Defence Life Science Journal, Vol. 2, No. 4, October 2017, pp. 391-398, DOI : 10.14429/dlsj.2.12281

Consciousness Levels Detection Using Discrete Wavelet Transforms on Single Channel EEG Under Simulated Workload Conditions

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ABSTRACT

EEG signal is one of the most complex signals having the lowest amplitude which makes it challenging for analysis in real-time. The different waveforms like alpha, beta, theta and delta were studied and selected features were related with the consciousness levels. The consciousness levels detection is useful for estimating the subjects' performance in certain selected tasks which requires high alertness. This estimation was performed by analysing signal properties of the EEG using features extracted through discrete wavelet transform with a moving window of 10 seconds with 90 per cent overlap. The EEG signal is decomposed in to wavelets and the average energy and power of the coefficients related to the EEG bands is taken as the features. The data is collected from standard EEG machine from the volunteers as per the protocol. C3 and C4 locations (unipolar) of the standard 10-20 electrode system were selected. The central region of the brain is most optimal location for the consciousness levels detection. The estimation of the data using discrete wavelet transform energy, power features provided better accuracy when the central regions were chosen. An accuracy of 99 per cent was achieved when the algorithm was implemented using a classifier based on linear kernel support vector machines.

Keywords: Discrete wavelet transforms; Signal power; Wavelet energy; Support Vector machines

1. INTRODUCTION

EEG is the biopotential originating in the human brain due to collective action of the neurons in response to some stimuli. The summation occurs after millions of the nerve cells discharge their potential in a synchronous fashion to emanate as a waveform on the surface which is manifested as Electroencephalogram[5,6,10]. The electroencephalograph (EEG) is an instrument which records the brain potentials corresponding to the electrical activity which is the picture of general function of the superimposed neuronal activities in a non-synchronised and which is highly stochastic[8]. EEG monitoring is considered as an effective method of diagnosing critical neurological diseases such as epilepsy, tumours, cerebrovascular lesions, lesions and problems associated with trauma. It is also used in the instruments which detects the anesthesia levels by the doctors to authenticate its integrity over the patient[3,4,8,6].

EEG has also become an indispensible tool for estimating the alertness and drowsiness for various applications which require higher levels of vigil. The psychological test battery is run with predefined protocols to measure the subjective changes of alertness and drowsiness[14]. These changes are utilised by the algorithm to maintain the baseline values and predict the current status based on these values based on computerised vigilance task (CVT)[14]. The CVT based tasks are also used for fatigue, drowsiness, and engagement index and alertness status determination too[14]. These vigilance task based battery tests helps to provide a baseline and simulate stressful conditions to gauge the variation in a subject[14]. The class identification is best achieved in the studies of brain computer interface (BCI) where the EEG is used to provide signatures for the classification of specific cognitive status[6,8]. The heart rate variability (HRV) is a parameter and along with the blinks (EOG) as additional parameter is utilised to achieve better classification[1,9].

The device has to take the inputs from the optimised EEG electrodes onto a conditioning unit which in turn performs the calculations to estimate the consciousness levels of the subject. The human machine co-ordination is vital in achieving the desired output in the working conditions[10]. Self-constructing fuzzy neural networks were also used in determining the driver's drowsiness states[12]. Vapnik has introduced the support vector machines for solving binary classification problems which have the flexibility of defining the kernels for separating most difficult datasets[15,17]. The SVM based single channel EEG data from dry electrodes was used to determine the attentive and inattentive subjects. The Power Spectral DensityPSD based features were used for the study and the classification accuracy was mentioned as 76.82 per cent[14].

The EEG signals were decomposed using the discrete wavelet transform (DWT). The auto decomposition of the bands for respective EEG bands was taken and using the artificial neural networks (ANN) the classification was performed. The

Received : 18 March 2017, Revised : 05 May 2017
Accepted : 10 June 2017, Online published : 09 November 2017

accuracy of the ANN was 95±3 per cent alert, 93±4 per cent drowsy and 92±5 per cent sleep[16].

Drowsiness detection was tested on single channel EEG using DWT but with m-term approximation[18]. It takes the first 'm' wavelets from the total 'n' wavelets and provides a sensitivity of 98.5 per cent[18].

