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Selection of Effective EEG Band for Estimation of Cognitive State while Listening Music

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***Abstract* – A new approach is represented in this paper in order to estimate the cognitive states depending on the variations of different effective frequency bands of EEG signal while listening music. In this work, EEG signals are collected for different types of songs to analyze the musical activity on human brain. Different types of songs have specific frequency which can either resonate or anti-resonate with human brain. Spatial and temporal analysis are applied to the brain signals to extract the salient features for estimation of human cognitive state. The extracted features are trained with SVM classifier to show the effectiveness of different EEG bands with different songs. The classification accuracy of different frequency bands indicates the larger alpha or beta activity on human brain for the selected songs. The highest classification accuracy for soft song was found for θ band which indicates the state of catnap. For medium and fast song the effectiveness of α band and β band are noteworthy, which indicate the state of relax and stress respectively. Therefore, human cognitive states can be estimated with our proposed approach which is innovative and efficient to show the impact of music on human brain activity.**

***Keywords* – Brain Activity, Cognitive State, EEG, Frequency Band, Music Signal.**

I. Introduction

Cognitive state estimation has drawn an extensive attention in the field of cognitive neuroscience which can monitor cognition and human mental behavior. Cognitive state comprises the functional activity of brain and subjective experience, expressions and biological stimulation for specific person in different environmental conditions. The basic socio-cognitive domain of human life is music. Different researchers from different eras used music for therapeutical purposes are trying to establish the relationship of music with emotional activity. The inner mechanism of the brain evoked cognitions and changes mental behavior while listening music because it has been proven that music as a consequence to evoke emotions. Listening music helps to keep the neurons and synapses more active and which varies the effective frequency bands of brain signal which is named as electroencephalogram (EEG). When sound waves are listened or pronounced, they have an impact in neurological (brain and nerve) system work in human body [1]. When neurons are activated, local current flows and generate electrical activity which is recordable on the head surface [2]. This electrical activity is termed as EEG signal which activates different parts of the brain during listening music [3]. It also indicates the cognitive states with the variations of functional activities of brain which are more influenced by exposure to music. Each of the music or song has specific frequency and bits according to which the brain activity and the effective frequency band of EEG signal may vary and the cognitive activities also change according to the frequency bands. Fig. 1 shows the corresponding EEG signal when human brain is stimulated with audio signal. The assignment of different cognitive states with their effective frequency band is shown in Table I.

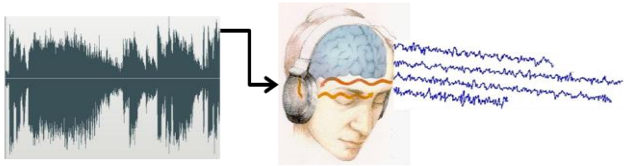

Fig.1. Brain stimulation while listening audio signal (songs) and correponding EEG signal.

The objective is to detect human's mental state according to the influence of different types of songs. In Table II the soft music is selected which composes a softer, more toned-down sound putting more emphasis on melody and vocal harmonies. The medium and fast music are selected according to the tempo of music i.e. rate of speed or number of beats per minutes. While listening different types of songs such as loud or soft, high pitch or low pitch, audible or inaudible etc., our brain responses differently. Low frequency indicates the state of relax while high frequency indicates the state of stress [4]. The human brain produces different electrical activity due to the different levels of music [5]. Each type of music or songs has its own frequency. While listening music the frequency of the music can be either resonate or in conflict with the body's rhythms (heart rate) and also with the frequency bands of EEG rhythm which authorizes specific functions of brain [6]. The categorization of selected songs for cognitive state estimation is shown in Table II. So, music can be used as a tool to estimate the cognitive states such as tension/ stress, solitude, relax and these changes are reflected clearly in physiological system for human body [7]. The major concern of this research are: (i) to propose a technique for extracting some salient statistical and time-frequency analysis based features according to the variation of effective frequency band due to different types of music and (ii) to evaluate the efficiency of the extracted features for different EEG bands to detect the cognitive states using support vector machine.

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Table I: Frequency band region of EEG signal

EEG Wave	Frequency Band Region	Cognitive States
Delta (δ) wave	(0.4-4) Hz	Unconsciousness (Associated with deep sleep)
Theta (θ) wave	(4-8) Hz	Catnap (Associated with drowsiness)
Alpha (α) wave	(8-14) Hz	Relax (Associated with relaxed, alert state of consciousness)
Beta (β) wave	(14-35) Hz	Stress/Tension (Associated with active, busy or anxious thinking)

Table II: Category of songs selected for cognitive state estimation

Song type	Soft song	Medium fast song	Fast song
Bangla	Rabindra sangeet	Adhunik sangeet	Hard Rock
Hindi	Carnatic	Patriotic song	Pop
English	Melody	Folk song	Hard Rock

The main steps of the proposed method are shown in Fig. 2. In this research, the BIOPAC data acquisition unit MP36, C++ source code and AcqKnowledge® 4.1 software are used for data acquisition, analysis, storage, and retrieval [8].

