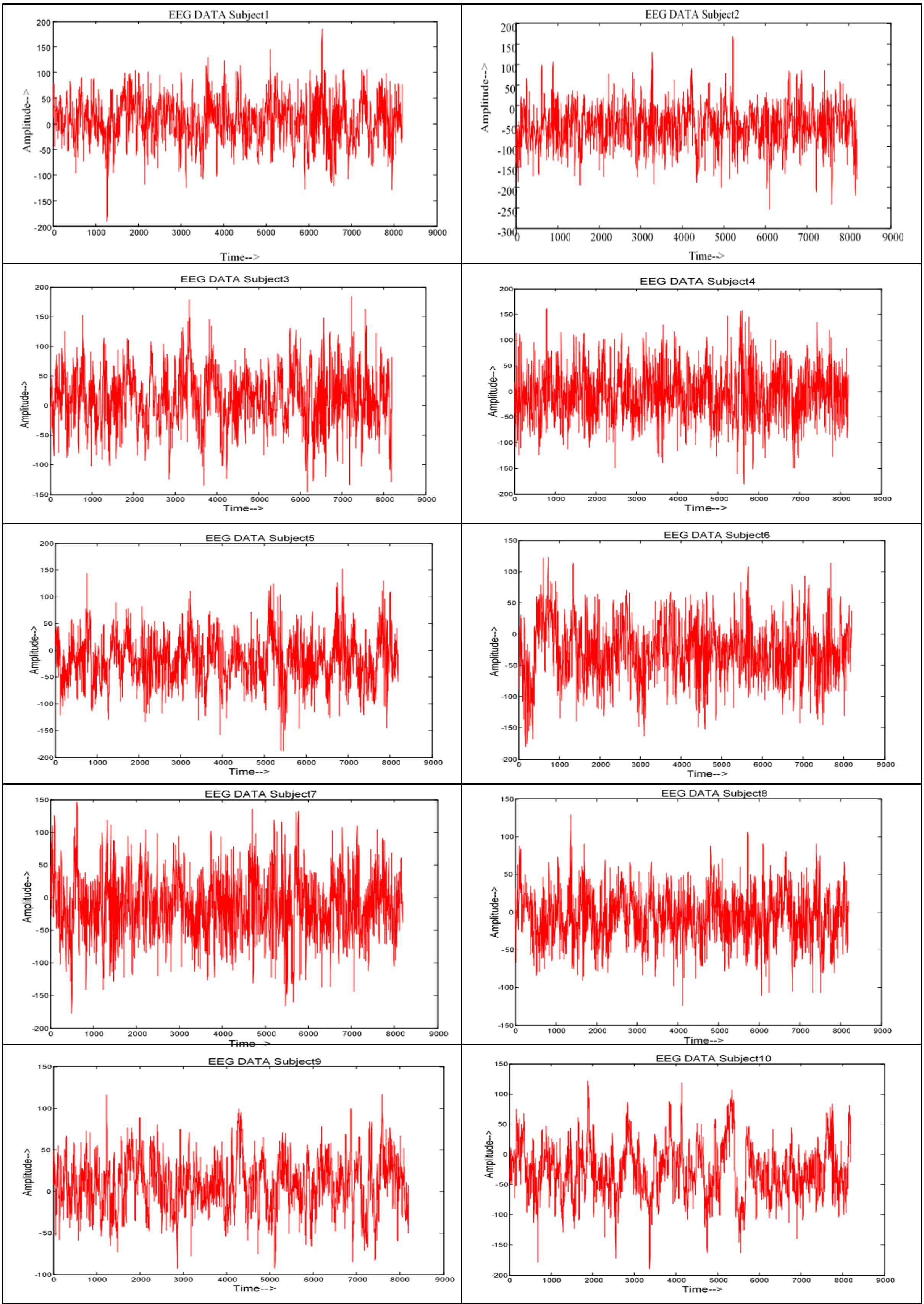


Fig.3 EEG Data acquired for ten subjects (Patients)

The Nyquist's theorem eliminates one half of the sampled signals, which possesses $\pi/2$ radians i.e highest frequency range. The subsampling of this signal is done by the factor 2 and discard each second sample. This is a kind of a higher-level decomposition of x[n] and is expressed in mathematical form as:

$$y_{high}[i] = \sum_n x[i] g[2i - n], \tag{3}$$

$$y_{low}[i] = \sum_n x[i]\, h[2i - n], \tag{4}$$

where $y_{high}[i]$ and $y_{low}[i]$ are the results of the respective high and lowpass filters after sub-sampled by 2. The process shown above has a tendency of repeated extra decomposition. In a signal processing application, the usage of two-dimensional wavelet is limited to only square matrix data with the height and width equal to the power of two. If the data is in the form of N × N size, then it can be said that, $N = 2^n$. Fig.4 presents a one level DWT decomposition of an input signal.