The vigilance states of the pilots on-board was identified using single channel EEG using the ratio$(\alpha + \theta)/\beta$ with 98.4 with good detection. The system also uses the Karolinska Sleep State (KSS) for determining the sleep status of the pilot[19].

The single channel EEG based automatic sleep stage detection algorithms have also been developed[20-22].

Here the algorithm which takes up the task of differentiating the alert and sleepy states of the subject by using the energy of the signal from central regions is used. The variations continuous plotted data, which is optimally processed, gives the indication of the change in the consciousness levels of the subject. The plot also gives the time when the subject has come to vigil after the sleepy state. The present study is based on single channel EEG of the standard 10-20 electrode system. The channels which are referenced to the central and frontal regions gave better results. The mastoids are taken as the reference for the current study. The robust support vector machines were used for the study. The algorithm is developed for auto calibration with every user. The status is given in every 5 seconds. Beta and delta variations are taken into account for calculating the ratio to quantify the consciousness levels.

Table 1. Time periods for the events as per the protocol

	Time taken (mins)	Time for shifting tasks(mins)
Sleeping	30	1
Relaxed/Awake	10	5
Mathematical Tasks	5	2
Simple calculations	3	1

2. METHODS

EEG is collected from the volunteers who have been given the information about the protocol for their participation in the study. The data was collected using the commercial wireless EEG machine with a definite protocol of alertness at 512 Hz sampling rate and sleep stages. The data was collected from all the lobes of the brain from 20 subjects, which was further processed in MATLAB for filtering and analysis[3,4]. The regions from central brain were selected for analysis as they provided dynamic changes with respect to the mathematical tasks. The first half of the protocol the subject will be sleeping followed by the mathematical tasks.The subjects were in the age group of 20-40 who were performing regular tasks.

2.1 Data Collection

The subjects were normal and not having any neurological history. They were asked to lie down and sleep after the lunch hours in a sleep lab where they can easily dose off. The subjects were left undisturbed for half an hour. They are awaken after half an hour and administered the mental arithmetic (addition, subtraction, multiplication and division) tasks. Arithmetic task was given through simulation software. There were even some errors noticed in solving the problems by the volunteers but our aim was only to simulate mild stressful conditions.

2.2 Data processing

The raw data from the equipment was collected and optimally processed to eliminate all the undesired signal components and artifacts.

2.2.1 Averaging the DC components

The dc components add to the noise and they are filtered by taking the median values and averaging them out[2]. The median filter takes the values of the visually chosen data without much noise and the current value is subtracted and averaged to maintain the most relevant components and leaving the non-important components.

2.2.2 Blink artifacts

Eye artifacts includes the artifacts due to both eye movement and eye blink, these two signals will overlap with the recorded EEG Signal. They have to be filtered suitably before processing for calculating the alertness Fig. 1.

The blinks form a potential artifact to reduce the accuracy for determining the alertness of the subject. The coefficients of the wavelets which are used to determine the energy/power of the signal have to be optimally filtered to eliminate the effect of this artifact. A blink reduction algorithm is applied on the signal by calculating the amplitude based blink peak values and eliminating the unwanted values which are out of range Fig. 1.

The subject is asked to blink to determine the threshold value of the blink amplitude and correlate it with the average signal value when the subject is not blinking. The algorithm takes the correlation value to determine the blink and counts the number of blinks apart from filtering that part of the signal which is corrupted. The samples which are eliminated are replaced by the average values from the near samples which are well within the threshold values.

Some of the algorithms determine the consciousness levels by using the blinks and calculating the time for each

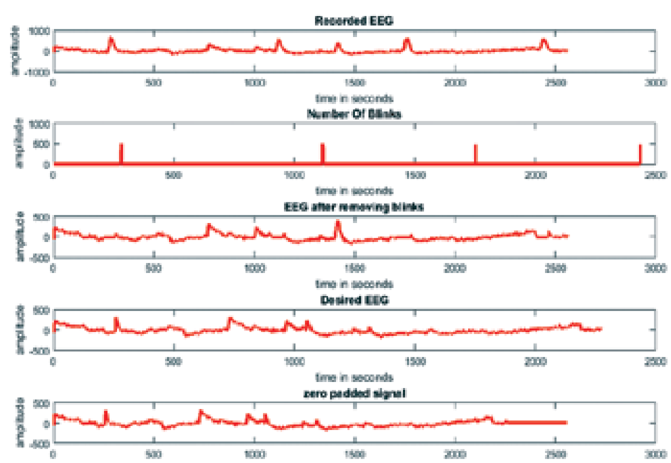


Figure 1. The first row is the data with blinks which are quantified and eliminated by suitably appending the average values for an epoch of 10 s. The plot is for seconds versus amplitude of the signal.

blink[9]. Here the blinks are counted as well as the portion of blink is removed from the signal of interest.