A lot of works have been carried out for addressing the problem of musical influences on the functional responses of human brain. Gerra et al. found that while listening music the corresponding changes will be induced in neurotransmitters, peptides and hormonal reactions [9]. In [10]-[12], Authors shows the variations of functional activities of different frequency band relating the cognitive activity with music levels. They found that beta activity relates to increased alertness and cognitive processes [10] and unpleasant music produces decrease in alpha power at the right frontal lobe [11]. Alpha waves have been thought to indicate both a relaxed awareness without any attention or concentration whereas a beta wave is the usual waking rhythm of the brain associated with active thinking, active attention, focus on the outside world, or solving concrete problems. A high-level beta wave may be acquired when a human brain is in a panic state while listening different unpleasant music. Authors in [12] showed when subjects listen to the pleasant music the changes were reflected in the EEG and there was an increase in frontal midline (Fm) theta power. Authors in [13] showed the dependence of EEG spectral power on the intensity and style of music. The effect of Indian classical music and rock music on brain activity was studied using Detrended fluctuation analysis (DFA) algorithm, and Multi-scale entropy (MSE) method [14]. The brain wave variation was monitored in [15] by changing the music type (techno and classical) and the results showed that when the music was switched from classical to techno, there was a significant plunge of alpha band and from techno music to classical there was an increase in beta activity. Authors in [2] presented a brief study of various effects of sound on the human brain

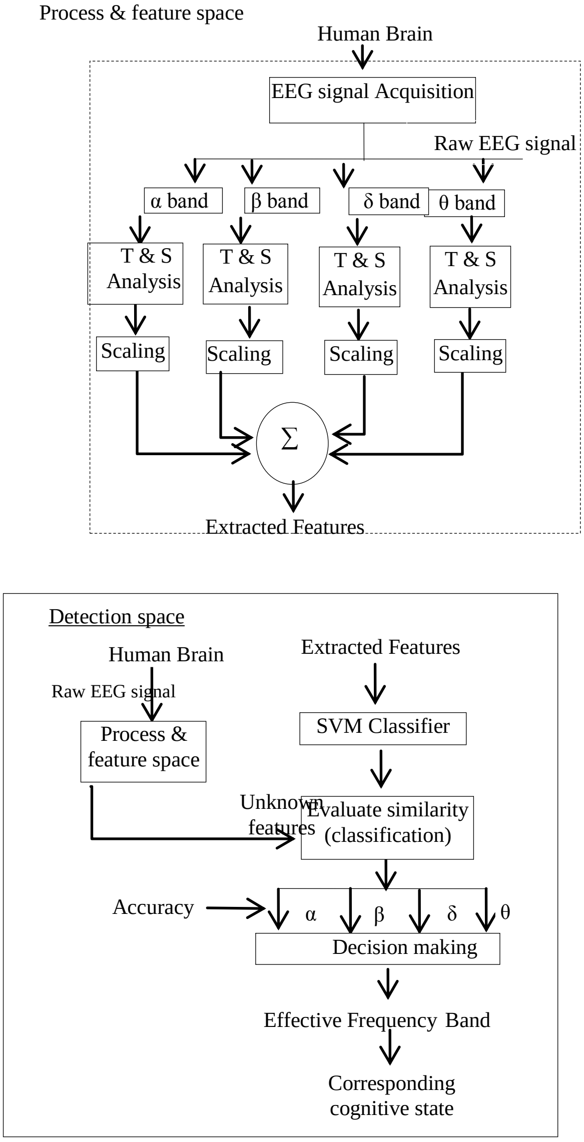

Fig.2. Proposed approach for cognitive state estimation.

activity employing the time-frequency analysis technique. R.S. Schaefer et al. showed a difference in alpha power in different directions to indicate that both the tasks and the stimuli modulate an attentional network, which may relate to the inhibition of non-task relevant cortical areas, as well as engagement with the music [16]. In this work, a new approach is proposed to identify the cognitive states from the variation of effective EEG band. Different statistical, frequency and time-frequency analysis i.e. temporal and spectral analysis (T & S analysis) are done to extract the effective features to estimate the cognitive states. The effective features show the how the brain activity varies during listening different musics.The musical activity of brain determine the cognitive states.

