



# EEG power spectrum analysis for schizophrenia during mental activity

B. Thilakavathi<sup>1</sup> · S. Shenbaga Devi<sup>2</sup> · M. Malaiappan<sup>3</sup> · K. Bhanu<sup>4</sup>

Received: 19 February 2019 / Accepted: 12 July 2019 / Published online: 30 July 2019  
© Australasian College of Physical Scientists and Engineers in Medicine 2019

## Abstract

Cognitive dysfunction is a core defect for schizophrenia subjects. This is due to structural and functional abnormalities of the brain which can be determined using Electroencephalogram (EEG). The objective of this study is to analyze EEG in patients with schizophrenia using power spectral density during mental activity. The subjects included in this study are 52 schizophrenia subjects and 29 Normal subjects. EEG is recorded under resting condition and during mental activity. Two modified odd ball paradigms are designed to stimulate mental activity and named as stimulus 1 and stimulus 2. EEG signal is filtered using FIR band pass filter to extract delta, theta, alpha, and beta band EEG. This method measures powers of each band using Welch power spectral density method called absolute power. The absolute power of alpha band is low and beta band is high for schizophrenia subjects compared to normal subjects during rest and two stimuli. Student's t-test is used to find the significant features ( $p < 0.05$ ) at each recording condition. The significant features from each recording condition are used to classify Schizophrenia using both BPN and SVM classifier. SVM classifier is produced maximum sensitivity of 91% when features from all recording conditions are combined together. Thus this work concludes that the mental activity EEG supports for classifying Schizophrenia from normal and hence absolute band powers can be used as features to identify Schizophrenia.

**Keywords** Schizophrenia · EEG · Power spectrum · BPN · SVM

## Introduction

Schizophrenia (SCH) is one type of psychiatric disorder which is characterized by disordered cognition and by either positive psychotic symptoms such as hallucinations and delusions or negative psychotic symptoms such as social withdrawal and poor emotional response. In the whole world population, 1% of the people are being affected by SCH. Treatment is a greater challenge for SCH subjects due to the facts that the symptoms of SCH vary from patient to patient and factors such as environmental factors and also

medication related factors can alter the symptoms [1, 2]. Diagnosis of SCH is fully based on the self-report experience given by the patients and their abnormal behaviour reported by others. Based on the information gathered, physician uses the current version of the Diagnostic Statistical Manual for Mental disorder DSM-IV for diagnosing SCH [3]. Definition of SCH states that it is related with mind and brain and also it means split mind. This might happen due to structural and functional abnormalities of brain. These abnormalities reflect changes in Electroencephalogram (EEG) rhythm which is a graded potential generated by many neurons [4]. However, it is not yet incorporated into clinical practice. Therefore, it is required to identify a cost effective clinical tool which is helpful to assist the existing diagnostic method without causing any harmful effects to the patients. This work aims at analyzing routine clinical EEG in order to extract useful features which help to relate cognitive dysfunction of SCH and hence to see whether these features can be helpful to classify SCH or not.

Analyzing EEG will pave a way to classify SCH subjects from normal subjects, because psychomotor poverty, hallucination and delusion have relationship with EEG

✉ B. Thilakavathi  
thilaka\_76@yahoo.co.in

<sup>1</sup> Department of ECE, Rajalakshmi Engineering College, Chennai 602105, India

<sup>2</sup> Department of ECE, College of Engineering, Guindy, Chennai, India

<sup>3</sup> Department of Psychiatry, Kilpauk Medical College, Chennai, India

<sup>4</sup> Department of Neurology, Dr. Metha's Hospital, Chennai, India

rhythm changes [5]. EEG waveforms are divided into many subbands according to the frequency range. Each subband occupies a specific portion of the spectrum and has its own characteristics. The amplitude of EEG is lying in the order of microvolt ( $\mu\text{V}$ ) and its frequency is ranging from 0.1 Hz to 70 Hz [6] and it is better to use frequency domain methods for analyzing EEG characteristics waveforms. Therefore quantification of EEG by power spectrum methodology is preferred. The amount of power actually contained in each band of EEG is known as Absolute power which will quantify information about state of the brain.

Many researchers addressed EEG power spectrum analysis for SCH to find specific problems. It is as follows. Some researchers conducted an extensive literature review on EEG spectral abnormalities of SCH in which 53 papers are reviewed and concluded that the SCH subjects have increased delta with respect to normal subjects and these are more localized at frontal region [7]. In general, higher delta and lower alpha power are observed for SCH subjects in comparison with healthy subjects during rest condition [8]. Some researchers calculated each EEG channel power to find higher order pattern discovery for classifying SCH from healthy subjects. 90% classification accuracy is obtained for the 6th order patterns [9]. Disintegration problem of SCH is addressed using EEG during 40 Hz photic stimulation and showed higher phase locking in gamma band but lower phase locking in theta, alpha and beta bands over the anterior part of the brain for SCH [10]. In order to study the effect of clozapine therapy, EEG band powers are used by some researchers, and found it is greatly augmented in delta and theta bands. This is marked in frontal areas for SCH subjects [11]. Few authors made EEG power spectrum study during auditory stimulation and compared with resting state power of SCH and normal subjects. During auditory stimulation delta band power and beta band power are less than the resting period and also these results are significant in the left frontal area [12]. Akbar et al. reported that for SCH, high increase in delta and theta band powers are confined to frontal lobe and decrease in alpha power is found at occipital lobe [13]. It is understood that each researcher addressed EEG analysis in particular brain condition for specific finding. Their findings are also related to SCH. This paper tried to study the various EEG band activities during mental task and find whether the related features can be used to classify them from SCH.

## Materials and methods

In this section, details of the subjects and method of EEG recording are explained. For this work, EEG is acquired from 81 subjects. Among them 52 are Schizophrenia patients (20 women and 36 men of average age 42.78), remaining

29 (13 women and 18 men of average age 42.1) are normal subjects. Study is approved by Institutional ethics committee of Madras Medical College and the work is carried out at Institute of Mental Health, Chennai, India. The SCH patients are diagnosed using DSM IV criteria by doctors and all SCH subjects have undergone Mental State Examination. Informed consent is obtained from them. All SCH subjects who are participating in this study are taking antipsychotic medications.