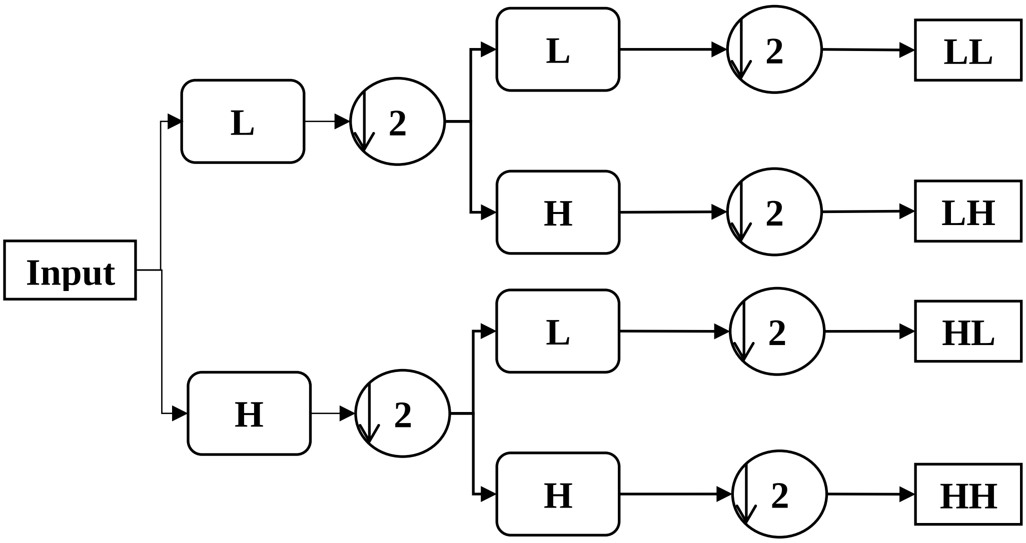


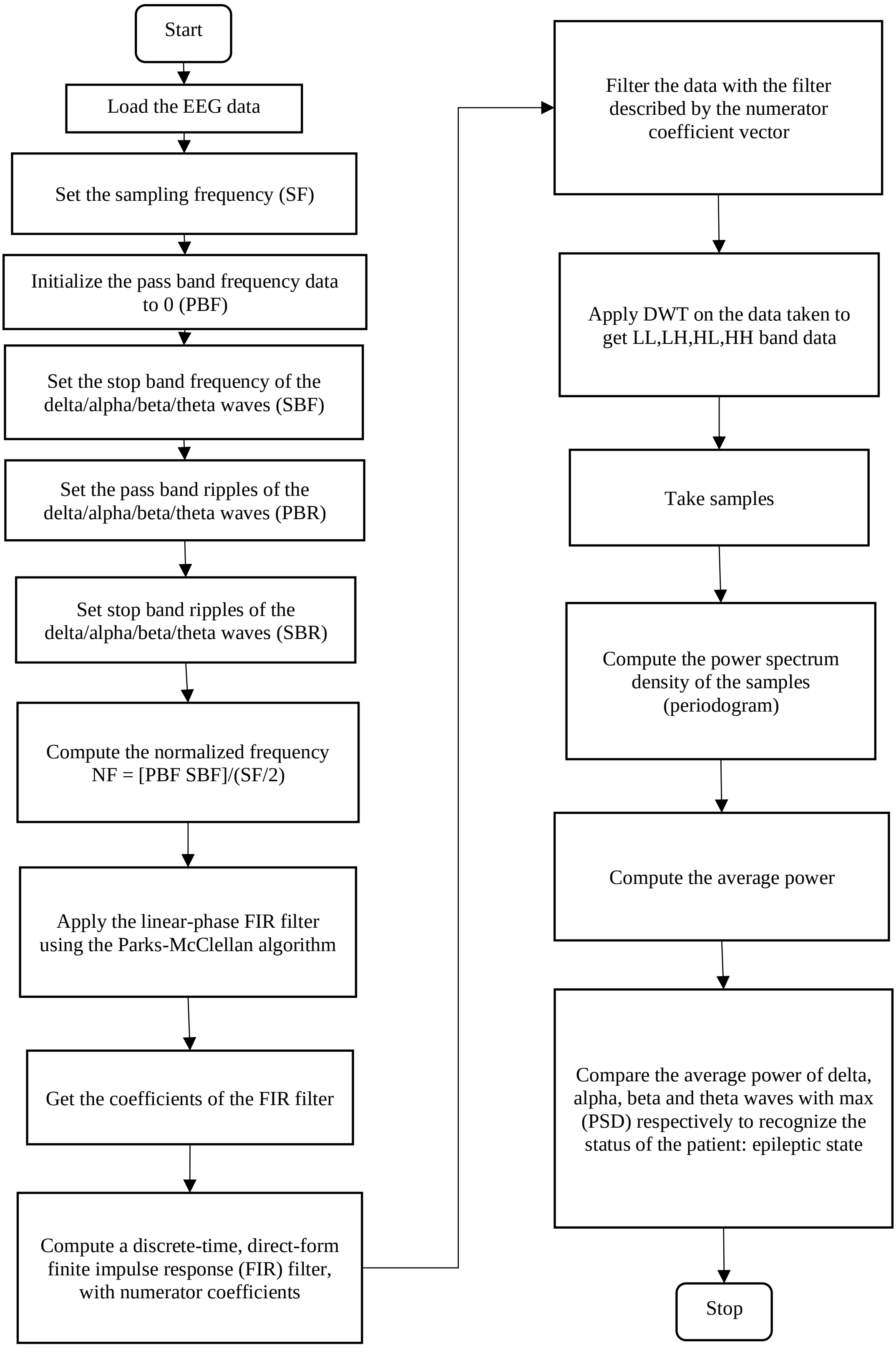
Fig. 4. Example of a one level wavelet signal decomposition.