2.2.3 Movement artifacts and other biopotentials

Muscle artifacts include the signals generated by the activity of muscles this includes mainly EMG. Cardiac artifacts include the signal generated by the activity of heart. Motion artifacts created by the subject's movement. The frequency range of ECG varies from 0.5 Hz to 100 Hz, that of EMG varies from 5 to 200 Hz and that of EOG varies till 100 Hz and the frequency range of EEG varies from 0.1 Hz to 100 Hz. All these artifacts may interfere with the EEG which all leads to wrong interpretations in analysis. The signal of interest from these undesired components is selected by suitably decontaminating it. The db4 wavelet which has close matching signal characteristics with the EEG signal is used for signal de-noising. It will optimally provide us the EEG signal coefficients for further processing.

2.2.4 Electrode contact noise

The contact of the electrode is critical as it is supposed to maintain an impedance of 5 kΩ - 10 kΩ. The electrolytic gel reduces the contact impedance and helps in maintaining impedance below 20 kΩ. This requires proper skin preparation to remove the dead tissues in the skin on stratum corneum. In the current application the long lasting gel based electrodes are used[4,5,8].

3. DISCRETE WAVELET TRANSFORMS AND EEG

The wavelet transform (WT) is another alternative for a time–frequency analysis. Unlike the STFT, the time–frequency kernel for the WT-based method can better localize the signal components in time–frequency space. This efficiently exploits the dependency between time and frequency components. Therefore, the main objective of introducing the WT by Morlet was likely to have a coherence time proportional to the sampling period[1,3,7].

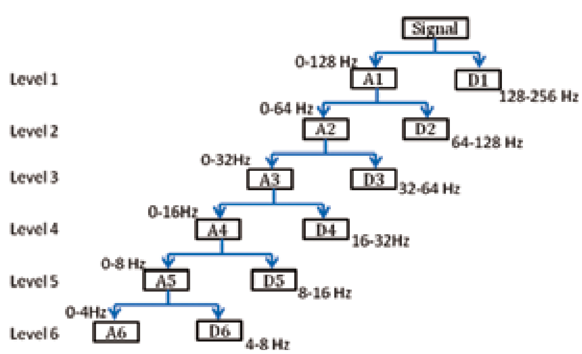


Figure 2. The wavelets transform approximation and decomposition.

EEG signals are non-stationary signals and their analysis is quite challenging. Therefore a definite quantification in time frequency domain is necessary for optimal signal analysis. Heisenberg's uncertainty principle explains the same uncertainty related to time and frequency analysis simultaneously. Hence the usage of the scaled and shifted signal using Wavelet transform (WT) Fig. 2 provides us the tools for processing. The one dimensional wavelet transform is used to denote the signals using the db4 wavelets. The frequency bands of the EEG could be matched with the coefficients of the WT and hence the filter banks could be built by analysis and decomposition and finally added.