EEG is recorded using a 23 channel Brain Clarity –Brain Tech +40 equipment at electrodes  $\text{FP}_2$ ,  $\text{F}_4$ ,  $\text{C}_4$ ,  $\text{P}_4$ ,  $\text{F}_8$ ,  $\text{T}_4$ ,  $\text{T}_6$ ,  $\text{O}_2$ ,  $\text{FP}_1$ ,  $\text{F}_3$ ,  $\text{C}_3$ ,  $\text{P}_3$ ,  $\text{F}_7$ ,  $\text{T}_3$ ,  $\text{T}_5$  and  $\text{O}_1$  position of International Standard 10–20 system using mono polar montage with linked ear as reference. The sampling frequency of EEG is kept at 256 Hz. In order to remove power line interference, notch filter (50 Hz) is kept on in the equipment. EEG signals are filtered by a band pass filter with upper and lower cut off frequencies of 0.1 Hz and 70 Hz respectively. The sensitivity of the equipment is set to  $7.5\mu\text{V}/\text{mm}$ . The subjects are asked to sit in a chair in a relaxed position. They are instructed to close their eyes while recording EEG. Firstly, EEG is recorded as per conventional recording conditions namely eyes opened, eyes closed, during hyperventilation, post hyperventilation and photic stimulation. Secondly, EEG is recorded by providing visual stimuli with eyes opened condition. Oddball paradigm is a most popular stimulus used for the cognitive study [14]. So we have designed two paradigms based on the standard oddball task to examine the cognitive impairment and they are named as Stimulus 1 and Stimulus 2 in this paper. The subject is seated at a distance of 1.5 m from a 15 inch colour monitor. With reference to the standard oddball task, two stimuli are designed as given in Table 1. The information about the stimuli is explained prior recording of EEG. It is informed that the subjects should count the number of target pictures mentally. The stimuli are presented one by one in the computer monitor using windows media player at the end of conventional EEG

**Table 1** Description about the designed stimuli

Factors	Stimulus 1	Stimulus 2
Target pictures	Baby	Baby
Non target pictures	Animals, scenery, transports, birds, flowers	Flowers
Display duration of target pictures	500 ms	1 s
Display duration of non target pictures	750 ms	1 s
No. of runs	5	1
No. of repetitions	Each run 5 times	9 times
Remarks	In each run set of non target pictures are changed	No changes

recording procedure. The start and end time of each stimulus is marked by the EEG marker during recording. For the purpose of analysis, we considered 10-second epoch of EEG data during mental activity which contains minimum eye blink during recording.

EEG recordings are visually inspected by a physician to avoid movement and sweat artifacts. Eye blink artifacts are corrected using AMUSE (Algorithm for Multiple Unknown Source Extraction) algorithm in ICA LAB environment.

Feature represents the recognizable measurement from a portion of any pattern. Varieties of methods are widely employed to extract features from EEG. Here analysis of EEG signal via power spectrum method is chosen and as per the previous researchers discussed in Sect. 1, this should yield some measurement capable of providing information about SCH. Firstly, the total band power is derived from the EEG signal and then each band power is calculated using a suitable filter. The Welch method of modified periodogram is used to estimate the power, because this method reduces noise heavily thereby smooth spectrum and less spectral leakage can be obtained [15]. Let  $x[n]$  be an EEG sequence and it is normalized by dividing the maximum value. Hereafter, for all the analysis, 10 s EEG sequence  $x[n]$  is considered because it is already used by many researchers for EEG signal analysis of SCH [16]. Windowing technique is mainly used to reduce the spectral leakage and smoothing the spectrum. In this Welch method, the EEG sequence  $x[n]$  is windowed by window sequence  $w[n]$  with  $R$  overlapping portions of length  $M$ . Let the overlap between adjacent samples be kept as  $K$  samples. Then the windowed  $r$ th segment of the data  $x[n]$  is represented using Eq. (1).

$$x_r[n] = x[n + rK], \quad 0 \leq n \leq M - 1, \quad 0 \leq r \leq R - 1 \quad (1)$$

Since, EEG waves are non-stationary, it is essential to consider piecewise stationary portion of the signal for analysis. So, 2 s epochs are considered as a stationary wave. Windowing technique is done using Eq. (2) with hamming window  $w(n)$  of length 512 samples (2 s) to control the abruptness of the transition to zero with 50% (256 samples) overlap [16, 17].

$$x_r[N] = w(n)x(n + rK) \quad (2)$$

The shape of the hamming window is almost always decreasing to zero at boundaries. Hence there is a possibility of losing some information. In order to avoid information loss, overlapping of windows are allowed with 50% overlapping. For each  $x_r[N]$ , the power spectrum is calculated using Eq. (3) and it is represented as  $P_{r,xx}(e^{j\omega})$ .

$$P_{r,xx}(e^{j\omega}) = \frac{1}{RM} \sum_{r=0}^{R-1} \left| \sum_{n=0}^{M-1} w(n)x(n + rK)e^{-j\omega n} \right|^2 \quad (3)$$

$P_{r,xx}(e^{j\omega})$  is calculated for all  $R$  overlapping portions and the Welch estimate is then given by the average of

all  $R$  periodogram using Eq. (4). This is considered as a absolute power of a given spectrum.

$$P_{xx}(e^{j\omega}) = \frac{1}{R} \sum_{r=0}^{R-1} P_{r,xx}(e^{j\omega}) \quad (4)$$

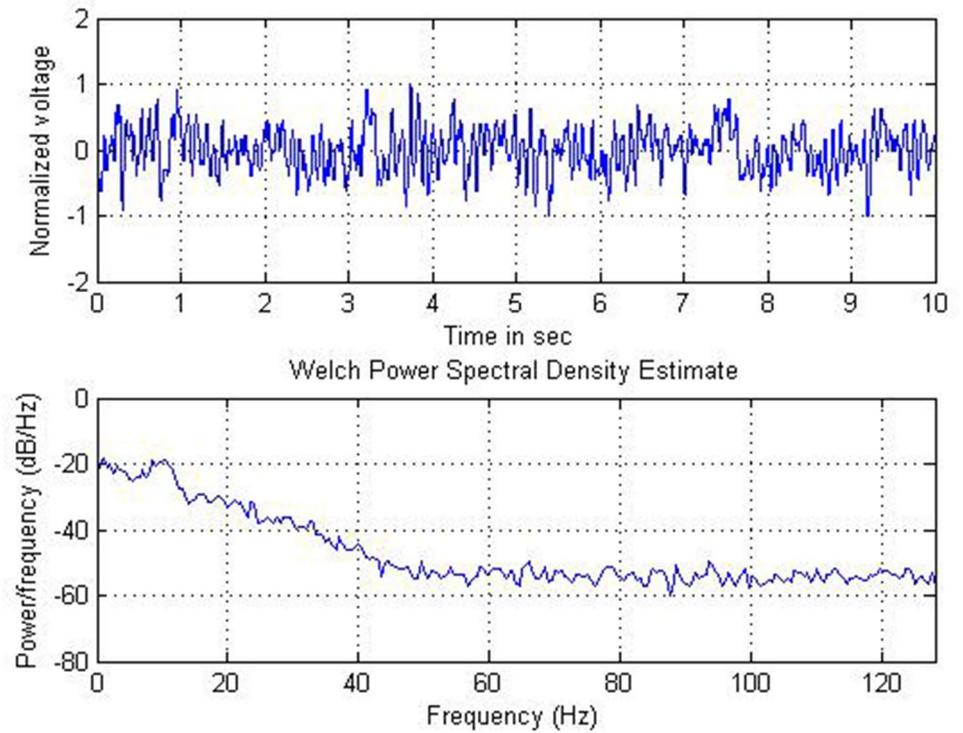
The 10 s EEG signal and its Welch power spectrum in dB/Hz are shown in Fig. 1 for both normal and SCH subjects. Here as example, signal from  $C_4$  electrode position is shown in Fig. 1. In both Fig. 1a, b top plot shows the EEG signal of 10 s duration and the plot below shows the spectrum of the signal given in the top plot.