The higher-level decomposition of x[n] is considered as an input to obtain periodogram. This periodogram is the Fourier transformation of a bias estimate of the autocorrelation sequence. In this case a signal **x[n]** is sampled at **fs** samples per unit time, then the periodogram is defined as:

$$\hat{P}(\omega) = \frac{\Delta t}{N} \left|\sum_{k=0}^{n-1} x[k] \times e^{j2\pi f \Delta t k}\right|^2, \qquad -{}^{1}\!/_{2}\,\Delta t < f < {}^{1}\!/_{2}\,\Delta t, \tag{6}$$

where Δt is considered as the sampling interval and for a one side periodogram, the values at all frequencies (except zero) and the Nyquist, ½ Δt, are multiplied by 2 to conserve the total power. Compute the average of power for classification (behavioral patterns) to make decision by comparing with alpha, beta, theta and delta signals. Based on the comparison, the proposed methodology reasserts (recognition) the patient under test is in epileptic state and is summarized in the flowchart-1.

Flowchart 1 : Epileptic seizure detection process using Non-invasive method



4. Results and discussion

The impact and accuracy of the results obtained are addressed in this section. The contribution of the linear impulse FIR filter along with DWT in the process of classification and recognition is discussed, and also about how the LH and HH bands of DWT have given excellent outputs to justify the results. The results were obtained from EEG data [32] of ten epileptic patients. Table. 1 shows the comparison of the obtained results in terms of the standard frequency range. Fig. 5 shows the layout of the 16 EEG channels cap used to acquire the studied signals [32].

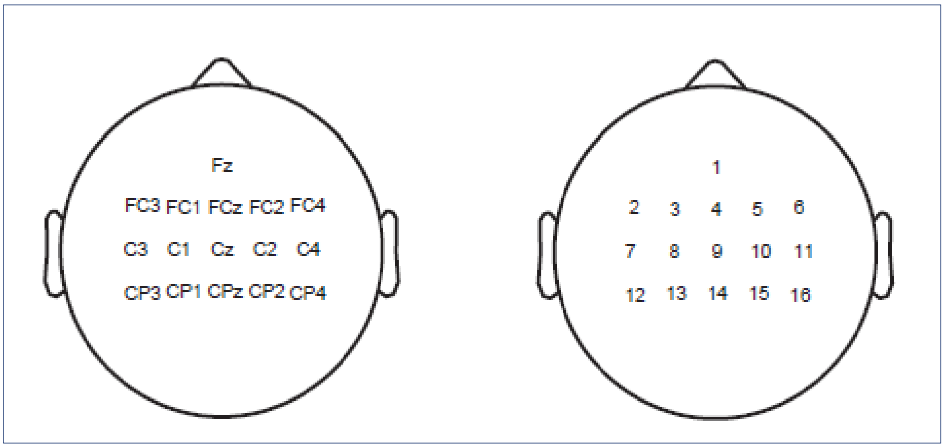


Fig. 5 Layout of the used 16 EEG channels cap.

The LL, HL bands of DWT have shown slight deviation indicating the subject's brain is not in a coma or in an unconscious state but is in the state of epilepsy. Epileptic seizures can jump from imperceptible and brief periods to significant stretches of vivacious shaking. From Fig.6 and Fig.8, it can be observed that during epilepsy, seizures tend to repeat and have no basic speedy cause. The fundamental system of epileptic seizures is excessive and non-uniform neuronal movement in the cortex of the brain. Ten subjects' data is tested in the proposed scheme with different types of epileptic variants (Table 1). The linear phase FIR filter using Parks-McClellan [33] algorithm is applied to get coefficients of the FIR filter. The DWT is used to get the LL, LH, HL, and HH bands to obtain precise data for computing the power spectrum in decision-making. Then the average power of delta, alpha, beta, and theta waves were compared in order to recognize the status of the patient. The sampling frequency is set equal to 128 Hz [19, 20, 33]. The conversion of EEG data from a time domain to a frequency domain is done with the help of DWT. It can be realized from Table 1 that the signal strength obtained from LL and HL bands indicated that the subject under study is epilepsy. The strength of the signal obtained from LH shown the result as 0 (zero) because of the lowpass filter used as the first filter and then high pass filter in DWT, as also occurred in the case of the HH band. A filter here with cutoff frequency 128Hz passes the signals higher than a cutoff frequency (here equal to 128 Hz) and blocks the signals with frequencies lower than the cutoff frequency. However, HL and LL bands shown negligible strength and succeeded in showing the subject under study is epilepsy. As the EEG signal is of a low-frequency component, the