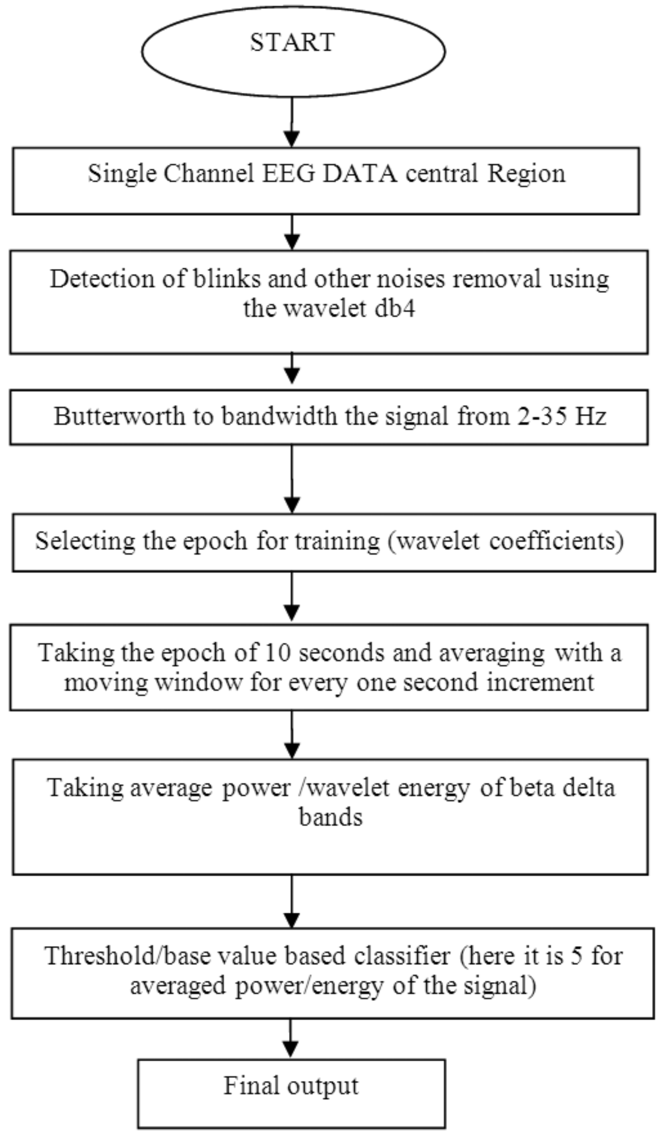


Figure 3. Flowchart for the algorithm.

4. QUASI REAL TIME MOVING AVERAGED POWER PLOT

The single channel EEG data is used as the input signal for the analysis. The data is filtered as per the above procedure and put up to further processing which includes the power or energy calculation of the signal as per the epoch selected. The epochs are selected for the time interval selected for the alert, sleep, high and low mathematical tasks and as well as the overall activity. Here a new method, quasi real time moving averaged power plot (QRMAPP) is proposed which calculates the signal energy on a moving averaged window Fig 3.

The power of the signal is calculated by averaging the signal for 10 s using moving window with 90 per cent overlap.

Hence the values for the moving averaged window take 10 averaged values with an increment of one second. Then they are plotted with a delay of 10 s after which the data is logged for every second taking the average of the previous 10 s. This method QRMAPP is required for averaging the power values of the signal which is given every second calculated over an epoch of 10 s.

As per the algorithm the raw signal is initially given as an input from the cental location of the brain. The electrodes C3 and C4 are selected from the 10-20 standard EEG electrode placement and analysis as it has shown dominanat changes with the cognitive tasks. The signal is denoised using the db4 wavelets as the signal characteristics of EEG has close morphology with db4. Then the blink detection algorithm is applied to eliminate the blinks which contaminate the signal. The signal is bandwidthed between 2 Hz - 35 Hz using a Butterworth filter. The considered only the stage wherin the subject is undergoing mild sleep so the 2 Hz - 4 Hz range along with beta was chosen. Then the epoch of ten seconds is taken by applying the moving averaged window for 10 s with an increment for each second. The averaged power and energy values are taken to determine the alert and sleepy state of the subject. The averaged power value of 5 (in ratio to total power/energy) is taken as threshold for the high and low values of delta and beta.

The flowchart Fig. 3 describes the data flow in the algorithm and various stages of processing the data. The energy is given as:

$$\mathbf{E = (1/2\pi)\int_{-\infty}^{\infty} \left| X(\omega) \right|^2 d\omega = \int_{-\infty}^{\infty} \psi(\omega) df}$$

Where $\psi(\omega)$ is the energy density function i.e. it represents the energy per unit bandwidth.