It is understood from the power spectrum of both normal and SCH, that there is a difference in the shape of the power spectrum between the two subjects. In order to calculate the total power, total EEG band is considered from 0.1 Hz to 70 Hz. Power values estimated for the  $C_4$  channel of one normal and SCH EEG are 0.0557 and 0.1517 respectively. The unit for the power measured in this method is normalized to one (per unit), since the signal is normalized by the maximum value in the considered epoch. As specified above, the total power at each channel is calculated for all 81 subjects where 52 are SCH and 29 are normal subjects. Each channel average of 52 SCH subjects and 29 normal subjects are calculated using Eq. (5) where  $L$  is the total number of subjects in each group separately.

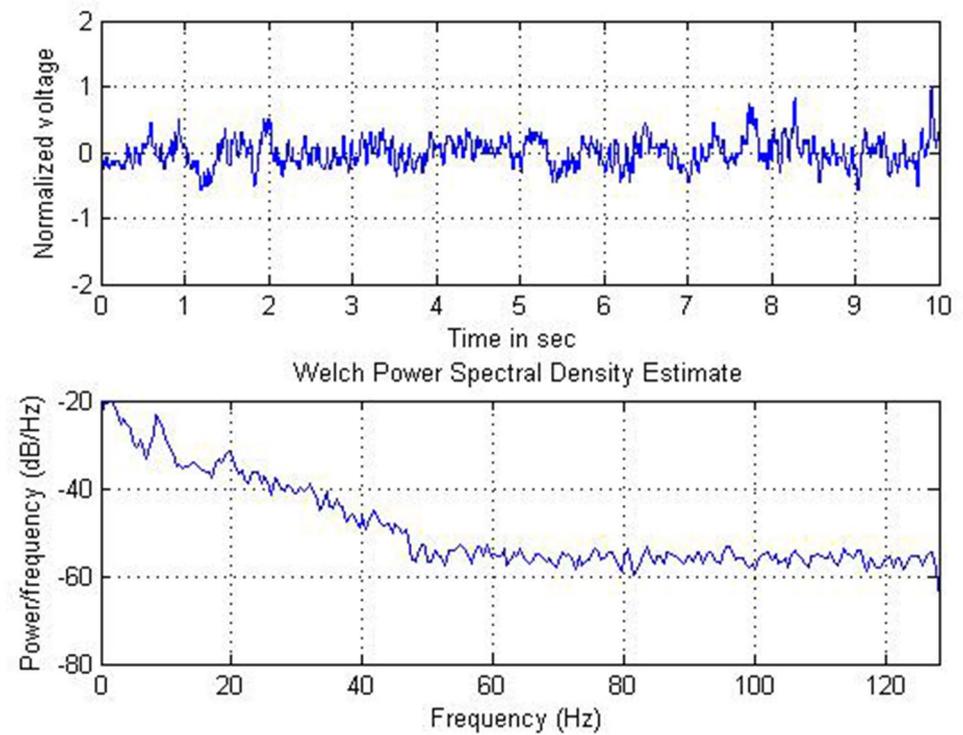
$$Channel Power_{per\ group} = \frac{1}{L} \sum_{k=1}^L P_{xx_k}(e^{j\omega}) \quad (5)$$

where  $P_{xx_k}(e^{j\omega})$  is particular channel power for  $k$ th subject. We know that EEG is recorded from 16 channels, thus the total band power for the remaining channels are determined by using Eq. 5. The total band power reflects the total capacity of information for the whole brain. In order to analyze the characteristics of EEG, individual band power is calculated and it is enumerated as follows. EEG band powers are directly obtained by filtering EEG signal with Finite Impulse Response (FIR) band pass filters. The order of the filter  $N$  is chosen as 128. Each band has lower and upper cutoff frequencies and it is chosen for  $\delta$  band from the frequency range 0.1 Hz and 4 Hz,  $\theta$  band from 4 to 8 Hz,  $\alpha$  band ranging from 8 to 13 Hz and  $\beta$  bandwidth is set from 13 to 32 Hz to avoid boundary conflict [7, 18]. Each individual band is extracted using FIR band pass filter from the 10 s recorded EEG and are shown in Fig. 2a–e. For illustration purpose, it is also given for one channel ( $C_4$ ) of both normal and SCH subjects. In a similar approach, the remaining EEG band powers are estimated for both normal and SCH subject's EEG signal.