HL band first attenuates low frequencies and allows high frequencies then attenuates high frequencies to allow low frequencies. This led to identifying the frequencies required to classify and make a decision to identify the subject's status. HL and LL bands gave more accurate results using the Haar wavelet. LL and HL bands corresponding to delta waves of Fig.6 and Fig.8 show very clear indications that as frequency increases, the amplitude decreases to zero leading to the observation as prepotent rhythm. Theta wave represents "slow" activity, "in general distribution with diffuse lesions", "metabolic encephalopathy hydrocephalus or deep midline lesions", showing a type of epilepsy, and also a similar observation can be found in the case of alpha wave activity. On the other hand, as the beta wave indicates a "quick" action, with low amplitude against an increase in frequency emphasizing epilepsy can be observed.

The various sorts of seizure include muscle firmness, loss of muscle control, jerky muscle developments of the face, neck, and arms, unconstrained fast jerking of the arms and legs, hardening of the body shaking, loss of bladder or inside control, staying quiet, loss of cognizance and so on. The results when compared with the literature available, data set and techniques were different. So, the comparison needs uniform and standard data – like the type of epilepsy, type of patients, age, whether under any other medical specific treatment, etc. The comparative study needs uniform data set for different techniques employed; so, in this article reassertion of epilepsy is demonstrated. The results, for example, subject-1 from fig.6 demonstrate that for the frequency range from 1 to 140 Hz the waveform is declining from 1 to 40 Hz show the probability of slow activities in the case of LL bands of delta and theta waves. On the other hand, the alpha and beta waves show that very low amplitude movements showing a lack of high thinking and quick action movements. For subject-2, a few quick action movements can be observed in comparison with subject-1. The various types of body movements may be observed during epilepsy. In addition, the main focus of the present analysis is to identify the different relations between delta, theta, alpha, and beta waves and their significances for 10 subjects and as shown in the graphs of fig.6 and fig.8. We found indentations for the power spectrum for frequency of 1 Hz and its harmonics at 130 Hz. Similarly, in the case of HL bands, the observations from fig.8 indicate the epileptic activities for the ten subjects that have been considered here.

The higher frequency components suggest that muscular activity might have domination or possibly influenced the results, as the activity of EEG can be observed as higher in awareness and lower in unresponsiveness. Classical EEG analysis is usually performed in frequency bands below 30 Hz, i.e. the delta, theta, alpha, and beta bands.