$$\mathbf{E_n = \sum^{10}_{n=1} (E1) + \sum^{11}_{n=2} (E2) + \ldots.. + \sum^{g+10}_{n=g} (Eg)}$$

$$\mathbf{E_{tot} = \sum^{g+10}_{n=g} (E_n)}$$

$$E_{avg} = \sum_{n=-N}^{N} |x(n)|^2$$

$$E_{total} = \sum_i E_{avg}(i)$$

i = 1 to total number of windows

window length = 50 samples with overlapping

As per the above equation the total energy of the signal is calculated and the threshold is determined to find the alertnes state. The power of the signal based on spectral density is taken as

$$P_{avg} = \lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} |x(n)|^2$$

$$P_{total} = \sum_i P_{avg}(i)$$

i = 1 to total number of windows

window length = 50 samples with overlapping

As there is shift, which is easily identified by using the continuous plotted data, thereby, reducing the usage of any complex statistical correlation functions. The threshold for each subject is found when he is in relaxed state and it determines the per centage of this change towards extreme

(a)

(b)

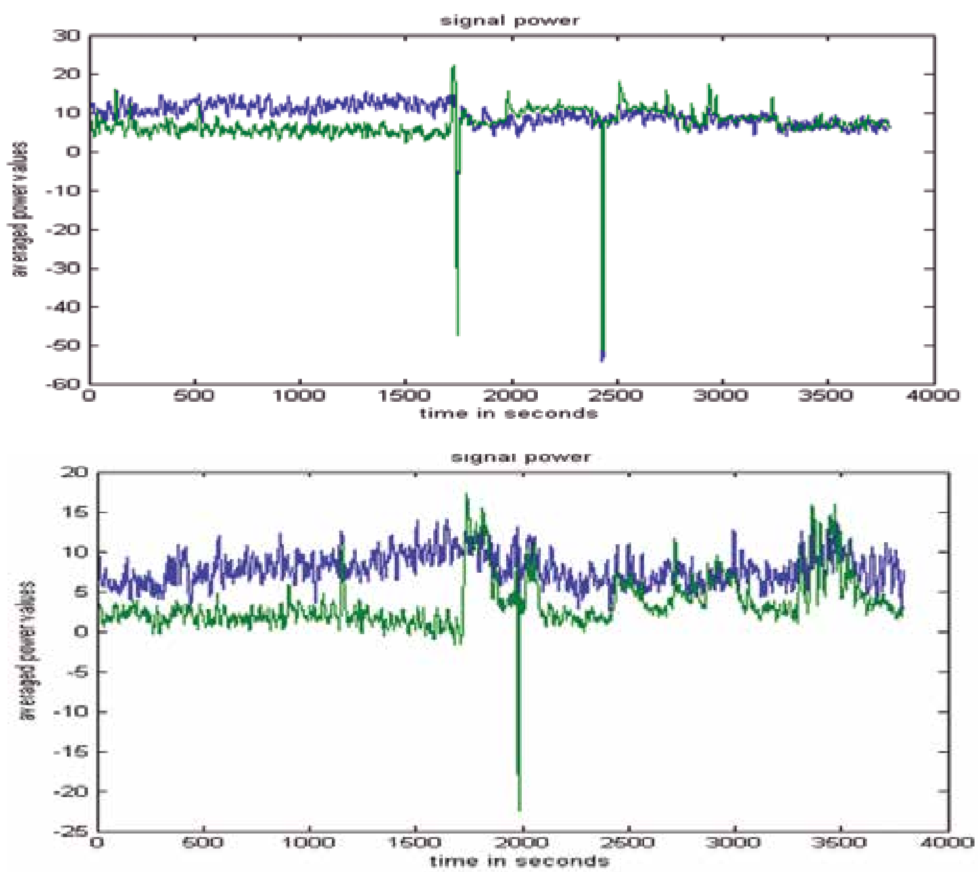
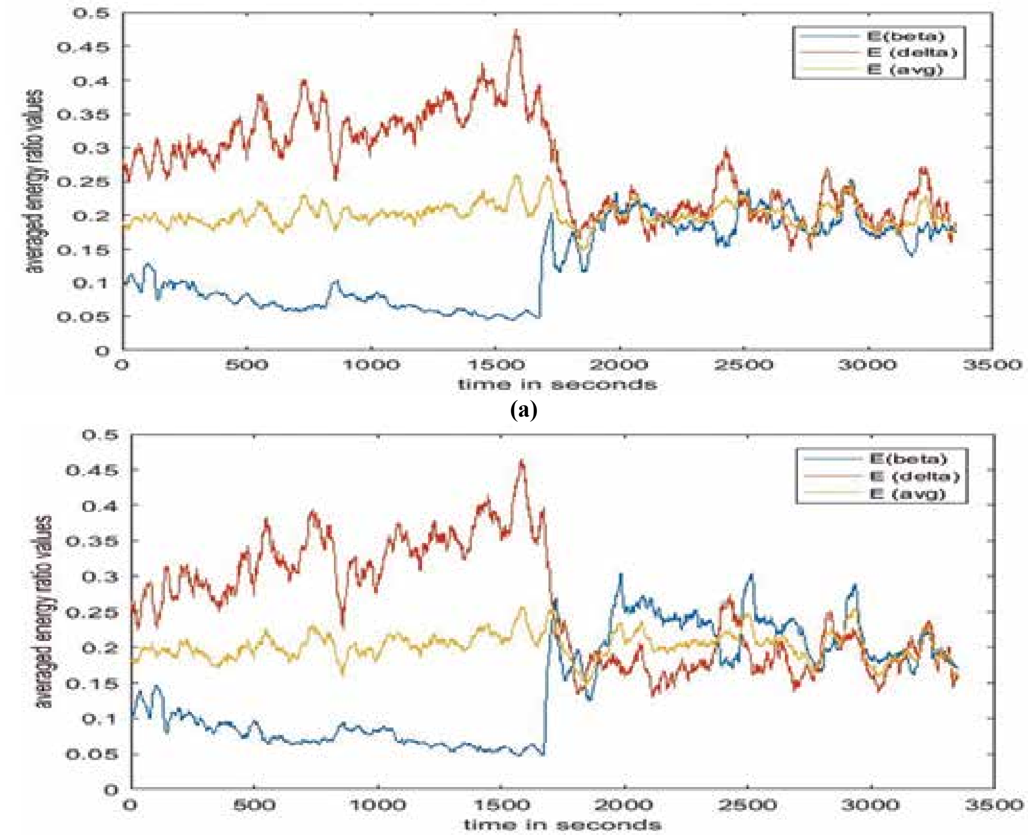