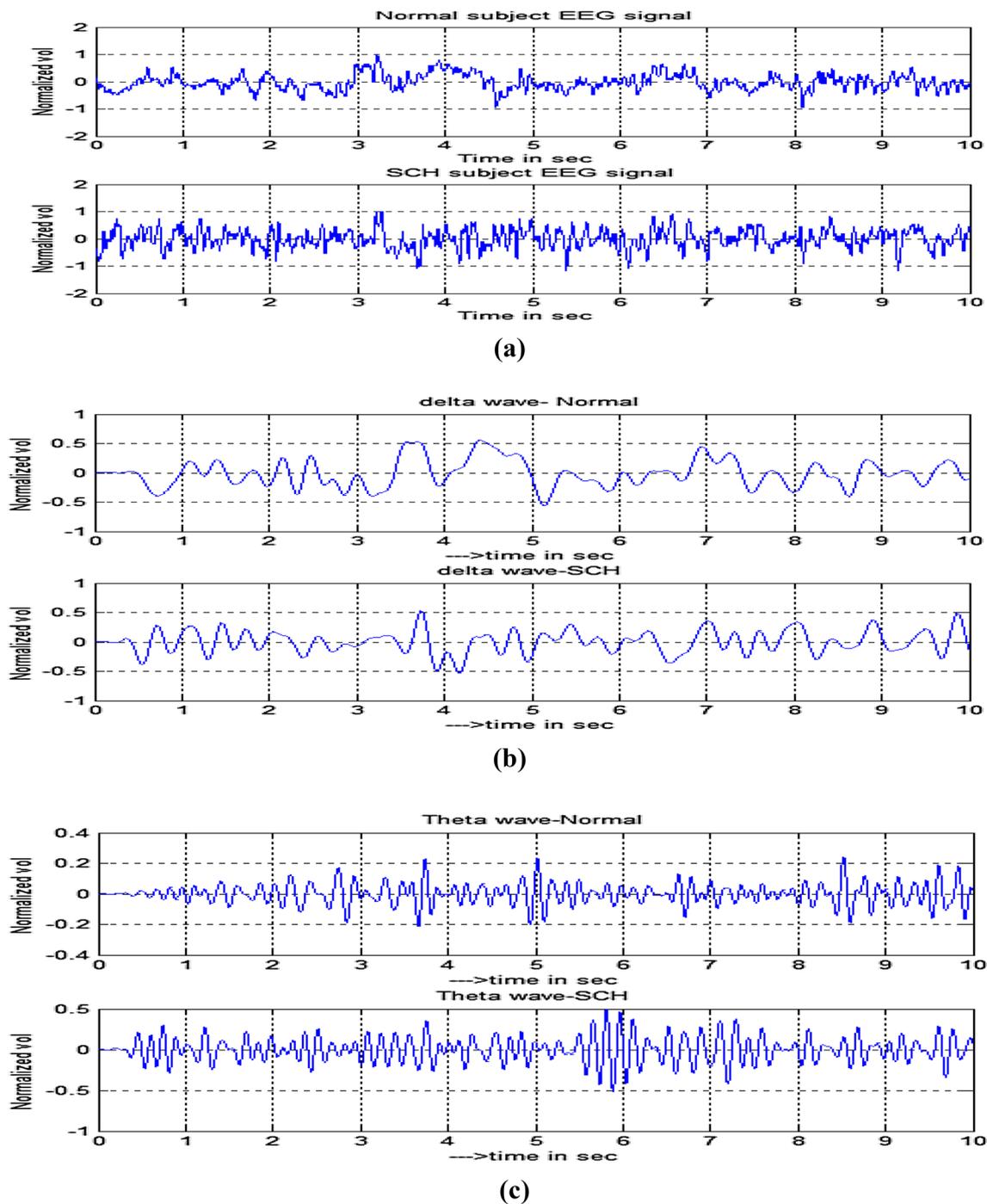
**Fig. 1** EEG signal and its power spectrum  $C_4$  (a) For normal subject (b) For SCH subject



(a)



(b)



**Fig. 2** Extracted EEG Bands for the channel  $C_4$ : **a** 10 s EEG of normal and SCH subjects, **b** delta band, **c** theta band **d** alpha band, **e** beta band

## Results

Various EEG band powers at rest condition, stimulus 1 and stimulus 2 are shown in Table 2 and these are explained as follows. For the 29 normal subjects, the total  $\delta$  band power ( $\delta_{pr}$ ) is found to be 0.052068 which is the mean value of all 16 channels and it is rounded off to three digits as 0.052.

Similarly for the EEG of 52 SCH subjects, the average  $\delta_{pr}$  is found to be 0.055343 which is rounded off to 0.055. Similarly the band powers of  $\theta$  ( $\theta_{pr}$ ),  $\alpha$  ( $\alpha_{pr}$ ), and  $\beta$  ( $\beta_{pr}$ ) for normal subject are respectively 0.01, 0.018 and 0.008. Similarly, for SCH the  $\theta_{pr}$ ,  $\alpha_{pr}$  and  $\beta_{pr}$  are found to be 0.01, 0.015 and 0.008 respectively. The fourth major column of Table 2 indicates the band power difference between normal and SCH

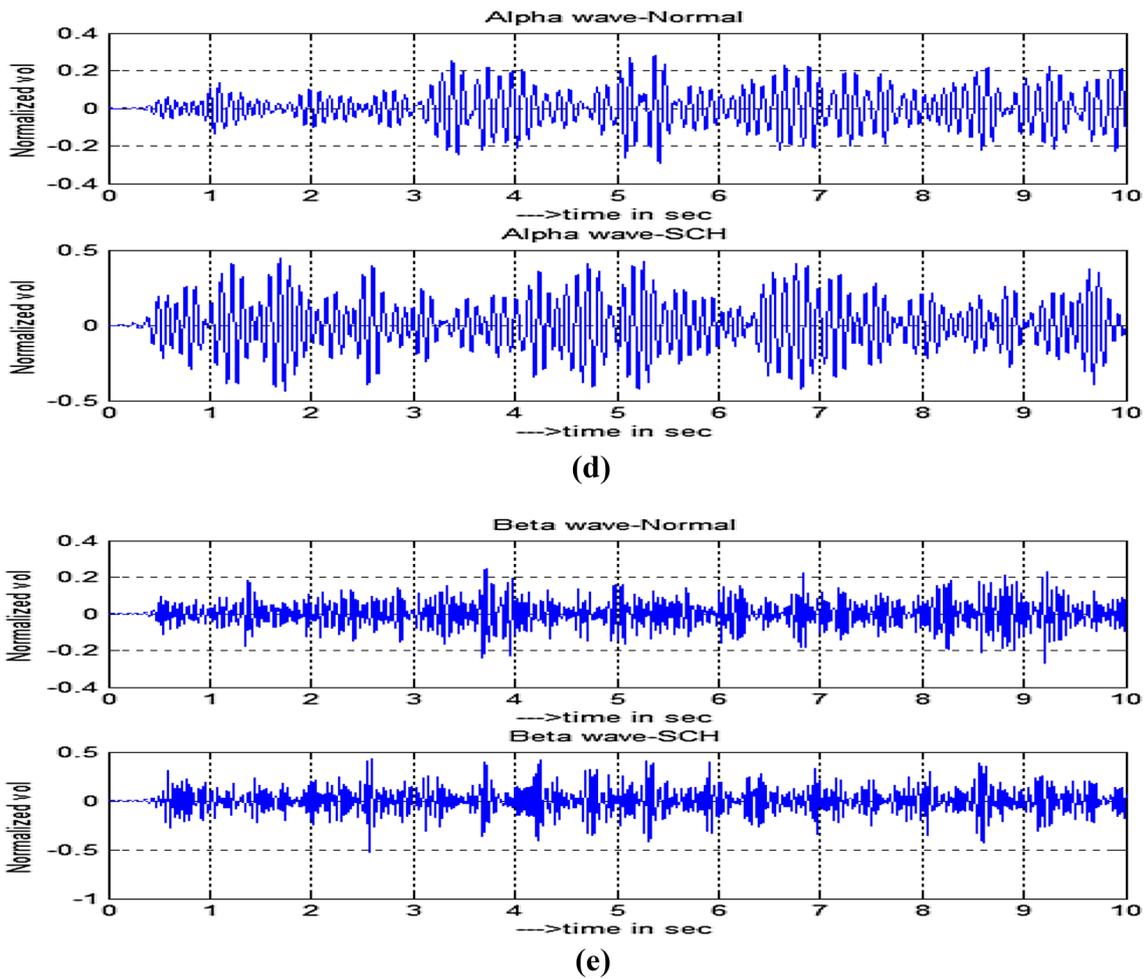


Fig. 2 (continued)