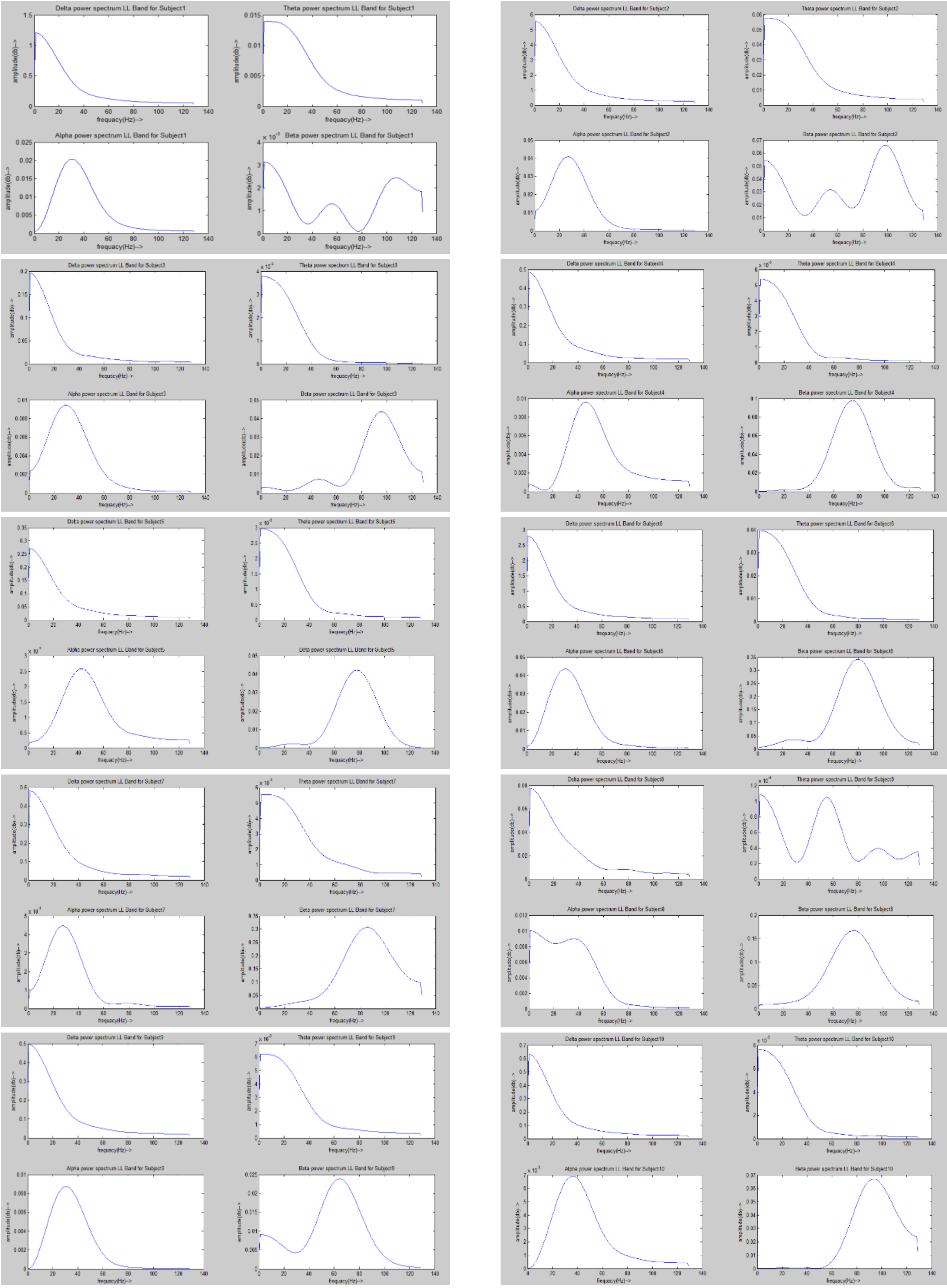


Fig. 6 Nature of Power Spectrum on LL band extraction (DWT applied on FIR Filtered data).