Figure 4. Complete epoch analysis of two different subjects with power change in blue (delta) and green(beta), first 50 per cent plot sleeping followed by math task.



(a)

(b)

Figure 5. Complete epoch analysis of 2 different subjects with energy change in blue (beta) and red (beta) and yellow an average. First 50 per cent plot sleeping followed by math task.

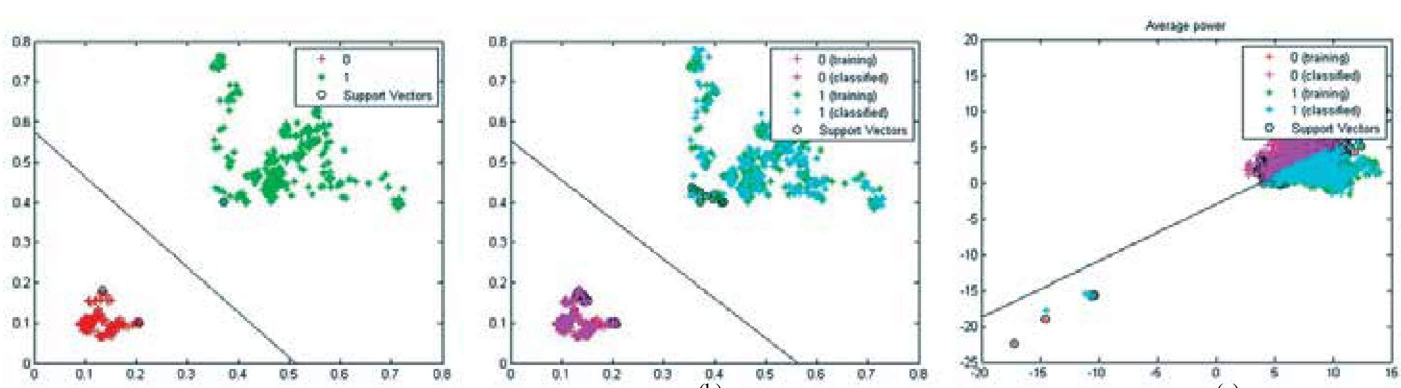
alertness or sleepiness. For example for subject 1 in Fig. 5(a) we can observe that the value of beta below 5 of averaged wavelet energy values (y-axis) when he is asleep and around 5 when he is in relaxed state. The wavelet decomposition is taken into 7 levels and 4th along with 7th were considered for bet and delta respectively.The beta value increases after he is awaken and administered certain mathematical tasks and in between it returns to his base value of 5. The SVM algorithm was used to determine the alert and sleep status of the subjects. The entire session data was fed into the SVM algorithm.