The rest of the paper is organized as follows: Section II describes the EEG signal recording. Section III describes the signal analysis and feature extraction procedure. Section IV illustrates the cognitive state estimation by using SVM technique. Section V discusses the results of estimated cognitive states while cognitive sates while listening music. Finally, Section VI concludes the result.

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II. EEG Signal Recording

In case of mental state evaluation brain signal is most essential so EEG data acquisition plays a significant role in this research. While listening music the electrical activity of human brain gets affected. The electrical activity is measured at the scalp through a set of electrodes which are rich in information about the cognitive activity at different frequency bands of EEG signal. In this research brain signals had been captured while subjects were listening to emotional evoking music in different categories: relax, stress and catnap. Due to musical preferences is a subjective matter the participants were asked to pick three songs (one song for each category). Moreover three songs (one song for each category) were chosen that the songs were previously classified according to their frequency to make a relation with the variation of human brain with musical activity. The acquired EEG data and musical features are classified by machine learning algorithms and correlations among them were investigated.

A. Music Selection for Cognitive State Estimation

Several research in this field mentioned that different music has different physiological effect on human body rhythms and brain. The effect of music on brain functions rate based on subject's choice of like music (slow, medium and fast song) at different languages such that Bangla, English, Hindi. The selected songs have different spectral stimuli depending on their number of bits per second and affect separately on the EEG band waves and changes the signal characteristics. According to the selected salient features it is determined that which state is more affected with the effective frequency band influenced by the different types of selected songs.

Figs. 3(a), 4(a) and 5(a) show the frequency spectrum of soft, medium and fast song and Figs. 3(b), 4(b) and 5(b) show the corresponding brain signals respectively. In this work the Bangla, English and Hindi slow, medium and fast songs were played one after another taking a proper interval to evaluate the effect of cognitive activities of brain influenced by these songs. It is observed that the power spectral density is higher for fast song than medium and slow depending which the effect of frequency bands for brain signal varies with the cognitive activities of brain.

B. Subject Selection and Data Acquisition

The EEG signals were collected in biomedical signal processing laboratory, KUET. The experimental data were collected from 48 numbers of subjects and the subjects were male, and were in good physical and mental conditions and able to react with different types of songs. Their average age was 23 years so that they are sensitive to all the mental activities. The room was air conditioned and approximately noise free. In Fig. 6 the position of electrode on the scalp is shown for EEG data acquisition in the period of listening music.

III. Signal Analysis and Feature Extraction

The extracted EEG features are considered as the ideal characteristics to identify the variation of brain activities and represent the non-stationary characteristics of EEG signal which are particularly effective for recognition of human cognitive activities while listening different types of music. Different types of music affect human brain differently. The variations of brain activities can be patterned with the effective features obtained from tempo-spatial analysis.

A. Time Domain Feature

The effective features of the collected raw EEG signals are obtained with time-domain analysis. The most effective property of the statistical measures on time domain signal is that they will vary in magnitude with the variations of brain signal but maintains essential element of homogeneity. In this work, six different kinds of time-domain feature such as mean amplitude, median, standard deviation, variance, skewness, and kurtosis have been considered to show the influence of listening music on human brain. The expressions for different statistical features were briefly discussed in [18].

B. Frequency Domain Feature

The frequency spectrum of a signal is basically the frequency components (spectral components) of that signal. Among frequency analysis techniques, Fourier transform is considered to be the best transformation between time and frequency domains because of it being time-shift invariant [19]. The frequency spectrum of a signal shows what frequencies exist in the signal. The frequency domain features used in this paper are based on the power spectrum of each 128-point of EEG samples. Each epoch of the EEG data is processed with Hamming window by zero padding for 128-point fast Fourier transform. The power spectrum of all the sub-epochs is averaged to minimize the artifacts of the collected EEG signals in all sub-windows. Finally, EEG power spectrum is extracted in different channels such as Alpha, Beta, Delta and Theta. Different features for FFT analysis are obtained at alpha, beta, delta and theta component of EEG signal individually to determine the cognitive states influenced by different types of music is given in (1).

$$X(k)_l = \{X(0), X(1), ... X(n-1)\} \quad (1)$$

In (1), n represents the total number of frequency amplitude components; k represents the harmonic number of frequency components, and l represents alpha or beta or theta or delta. The real value, imaginary value, magnitude, phase angle and power spectral density are the effective features in this analysis. The power spectral density (PSD) divides up the total power of the EEG signal. It is integrated over its entire one-sided frequency domain (0, F) according to FFT analysis:

$$\int_0^F PSD(k)dk = \int_0^F 2\left|X(k)_l\right|^2 / (t_2 - t_1)dk \quad (2)$$