Table 2 EEG band powers at various recording conditions

Recording condition	Subject	Individual band power (unit power)				Band power difference of SCH with respect to Normal (Unit power)				Band power difference with respect to rest (unit power)			
		$\delta_{Pr}$	$\theta_{Pr}$	$\alpha_{Pr}$	$\beta_{Pr}$	$\delta_{Pr}$ diff	$\theta_{Pr}$ diff	$\alpha_{Pr}$ diff	$\beta_{Pr}$ diff	$\delta_{Pr}$	$\theta_{Pr}$	$\alpha_{Pr}$	$\beta_{Pr}$
Rest	Nor	0.052	0.01	0.018	0.008	0.003	0	-0.003	0	-			
	SCH	0.055	0.01	0.015	0.008								
stim1	Nor	0.052	0.012	0.01	0.011	-0.006	-0.001	-0.001	0.002	0	0.002	-0.008	0.003
	SCH	0.045	0.011	0.009	0.013						-0.01	0.001	-0.006
stim2	Nor	0.048	0.011	0.01	0.01	-0.008	0.001	0.002	0.003	-0.004	0.001	-0.009	0.002
	SCH	0.04	0.012	0.012	0.013						-0.015	0.002	-0.004

stim1 stimulus 1, stim2 stimulus 2, Nor normal, diff difference between SCH and Normal

Orange - Difference indicates SCH subjects have more power than Normal subjects

Grey - Difference indicates particular recording condition produced more power than rest condition

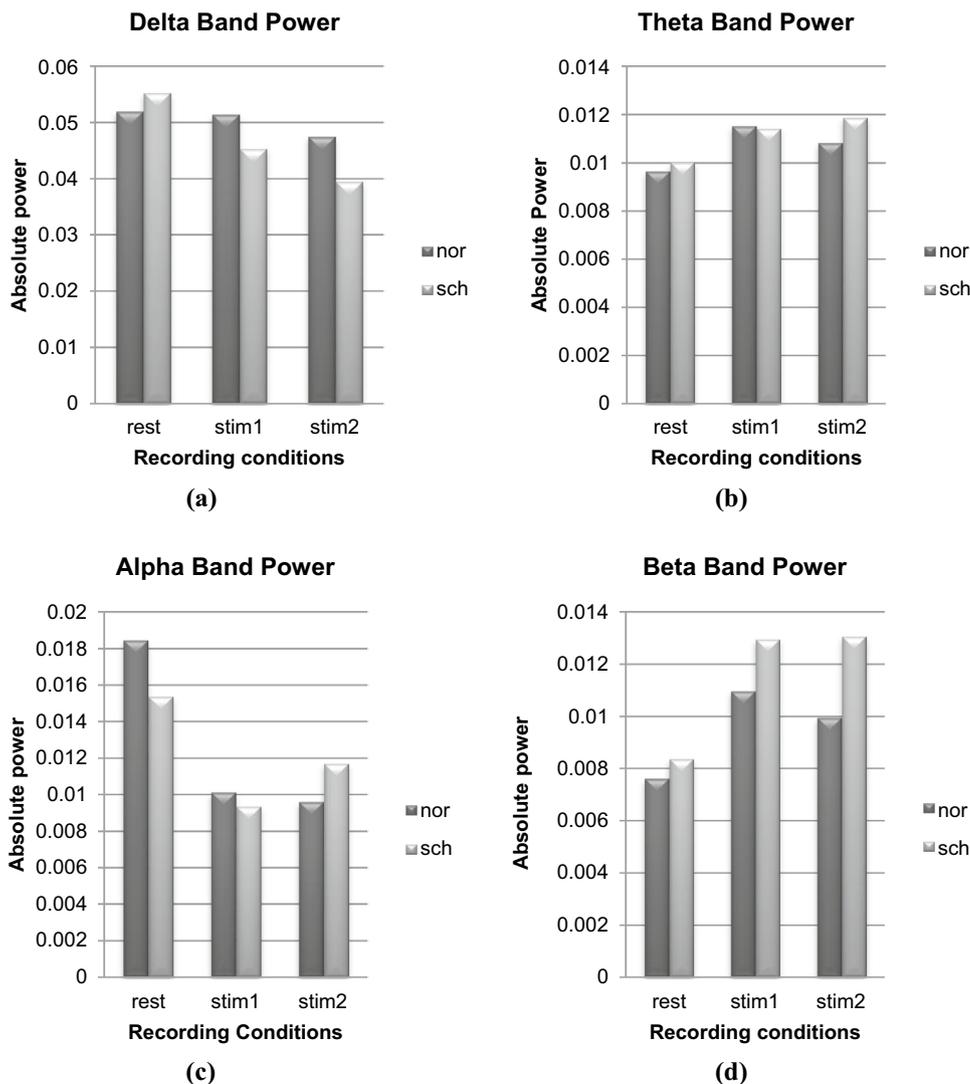
at each recording condition. Brown cell represents that the SCH subjects have more power than normal where as white cell indicates that the SCH subjects have lesser power than normal subjects. From this, it is inferred that the  $\delta_{Pr}$  is more for SCH with respect to normal subject and  $\alpha_{Pr}$  is low for SCH in comparison to normal subjects at rest condition.

In  $\theta_{Pr}$  and  $\beta_{Pr}$  there is no difference seen at this recording conditions. But during both the stimuli conditions, every band power has some differences between two subjects. Similarly for each subjects group, all four bands power values are also compared with respect to their rest state power. Hence, the fifth major column of Table 2 is obtained by subtracting each stimuli condition power from the rest state power. In this column, violet cell indicates that the the particular power for the corresponding subject is more than the resting condition. It is understood from the column 5 that the  $\theta_{Pr}$  and  $\beta_{Pr}$  are always remains more than the rest condition for both subjects group. The pictorial representation of  $\delta_{Pr}$ ,

$\theta_{Pr}$ ,  $\alpha_{Pr}$  and  $\beta_{Pr}$  for each subject group at various recording conditions are shown in respectively Fig. 3a–d. Since the differences between the two groups are very minimum, the diagram shows the actual power value (not round off) obtained, whereas in Table 2 they are rounded off.