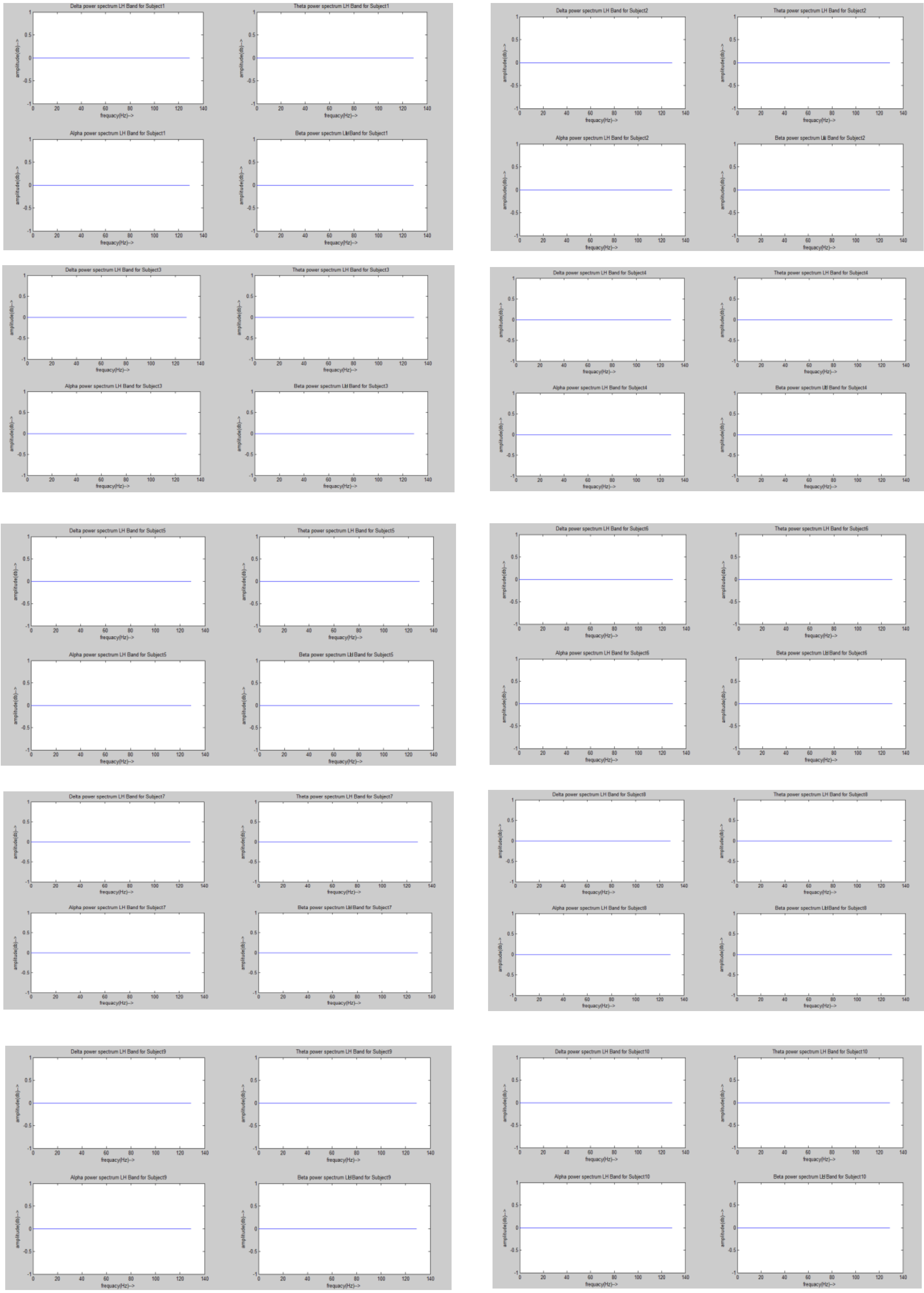


Fig. 7 Nature of the Power Spectrum on the LH band extraction (DWT applied on FIR Filtered data).

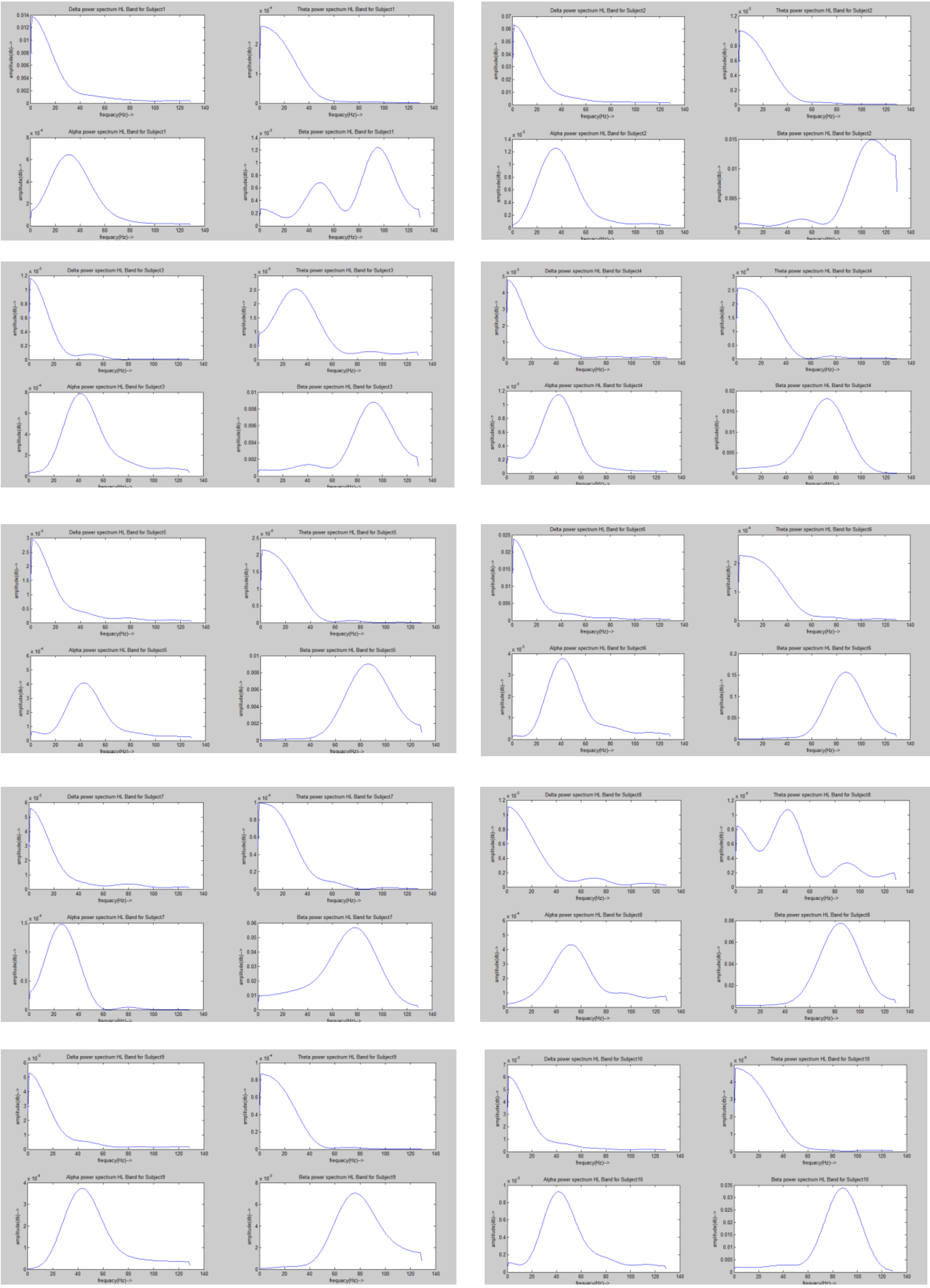


Fig. 8 Nature of the Power Spectrum on the HL band extraction (DWT applied on FIR Filtered data).