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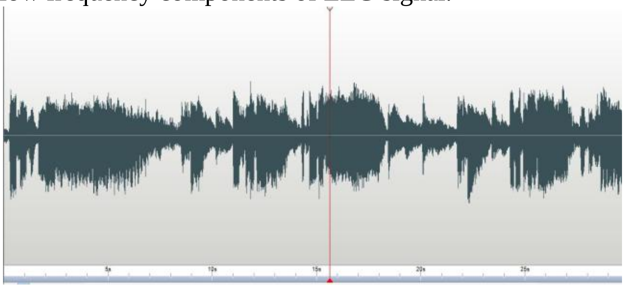
Equation (2) represents the expression of power spectral density in frequency domain where the average power of the signal is in the time range (t_1, t_2).

C. Time-Frequency Domain Feature

The discrete wavelet transform (DWT) analyzes the signal at different frequency bands to extract effective energy component by decomposing the signal into a coarse approximation and detail information [16]. In the present paper, the Daubechies4 wavelet function (“db4”) is used for extracting features from the EEG signal in time frequency domain because it decomposes the high and low frequency components of EEG signal.



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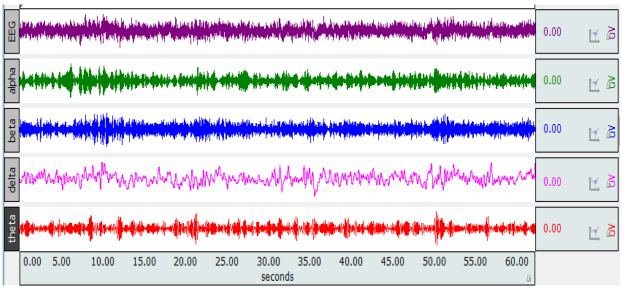
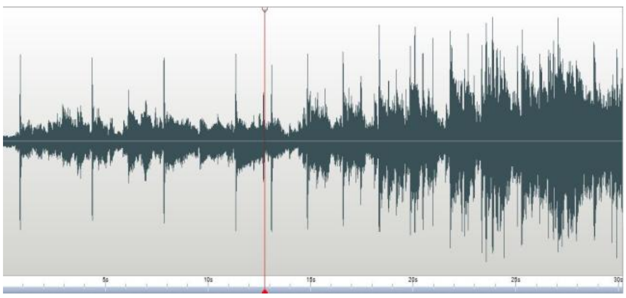


(b)

Fig.3. (a) Frequency spectrum of English soft song; (b) Corresponding EEG signal for soft song.



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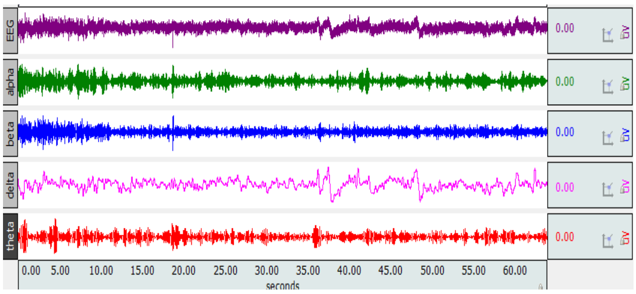
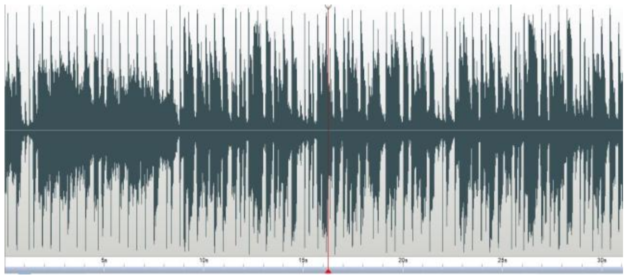


(b)

Fig.4. (a) Frequency spectrum of English medium song; (b) Corresponding EEG signal for medium song.