The delta wave occupies a frequency range of 0.1–4 Hz and it is commonly found in children. It is dominant during sleep. It is observed from the Fig. 3a, that the absolute power of  $\delta$  for SCH subjects group is higher than the normal groups at rest. During stimulus 1 and stimulus 2 conditions, the power of  $\delta$  is low for SCH in comparison with normal subjects. Having more  $\delta_{Pr}$  at rest for SCH is already proved by several studies and this is due to their pathologic condition [19, 20]. Bahar Guntekin et al. found that the evoked activity of  $\delta$  is generally reduced for SCH subjects while doing various tasks during EEG recording [21].  $\delta_{Pr}$  results determined by this research for both cognitive stimuli correlate well with them. Theta wave occupies a frequency range

**Fig. 3** Comparison of EEG band powers between normal and SCH: **a**  $\delta_{Pr}$ , **b**  $\theta_{Pr}$ , **c**  $\alpha_{Pr}$ , **d**  $\beta_{Pr}$



between 4 and 8 Hz. It is dominant in infant and childhood, but larger amplitude in adult is abnormal and it can appear during deep meditation. All channel average of  $\theta_{pr}$  for both subjects groups at various recording conditions are considered for analysis and it is shown in Fig. 3b. Although  $\theta$  power at rest and stimulus 1 recording conditions produces very less difference between normal and SCH subjects, it is high at rest and low at stimulus 1 conditions. Increase in  $\theta$  wave during mental concentration is common [5]. In this study,  $\theta_{pr}$  is high for both subjects during stimuli presentation. Generally increase in  $\theta_{pr}$  at rest for SCH subjects is due to the effect of (psychotropic) medications [8].

Alpha wave lies in the frequency range between 8–12 Hz. It is prominent in the occipital regions and can be seen during mental concentration and attention of the subject. Generally, the  $\alpha_{pr}$  should be dominant during rest stage for normal subjects. Therefore, less  $\alpha_{pr}$  at rest condition observed in this study for SCH compared to normal is treated as abnormal. Results of less  $\alpha_{pr}$  is already reported by many other researchers and this is due to brain perfusion [7, 8]. In this work, difference in  $\alpha_{pr}$  value is very less at stimulus 1, but for stimulus 2, SCH subjects show high value compared to normal subjects. High  $\alpha_{pr}$  during stimulus 2 condition observed in this study correlates with the result obtained by Knyazev et al. [20] who reported about  $\alpha_{pr}$  during task. It is also observed that  $\alpha_{pr}$  at stimuli conditions with respect to rest for both groups are less in this research which correlates with other study, although they used auditory stimuli [20].

The frequency range for beta wave lies between 13–32 Hz. It is normally found in adults and appears during active thinking, reasoning and during complex problem solving. The  $\beta_{pr}$  value is high for SCH in all recording conditions used with respect to normal subjects.  $\beta_{pr}$  is less at rest compared to stimuli EEG, for both groups.  $\beta_{pr}$  reaches a high value during cognitive stimuli and the difference between the two groups is maximum at these two stimuli conditions. The reason for having high  $\beta$  power for SCH at rest, might be due to the panic condition, even though the subjects are in eyes closed condition during resting state. High  $\beta$  power during cognitive stimuli presentation represents active thinking and cortical arousal which coincides with the previous

researches [8, 12]. In summary, the absolute power analysis at various recording conditions are compared with other researchers finding and shown in Table 3. The results in the Table 3 are derived from the  $\delta_{pr}$  diff,  $\theta_{pr}$  diff,  $\alpha_{pr}$  diff and  $\beta_{pr}$  diff mentioned in Table 2. In Table 2, wherever band power differences are positive, it is marked ‘High’ in Table 3 and similarly the negative indications are marked ‘low’ in Table 3. Table 2 has values as ‘0’ for some of the entries and they are rounded off values. But we consider the actual value, the actual value for  $\theta_{pr}$  difference is 0.000366 and for  $\beta_{pr}$  difference it is 0.00075.

It is observed from the Table 3 that the  $\beta_{pr}$  values are always high for SCH during rest, stimulus 1 and stimulus 2 recording conditions. The other band power values such as  $\delta_{pr}$ ,  $\theta_{pr}$  and  $\alpha_{pr}$  are having unique response (either low or high) in two recording conditions out of the three conditions used. Therefore, statistical method is used to infer the significance of the features in differentiating EEG of SCH from normal subjects. The average value of the four features ( $\delta_{pr}$ ,  $\theta_{pr}$ ,  $\alpha_{pr}$ ,  $\beta_{pr}$ ) show some difference between the two groups in the recording conditions namely rest, stimulus 1 and stimulus 2 conditions. This research utilizes Student’s t-test to verify statistical dependency of the results because it is suitable to compare two populations when mean values are random and the population is small [22]. The Student’s t-test is implemented using Statistical Package for Social Science (SPSS) 21 software. Here, the level of significance is termed as confidence level and it is set to 95% and hence  $\phi_1$  is 0.05. The actual level of significance ( $p$ ) is basically observed from t-table (in SPSS 21) and it is compared with  $\phi_1$ . [22]. When two features are compared and if its  $p$  value is less than 0.05( $\phi_1$ ), then that particular feature is said to be dominant and significant in discriminating SCH from normal. The EEG band power features namely  $\delta_{pr}$ ,  $\theta_{pr}$ ,  $\alpha_{pr}$  and  $\beta_{pr}$  are the parameters of the Student’s t-test. It is performed for all the recording conditions used and results are shown in Table 4. The actual  $p$  value is rounded to 0.0000, if it is very less.

In Table 4, the parameters those satisfy the condition of  $p < 0.05$  are considered for further analysis. Thus it is inferred from Table 4 that the  $\delta_{pr}$  becomes significant during

**Table 3** Comparison of Absolute power between Normal and SCH

Subjects conditions	Results obtained in this work for SCH with respect to normal				Results obtained for SCH by other researchers with respect to normal	
	$\delta_{pr}$	$\theta_{pr}$	$\alpha_{pr}$	$\beta_{pr}^{*}$	Results	Reference
Rest	High	High	Low	High	High $\delta_{pr}$ and High $\theta_{pr}$ Low $\alpha_{pr}$ and $\theta_{pr}$	Boutros et al. [7] John et al. [8]
Stimulus 1	Low	Low	Low	High	Low $\delta_{pr}$ during stimulus	Mahdi Moeini et al. [28]
Stimulus 2	Low	High	High	High		

\*Consistent in all recording conditions used

**Table 4** *p* values obtained from Student’s t-test for absolute power features

Description	$\delta_{pr}$	$\theta_{pr}$	$\alpha_{pr}^*$	$\beta_{pr}^*$
Rest	<i>p</i> = 0.074	<i>p</i> = 0.404	<b><i>p</i> = 0.000</b>	<b><i>p</i> = 0.026</b>
Stimulus 1	<b><i>p</i> = 0.000</b>	<i>p</i> = 0.630	<b><i>p</i> = 0.002</b>	<b><i>p</i> = 0.000</b>
<b>Stimulus 2**</b>	<b><i>p</i> = 0.000</b>	<b><i>p</i> = 0.001</b>	<b><i>p</i> = 0.000</b>	<b><i>p</i> = 0.000</b>

Bold value indicate the significant features and best performance of the classifiers the values and parameters are written with bold and italic

\*Most significant feature

\*\*Primary recording condition

stimulus 1 and stimulus 2 conditions, and  $\theta_{pr}$  at stimulus 2 condition.  $\alpha_{pr}$  and  $\beta_{pr}$  are significant in all recording conditions used. Thus  $\alpha_{pr}$  and  $\beta_{pr}$  are considered as the most significant feature and marked as ‘\*’ in Table 4 and at stimulus 2 condition, all the features are significant, it is considered as the primary recording condition and marked as ‘\*\*’ in Table 4.