5. RESULTS AND DISCUSSION

The data was taken from twenty subjects as per the defined protocol. The Fig. 5(a) describes the change in the power of the subject when he is sleeping for half an hour followed by his participation in the mathematical tasks. The high power of delta, for first half an hour, and increase of beta in the later half gives the gradual change in the status of the person from sleeping state to alert state.

The delta, theta and beta waves are dominant over the central region of the brain which indicates the sleep and alert states of a person. The alpha is present in the posterior region of the brain and is dominant when the subject is in relaxed state and in the initial stages of sleep. Hence we have chosen the central location of the brain as most suitable for this purpose.

The energy (Fig. 6) of the signal is another parameter which changes with the subjects consciousness levels. The



(a) (b) (c)

Figure 6. SVM classification for a session of EEG, when the subject is sleeping and performing a mathematical task, later.

Table 2. The confusion matrix relating to the levels of consciousness[3]

	Conscious	Sleepy	Error data
Conscious	19	1	1
Sleepy	2	18	2

beta is related with the high level of consciousness when the subject is in demanding tasks and delta is present when the subject is in the sleep condition. The Fig. 6 represents the change in the energy levels of the signal when the subjects are undergoing a shift from sleep to alertness and a jump in their beta levels in the later half when they are subjected to certain mathematical tasks. The threshold for individual subjects was calculated for sleeping and alert states and based on these values of average power and energy the consciousness levels are predicted.

The buffers are loaded with the energy or power data of the signal and were compared with the average threshold. After comparison the output was predicted in each cycle *i.e.* for every second the value is averaged over previous ten seconds.

As it is observed from the Fig. 6 that the energy level of the subject changes as he goes from alert to sleep status. To quantify this statistically the distance method was used. We take the subject's relaxing state as base and calculate every point distance to that point and find the maximum out of it. The threshold is calculated from the training data of each subject. The above subject has the value of 5 for the alert (below 5) and sleep (above 5) status which is subjective.

The support vector machines (SVM) based on the linear kernel is chosen as an optimal linear classifier for the current classification metric. SVM is a supervised learning model associated with learning algorithms that analyze the data used for classification[23,24]. The SVM classification (Figs. 6(a) & 6(b)) is based on the energy signals where greater than 99 per cent accuracy is achieved whereas in the power spectral features it was around 80 per cent with a moving average window overlap.

Error per centage = (2/20) X 100 = 10 per cent

Sensitivity = 90 per cent

Calculation by taking into account true positives and false negatives we can say that the accuracy can be given as

TP/ (TP+FN) =37/ (37+3) X 100 =92.5 per cent

The data was analysed using the linear kernel based support vector machine (SVM). The subject was undergoing the sleep stage followed by a mathematical task, just to keep him little active. When the individual subjects were trained for the SVM based classification the results for the same were around 99 per cent Fig. 7.