IV. Cognitive State Estimation using Support Vector Machine

In this work, temporal and spectral analysis based selection of effective frequency band of EEG signal for cognitive state estimation is proposed. In our proposed approach statistical



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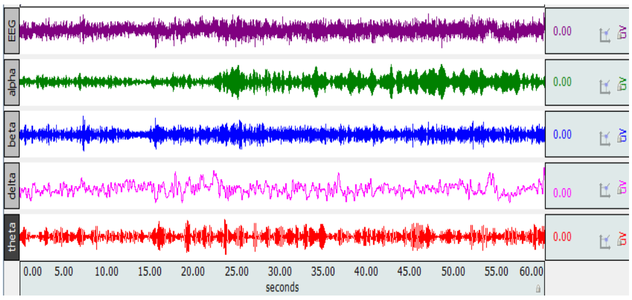

(b)

Fig.5. (a) Frequency spectrum of English fast song; (b) Corresponding EEG signal for fast song.

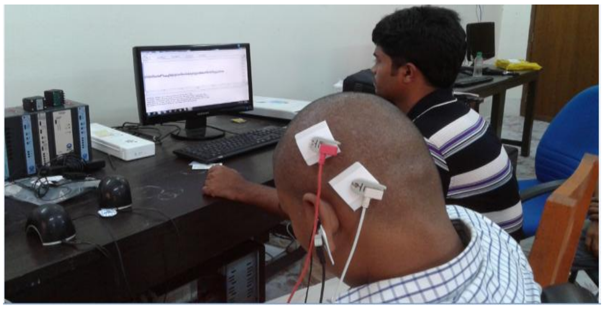

Fig.6. Signal acquisition at the time of listening different types of music.

and frequency based salient feature extraction are proposed for particular EEG bands under the influence of different types of songs for selection of brain activities according to the classification rate of efficient frequency bands and their power spectrum analysis. The steps in effective band selection for the proposed method are given below:

i) The raw EEG signals from several subjects during hearing of different types of music are collected using three electrodes in BIOPAC data acquisition unit which are placed on the scalp.

ii) This preprocessed signal is divided into different EEG frequency bands such as Alpha, Beta, Delta and Theta and the salient global features are extracted from the specific frequency bands.

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iii) From the classification rate of effective frequency band wave the pre-specified cognitive states can be determined.

For the evaluation of performance of cognitive states estimation, classification rate of different bands is achieved by using multiclass support vector machine. The human mental states are classified into the defined classes. For example, $\alpha = 1$, $\beta = 2$, $\delta = 3$, $\theta = 4$. In order to perform a more reliable classification process, three stages are implemented. Firstly, the EEG data are prepared in the specified format and scaling is performed if necessary for each subject. Secondly, the data are trained to create a model. Finally, the new input data of another subject are predicted/classified using the model. In case of classifying mental states through SVM, the radial basis function kernel is used and the scaling range was taken -1~3 for statistical features, 0~15 for FFT and -1~1 for DWT.

The MCSVMs require the solution of the following optimization problem: minimize (3) and (4)

$$\phi(\omega,\xi) = \frac{1}{2}\sum_{m=1}^{k}\omega_m.\omega_m + C\sum_{i=1}^{l}\sum_{m\neq y}\xi_i^m \quad (3)$$

With constraints

$$(\omega_{y_i}.x_i) + b_{y_i} \geq (\omega_m.x_i) + b_m + 2 - \xi_i^m,$$

$$\xi_i^m \geq 0, i = \{1,2,\ldots,l\}, m \in \{1,\ldots,k\} \mid y_i \quad (4)$$

Where C is the penalty parameter, l is the number of training data, k is the number of classes, y_i is the class of the ith training data ω points perpendicular to the separating hyperplane, b is the offset parameter to increase the margin, \ is set minus which is defined as ($m \in \{1,\ldots,k\}\backslash m \notin y_i$), and ξ is the degree of misclassification of the datum x_i. This gives the decision function as shown in (5):

$$f(x) = arg\max_{m=1,\ldots,k}\left[\omega_m.x + b_m\right] \quad (5)$$

This optimization problem for a dual variable is solved by finding the saddle point of the Lagrangian as shown in (6).