### Discussions

Although, there are significant features exist between normal and SCH, there is no clear threshold between normal subjects power value and SCH subjects band power value. So that it is necessary to use non linear classifier for classifying subjects. Classifying EEG of SCH from that of normal subjects will be helpful in the easy diagnosis of SCH. Various classification tools are available. In the first phase, Back propagation Network (BPN) is used as a classifier to classify SCH from normal. A three-layer feed-forward neural network is used to classify the EEG data of SCH from normal. Always the number of hidden nodes is set as  $2n + 1$  in order to have optimum number nodes to avoid over and underfitting of inputs where *n* is the number of inputs. Sigmoid activation function is used because this has been the most commonly used function in many BPN and limits the output

as either ‘0’ or ‘1’. The network is trained using backpropagation algorithm with mean square error value of 0.00001, momentum coefficient is set to 0.95 and the learning rate is set equal to 0.2. Out of 52 set of SCH features, 70% are used for training and remaining data of 30% are used for testing and validation purpose. Similar consideration is for normal subjects’ data set. The input features to the classifier are applied into a variety of combinations as shown in Table 5. The performance of the classifier is estimated using sensitivity, specificity and accuracy and they are found using the following equations [23]. The values are rounded off to the nearest integer percentage.

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{6}$$

$$Sensitivity = \frac{T_P}{T_P + F_N} \tag{7}$$

$$Specificity = \frac{T_N}{T_N + F_P} \tag{8}$$

where  $T_P$  = True Positive = Schizophrenia subjects correctly identified as having schizophrenia,  $T_N$  = True Negative = Normal subjects correctly identified as normal,  $F_P$  = False Positive = Normal subjects incorrectly identified as having schizophrenia,  $F_N$  = False Negative = Schizophrenia subjects in correctly identified as normal.

It is understood from the Table 5, BPN provides better performance for the feature set ‘Rest + St12’ which has sensitivity of 90%, specificity of 86% and accuracy of 88%. Feature sets for the individual recording conditions namely rest, stimulus 1 and stimulus 2 provide better sensitivity but specificity is very poor. The specificity is improved when significant features from all the three conditions namely rest, stimulus 1 and stimulus 2 conditions are combine.

In order to see whether the use of classifiers will improve the results or not, it is decided to use Support Vector Machine (SVM) as the other classifier. SVM is one of the most powerful classifiers and SVM has promising

**Table 5** Performance of the BPN classifier using Absolute power features

S.no	Feature set combination	Performance measures		
		Sensitivity (%)	Specificity (%)	Accuracy (%)
1	Rest	98	15	57
2	Stimulus 1	62	10	59
3	Stimulus 2	92	25	75
4	St12 (stimulus 1 and stimulus 2)	82	80	81
5	<b>Rest + St12</b>	<b>90*</b>	<b>86*</b>	<b>88*</b>

Bold value indicate the significant features and best performance of the classifiers the values and parameters are written with bold

\*Best classification performance all features are combined

**Table 6** Performance of the SVM classifier using Absolute power features

S.no.	Feature set combination	Performance measures		
		Sensitivity (%)	Specificity (%)	Accuracy (%)
1	Rest	89	50	73
2	Stimulus 1	89	93	88
3	Stimulus 2	89	89	88
4	St12 (stimulus 1 and stimulus 2)	79	93	73
5	<b>Rest + St12</b>	<b>91*</b>	<b>86*</b>	<b>88*</b>

Bold value indicate the significant features and best performance of the classifiers the values and parameters are written with bold

\*Best classification performance

classification accuracy for many psychiatric diseases [24] it is decided to use the same for this study. The distribution of feature vector is not linearly separable. Therefore the nonlinear kernel function Radial Basis Function is used. The SVM trains automatically, center the features of their mean and it is scaled by its standard deviation. The SVM uses convex quadratic program method to converge in the hyperplane. The k- fold cross validation technique is used to find the better classification performance. In k-fold cross validation the training data set is divided into k smaller sets called folds, then the SVM model is trained k-1 of the folds. The last fold is used for the testing purpose. The performance of the SVM classifier mainly depends on two parameters called regularization parameter C and the kernel parameters. The standard Gaussian kernel.

$$K(x, z) = e^{-\gamma \|x-z\|^2} \quad (9)$$

is used to obtain cross validation error for various values of C and  $\gamma$ , The error is computed by finding the distance in input space between all pairs. The median of these distances can be used as a measure of scale for finding  $\gamma$ . The regularization parameter C is computed by  $\ln \gamma$ . The lowest error cross validation used for training SVM [25–27]. Then the performance of the classifier is studied using sensitivity, specificity, and accuracy with tenfold cross-validation and it is listed in Table 6.

It is understood from the Table 6. SVM provides better performance for the feature set ‘Rest + st12’ which has sensitivity of 91%, specificity of 86% and accuracy of 88%. At the outset, specificity is well improved compared to BPN network output for the feature set ‘Rest’, ‘Stimulus 1’ and ‘Stimulus 2’. With reference to the Tables 5 and 6, it is understood that the use of classifiers are not play an important role in classifying SCH, because SVM classifier gives 1% improvement in sensitivity compared to BPN. However, both classifiers produced better performance for the future set combination ‘Rest + st12’. Therefore, it can be concluded that the features from stimuli EEG have greater impact in classifying SCH along with rest EEG features.

## Conclusions

Absolute band power from the  $\delta$ ,  $\theta$ ,  $\alpha$  and  $\beta$  bands are determined from the power spectrum of given EEG. Out of these four band powers,  $\alpha_{Pr}$  and  $\beta_{Pr}$  are identified as significant features. Various combinations of these feature sets are given as inputs of the two classifiers namely BPN and SVM. The best classification performance is obtained for the feature set combination ‘Rest + st12’ for both classifiers with more than 90% sensitivity, specificity of 86% and classification accuracy of 88%. This shows that the features obtained during mental activity strongly support for classification along with rest condition feature set. In this study, schizophrenia subjects are not categorized according to their symptoms, gender, and duration of illness. Although this study carried out with our own designed paradigm to stimulate mental activity, the results are distinct. This study is focused on entire EEG band powers during rest and mental activity. This study concludes that EEG of schizophrenia subjects could be identified using absolute powers during mental activity along with rest EEG features.