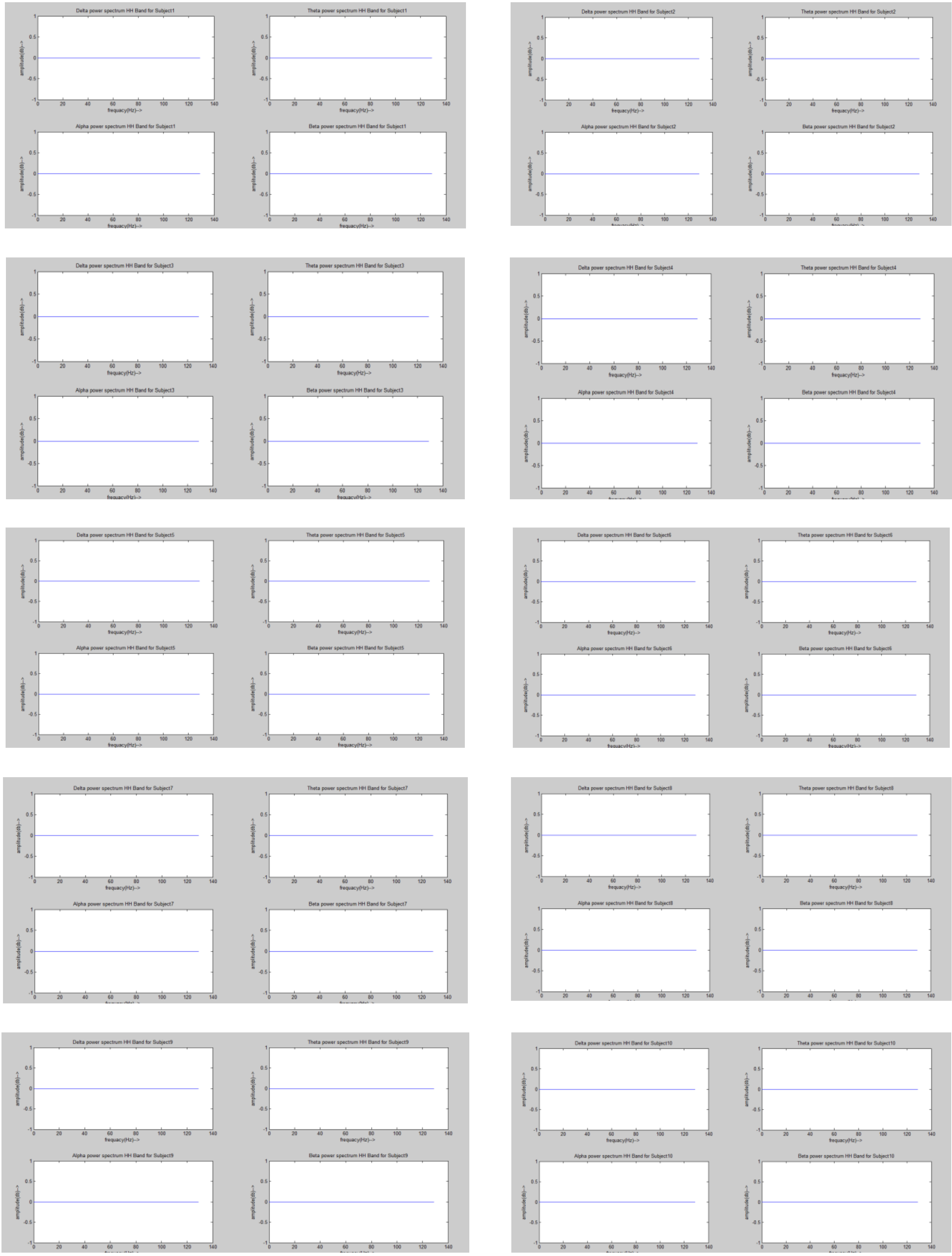


Fig. 9 Nature of the Power Spectrum on the HH band extraction (DWT applied on FIR Filtered data).

Table. 1 Comparison of the obtained results in terms of standard frequency range.