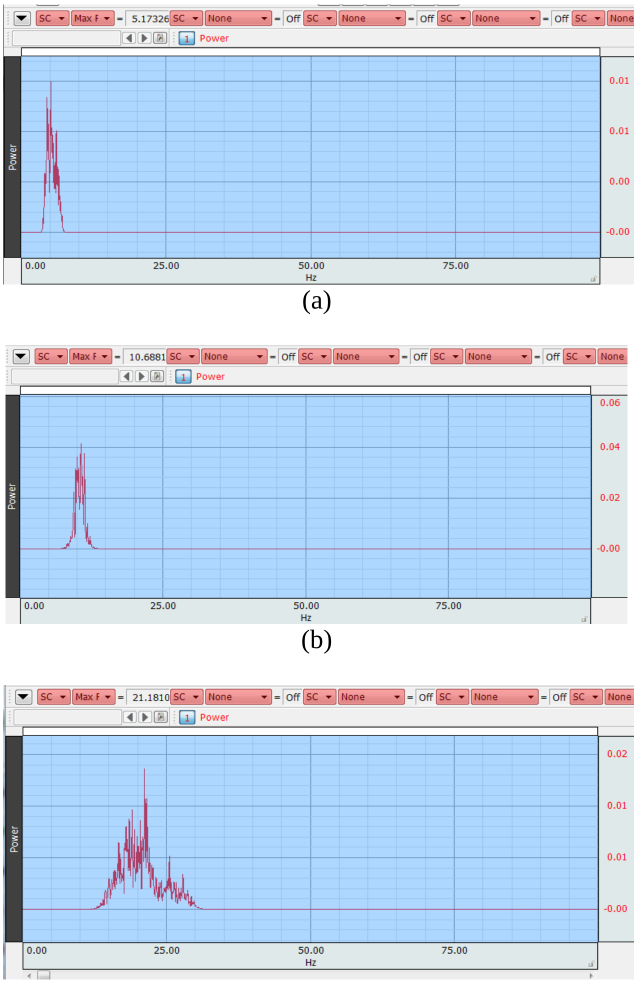
$$L(\omega,b,\xi,\alpha,\beta) = \frac{1}{2}\sum_{m=1}^{k}\omega_m.\omega_m + C\sum_{i=1}^{l}\sum_{m=1}^{k}\xi_i^m$$
$$-\sum_{i=1}^{l}\sum_{m=1}^{k}\alpha_i^m\left[\left((\omega_{y_i} - \omega_m)x_i\right) + b_{y_i} - b_{m-}2 + \xi_i^m\right] - \sum_{i=1}^{l}\sum_{m=1}^{k}\beta_i^m\xi_i^m \quad (6)$$

With the dummy variables $\alpha_i^{y_i} = 0, \xi_i^{y_i} = 2, \quad \beta_i^{y_i} = 0,$ $i = 1,2,\ldots,l$ and constraints $\beta_i^m \geq 0; \xi_i^m \geq 0; \ i = 1,2,\ldots,l$

Where, $m \in \{1,2,\ldots, k\}\backslash\ y_i$ has to be maximized with respect to α and β, and minimized with respect to ω and ξ. Thus the decision function is obtained [17]. In this work the classification rate of different frequency band is obtained by using SVM while listening music or sound from which the specified cognitive states effective for the specific frequency bands are determined.

V. Result and Discussion

In this paper, the variations of different frequency bands are determined under the influence of different types of song on brain activity to estimate the cognitive states. The analyzed features and signal characteristics are changed according to the variation of song and their frequency spectrum. For EEG signal, the amplitude of alpha wave changes with the subject's attention to mental task performed. The alpha activity is inversely proportional to concentration of mental activities. The value of alpha is the maximum for relax state and it decreases for the mental task or at stress.



(a)

(b)

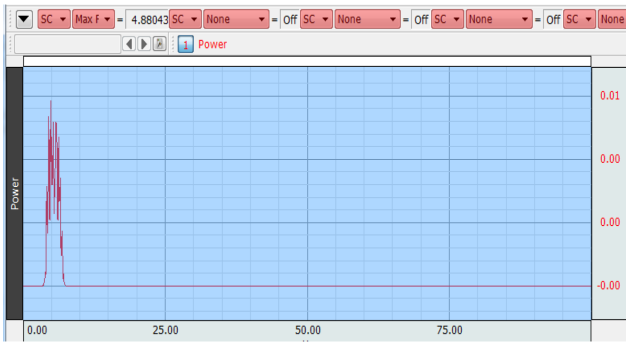
(c)

Fig.7. Power spectral density of EEG signal when subjected to (a) Bangla slow song, (b) Bangla medium song, (c) Bangla fast song.

Figs. 7(a), 7(b) & 7(c) show the power spectral density of EEG brain wave when the subjects were listening Bangla slow, medium and fast song respectively. The maximum power occurs at 10.68 Hz which lies within the alpha frequency band for medium song. So, alpha band is more effective for medium type of song. For slow and fast song the maximum power occurs at 5.17 Hz and 21.18 Hz respectively. Table III shows the train and test dataset for SVM and the classification accuracy of the frequency bands for Bangla song which can detect the effective cognitive states. The classification rate of theta band is higher for Bangla soft song and alpha band is more effective for Bangla medium and fast song and they are 86.5%, 71.18%, and 97% respectively. When human brain is subjected to Bangla soft song the cognitive state was drowsiness or may be called catnap and when medium and fast Bangla song was played the cognitive states indicate relax and tension respectively.