**Acknowledgements** The patients are recruited from Institute of Mental Health, Chennai, India, who attended either in patient or outpatient ward. The study was approved by Institutional Ethics Committee of Madras Medical College, Chennai, India. We would like to thank the subjects whoever involved in this study. We thank the Director, Institute of Mental Health, Chennai, India, who helped us to bring out this study. We also like to thank the Doctors, Dr. Vanishree, Dr. Sujatha, Dr. Arvind, Dr. Arun, Dr. Jayakrishnaveni, Dr. Sabitha, Dr. Sivalingam and Dr. Saravanan who provided patient support. We also would like to thank the technician Mrs. Umamaheswari for her support in EEG recording procedure subjects. We also thank all the staff members who supported for this study.

## Compliance with ethical standards

**Conflict of interest** There is no funding/ grant received from any funding agency. All authors have no conflicts of interest.

**Ethical approval** All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki

declaration and its later amendments or comparable ethical standards. This research is approved by ethics committee of Madras Medical College. The approval no is 24112011 and the study has been carried out at Institute of Mental Health, Chennai, India.

**Informed consent** Study protocol is explained and Informed consent is obtained either from subjects or from their first degree relatives.

**Research involving animal rights** This article does not contain any studies with animals performed by any of the authors.

## References

- Fenton WS, Blyler CR, Heinssen RK (1997) Determinants of medication compliance in Schizophrenia: empirical and clinical findings. *Schizophr Bull* 23(4):637–651
- Wirshing DA, Buckley PF (2003) Schizophrenia treatment challenges. *Psychiatr Times* 20(5): <https://www.psychiatristimes.com/schizophrenia/schizophrenia-treatment-challenges>
- Jacob A, Cohen S, Alavi A (2013) Abnormal brain circuitry and neurophysiology demonstrated by molecular imaging modalities in schizophrenia. *J Alzheimers Dis Parkinsonism* 3:1–5. <https://doi.org/10.4172/2161-0460.1000114>
- Cancro R (1981) Advances in the diagnosis and treatment of schizophrenic disorders. *American Handbook of Psychiatry* 7:3–34
- Gross A, Joutsiniemi SL, Rimón R, Appelberg B (2006) Correlation of symptom clusters of schizophrenia with absolute powers of main frequency bands in quantitative EEG. *Behav Brain Funct* 2:1–6
- Sanei S, Chambers J (2007) EEG signal processing. Wiley. Accessed 7 Aug 2014
- Boutros NN, Arfken C, Galderisi S, Warrick J, Pratt G, Iacono W (2008) The status of spectral EEG abnormality as a diagnostic test for schizophrenia. *Schizophr Res* 99:225–237
- John JP, Rangaswamy M, Thennarasu K, Khanna S, Nagaraj RB, Mukundan CR, Pradhan N (2009) EEG power spectra differentiate positive and negative subgroups in schizophrenia patients. *J Neuropsychiatry Clin Neurosci* 21:160–172
- Zhang S, Shini Q, Wei W (2010) Classification of schizophrenia's EEG based on high order pattern discovery. In: IEEE 5th international conference on bio inspired computing: theories and applications, Changsha, China
- Rieckansky I, Kasperek T, Jitka Reholova J, Katina S, Prikryl R (2010) Aberrant EEG responses to gamma-frequency visual stimulation in schizophrenia. *Schizophr Res* 124:101–109
- Maccrimmon D, Brunet D, Criollo M, Galin H, Lawson JS (2012) Clozapine augments delta, theta, and right frontal EEG alpha power in schizophrenic patients. *ISRN Psychiatry* 1:1–8
- Akar SA, Kara S, Latifoglu F, Bilgi V (2012) Wavelet-Welch methodology for analysis of EEG signals of Schizophrenia patients. In: Cairo International Biomedical Engineering Conference CIBEC, pp 6–9
- Akbar Y (2016) Spectral and brain mapping analysis of EEG based on Pwelch in schizophrenic patients. 13th South-East Asian Congress of Medical Physics-2015, Journal of Physics Conference Series 694: 362.
- Roschke J, Fell J, Beckmann P (1995) Non linear analysis of sleep EEG data in schizophrenia: calculation of the principal Lyapunov exponent. *Psychiatry Res* 56(3):257–269
- Mitra SK (2006) Digital signal processing: a computer based approach. Tata McGraw Hill Education, New Delhi
- Klimesch W (1999) EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Res Rev* 29:169–195
- Merlin EL, Floyd TC (1996) Negative symptoms and EEG alpha in schizophrenia: a replication. *Schizophr Res* 19:151–161
- Bruce EN (2009) Bio medical signal processing and modeling. Wiley Indian Edition, Wiley, New York
- Karson CN, Coppola R, Daniel DG, Weinberger DR (1988) Computerized EEG in Schizophrenia. *Schizophr Bull* 14:193–197
- Knyazev GG (2012) EEG delta oscillations as a correlate of basic homeostatic and motivational processes. *Neurosci Biobehav Rev* 3:677–695
- Guntekin B, Emek Savaş DD, Kurt P, Yener GG, Başar E (2013) Beta oscillatory responses in healthy subjects and subjects with mild cognitive impairment. *Neuroimage Clin* 3:39–46
- Kothari CR, Garg G (2014) Research methodology methods and techniques. New Age International Publishers, New Delhi
- Gorur K, Bozkurt MR, Bascil MS, Temurtas F (2018) Glossokinetic potential based tongue-machine interface for 1-D extraction. *Australas Phys Eng Sci Med* 41(2):379–391. <https://doi.org/10.1007/s13246-018-0635-x>
- Li YJ, Fan FY (2005) Classification of Schizophrenia and depression by EEG with ANNs. *Eng Med Biol Soc* 3:2679–2682
- Serdar-Bascil M, Tesneli AY, Temurtas F (2015) Multi-channel EEG signal feature extraction and pattern recognition on horizontal mental imagination task of 1-D cursor movement for brain computer interface. *Australas Phys Eng Sci Med* 38(2):229–239. <https://doi.org/10.1007/s13246-015-0345-6>
- Bascil MS, Tesneli AY, Temurtas F (2016) Spectral feature extraction of EEG signals and pattern recognition during mental tasks of 2-D cursor movements for BCI using SVM and ANN. *Australas Phys Eng Sci Med* 39:665–676. <https://doi.org/10.1007/s13246-016-0462-x>
- Bascil MS (2018) New approach on HCI extracting conscious jaw movements based on EEG signals using machine learnings. *J Med Syst* 42(9):169. <https://doi.org/10.1007/s10916-018-1027-1>
- Moeini M, Khaleghi A, Amiri N, Niknam Z (2014) Quantitative electroencephalogram spectrum analysis of patients with schizoaffective disorder compared to Normal subjects. *Iran J Psychiatry* 9(4):216–221

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.