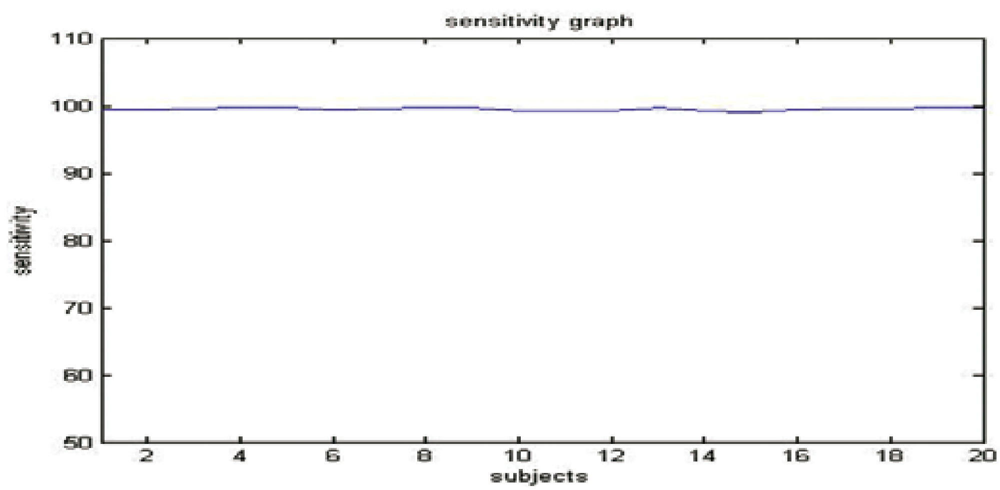


Figure 7. Sensitivity after the SVM algorithm.

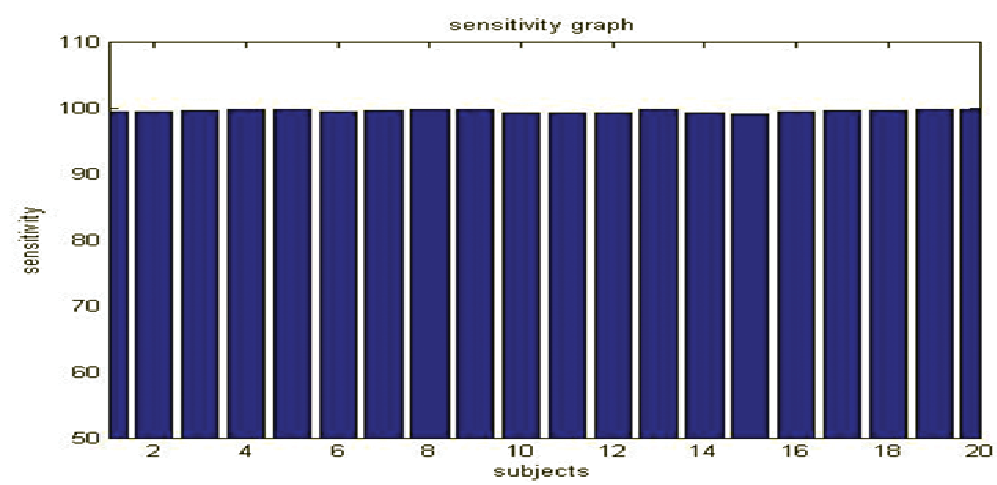


Figure 8.. Sensitivity bar graph after the SVM algorithm with 20 subjects.

	Conscious	Sleepy	Error data
Conscious	20	0	0
Sleepy	0	20	0

The class separation was quite simple and the current study could also be used when the data has high dimensionality with more features.

The power spectral features and the energy features of the signal in beta and delta were analysed from the single channel EEG in the central regions of the brain. The energy of the wavelet coefficients from the central regions through a liner SVM produced optimal results to identify the consciousness levels of the subject.

6. CONCLUSIONS

The experimental results were promising in determining the subjects alert and sleep status along with the transitional stages. The signatures of energy of wavelet coefficients (db4) with six levels from a single EEG channel provided the tools for frequency based analysis from the brain. The error was sometimes very high due to high impedance at electrodes as a result of improper contact in longer testing cycles. The study can be further extended with the usage of signature classification based on advanced statistical signal processing algorithms to increase the accuracy by taking into consideration the larger datasets wherein multi-dimensional kernel separation of SVM are desired. Study can be extended for sleep stage determination too for identifying the anomalies. The single channel based sleep detection methods have been reported but this method is effective in providing the status within 5 seconds calculation. There are even potential applications for the determination of BCI signals for augmenting the exoskeleton based orthotics and limb prosthetics devices too based on the level of disability.

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ACKNOWLEDGEMENTS

We thank Director, DEBEL for the support and also Dr K. Adalarasu, PSNA College, Dindigul for providing the inputs in devising a protocol for mathematical task design. We also specially thank Dr. Umamaheshwara Rao, Senior Professor, NIMHANS, for his guidance.

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In the current study, he conceptualised and developed algorithm for EEG based consciousness levels detection algorithm with data collection and validation.

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In the current study, he involved in development of the noise reduction algorithm and conceptualisation of the algorithms with hardware compatibility.

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