Table III: Classification Accuracy at Different Effective Bands using SVM for Bangla Song

Song type	**EEG frequency band**	**Train dataset for SVM**	**Test dataset for SVM**	**Classification accuracy**
Bangla soft song	Alpha(α)	58	36	64.28%
	Beta(β)	58	35	20%
	Delta(δ)	58	36	36.11%
	Theta(θ)	58	37	86.5%
Bangla mediu m song	Alpha(α)	62	35	71.18%
	Beta(β)	62	36	3.61%
	Delta(δ)	62	37	23.35%
	Theta(θ)	62	35	23.1%
Bangla fast song	Alpha(α)	56	32	2.5%
	Beta(β)	56	33	97%
	Delta(δ)	56	32	65.68%
	Theta(θ)	56	34	39.47%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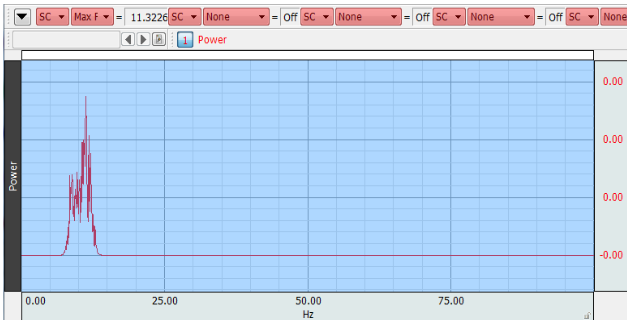
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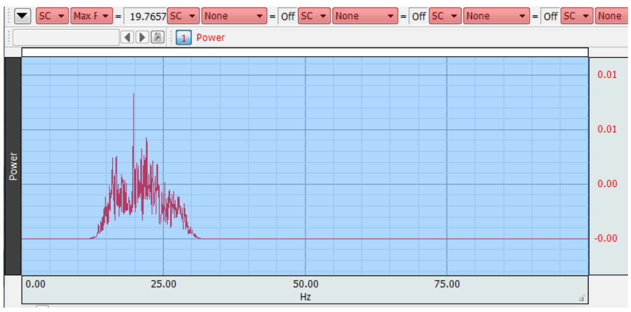
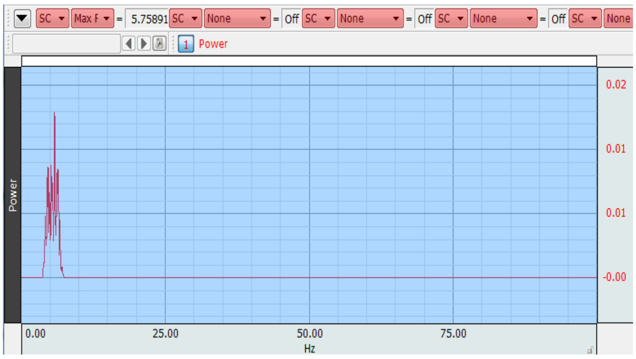

(c)

Fig.8. Power spectral density of EEG signal when subjected to (a) English slow song, (b) English medium song, (c) English fast song.

Table IV: Classification Accuracy at Different Effective Bands using SVM for English Song

Song type	**EEG frequency band**	**Train dataset for SVM**	**Test dataset for SVM**	**Classification accuracy**
English soft song	Alpha(α)	51	36	41%
	Beta(β)	51	35	31.76%
	Delta(δ)	51	36	44.44%
	Theta(θ)	51	37	84.85%
English medium song	Alpha(α)	49	35	85.7%
	Beta(β)	49	36	43.53%
	Delta(δ)	49	37	45.75%
	Theta(θ)	49	35	11.43%
English fast song	Alpha(α)	47	32	5%
	Beta(β)	47	33	88.57%
	Delta(δ)	47	32	54.54%
	Theta(θ)	47	34	31.81%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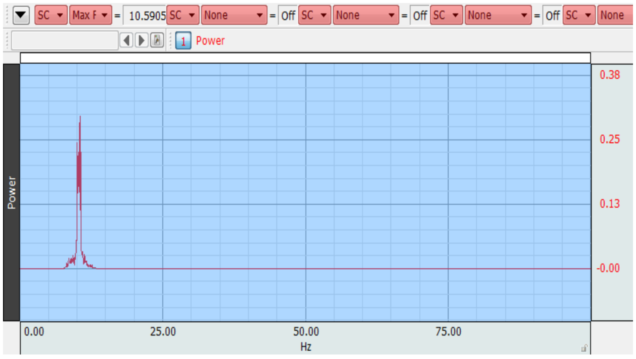
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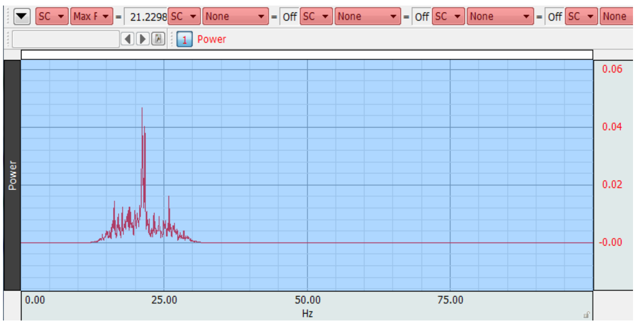
(c)