Average of Power Spectrum Density																
	LL Band				LH Band				HL Band				HH Band			
	Delta	Theta	Alpha	Beta	Delta	Theta	Alpha	Beta	Delta	Theta	Alpha	Beta	Delta	Theta	Alpha	Beta
	<4 Hz	4-7 Hz	7-13 Hz	13-39 Hz	<4 Hz	4-7 Hz	7-13 Hz	13-39 Hz	<4 Hz	4-7 Hz	7-13 Hz	13-39 Hz	<4 Hz	4-7 Hz	7-13 Hz	13-39 Hz
Subject 1	0.2938	0.0052	0.0063	0.0014	0	0	0	0	0.0027	6.4104×10^{-5}	2.165×10^{-4}	5.1783×10^{-4}	0	0	0	0
Subject 2	1.3423	0.0202	0.0119	0.0338	0	0	0	0	0.0125	2.2947×10^{-4}	4.0281×10^{-4}	0.0048	0	0	0	0
Subject 3	0.0378	9.5107×10^{-4}	0.0031	0.0144	0	0	0	0	1.7709×10^{-4}	9.4×10^{-6}	2.607×10^{-4}	0.0032	0	0	0	0
Subject 4	0.1065	0.0014	0.0033	0.0298	0	0	0	0	8.2712×10^{-4}	6.6508×10^{-6}	3.4812×10^{-4}	0.0061	0	0	0	0
Subject 5	0.0620	8.2423×10^{-4}	9.5388×10^{-4}	0.0131	0	0	0	0	5.7026×10^{-4}	5.1563×10^{-6}	1.3142×10^{-4}	0.0033	0	0	0	0
Subject 6	0.5924	0.0106	0.128	0.1172	0	0	0	0	0.0041	7.0151×10^{-5}	0.0011	0.0469	0	0	0	0
Subject 7	0.1164	0.0021	0.0013	0.1261	0	0	0	0	0.0011	2.6121×10^{-5}	3.7625×10^{-5}	0.0249	0	0	0	0
Subject 8	0.0212	5.1983×10^{-5}	0.0041	0.0660	0	0	0	0	2.6403×10^{-4}	4.6514×10^{-6}	1.6448×10^{-4}	0.0258	0	0	0	0
Subject 9	0.1166	0.0021	0.0024	0.0094	0	0	0	0	9.8804×10^{-4}	2.0336×10^{-5}	1.2705×10^{-4}	0.0027	0	0	0	0
Subject 10	0.1398	0.0020	0.0024	0.0226	0	0	0	0	0.0011	1.2751×10^{-5}	3.0029×10^{-4}	0.0104	0	0	0	0

“Beta waves”	“Active, busy thinking, active processing, active concentration, arousal and cognition”
“Alpha waves”	“Calm relaxed yet alert state”
“Theta waves”	“Deep meditation /relaxation, REM sleep”
“Delta waves”	“Deep dreamless sleep, loss of body awareness”

The use of DWT played a major role in more sophisticated feature extraction, when applied on data filtered by FIR filter. Power spectrum density (periodogram) helped in endorsing the outcome of the experiment. The experimental results of the propounded methodology show that the beta band frequencies have a quite different performance. When the lower part of the beta band (< 21Hz) is increased, it can be observed that, there is an increase in the unresponsiveness probability, but when there is an increase in the higher part of beta (> 21Hz) probability of awareness has increased. By looking into this kind of behavior of the beta band, it is acceptable to split the beta band into two for beta band power analysis. The components of the high-frequency range are suitable for the detection of awareness. It can also be stated that awareness detection has limitations if there is a presence of artifacts. The seizure characteristic behavior of delta and theta waves from Fig.6 shows that the variation in amplitude is found between 0 to 35 Hz for LL bands, the alpha and beta waves' behavior from Fig.6 shows the variation in amplitude is between 20 to 120 Hz for LL bands leading to the reassertion of epilepsy. Similarly, when observed from Fig.8, the seizure characteristics have the variation in amplitude from 0 to 40 Hz in the case of delta and theta waves for HL bands. The seizure characteristics have a variation in the amplitude from 40 to 120 Hz in case of alpha and beta waves for HL bands, leading to reassertion of epilepsy. Here ten epileptic subjects' data is taken for the study and LL, HL bands of DWT with power spectrum analysis, all ten cases are identified as epileptic.

5. Conclusion

The methodology proposed here has led to convincing results. Openly available EEG data were used to reassert the included subjects as epileptic. The usage of the linear impulse FIR filter with DWT led to an effective classification and recognition of the used data. Four EEG wave patterns, namely Delta, Theta, Alpha, and Beta waves, were addressed based on the combination of the signal power spectrum with DWT. The methodology starts with filtering the data using an FIR filter for selecting the data of interest and the Haar wavelet transform pairs up input values, storing the difference and passing the sum, which is repeated recursively, pairing up the sums to prove the next scale, which leads to 2n-1 differences and a final sum considering LL and HL band frequencies. The LH and HH bands of DWT made an excellent contribution to the obtained promising results. The computation of the average of DWT applied on the power spectrum is used to build the frequency vector to study the behavioral pattern of epilepsy.

DWT confirms that is a versatile tool to analyze signals that are not statistically predictable, especially in the region of discontinuities, a feature that is typical in EEG data. Finally, the decision is made by comparing the average power spectrum and the maximum power spectrum. Hence, from the results presented here, one can conclude that the combination of DWT and power spectrum leads towards achieving more accuracy in EEG data analysis and classification. Our future work will be on analyzing the EEG signals from the occipital lobe to judge the visual effects on the patient during epilepsy.

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