Fig.9. Power spectral density of EEG signal when subjected to (a) Hindi slow song, (b) Hindi medium song, (c) Hindi fast song.

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Table V: Classification Accuracy at Different Effective Bands using SVM for Hindi Song

Song type	EEG frequency band	Train dataset for SVM	Test dataset for SVM	Classification accuracy
Hindi slow song	Alpha(α)	46	36	85.6%
	Beta(β)	46	35	65.1%
	Delta(δ)	46	36	31.25%
	Theta(θ)	46	37	96.37%
Hindi medium fast song	Alpha(α)	63	35	90.32%
	Beta(β)	63	36	3.12%
	Delta(δ)	63	37	53.12%
	Theta(θ)	63	35	80%
Hindi fast song	Alpha(α)	56	32	35.29%
	Beta(β)	56	33	94.11%
	Delta(δ)	56	32	17.14%
	Theta(θ)	56	34	54.11%

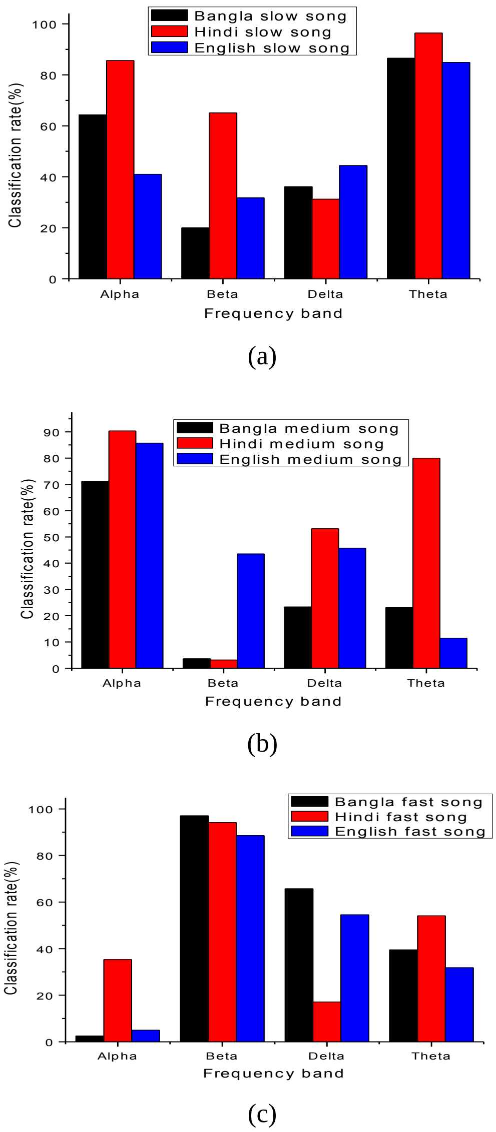

Fig.10. Classification accuracy of different types of music; (a) classification rate for slow types of song, (b) classification rate for slow types of song, (c) classification rate for slow types of song.

The power spectral density when subjected to English slow, medium and fast song are shown in Figs. 8(a), 8(b) and 8(c) respectively. It indicates that the maximum power occurs at frequency 19.76 Hz fast song but in case of slow and medium song they are 4.8 Hz and 11.32 Hz respectively. So in case of English fast song the beta activity is prominent which indicate stress or tension for the subject and theta and alpha band are most prominent for slow and medium types of song.

Table IV and Table V shows the classification accuracy of the different effective frequency bands for English song and Hindi song which can detect the effective cognitive states when respective songs were played. In case of English fast, medium and soft song the higher accuracy is found at beta and alpha and theta band which indicate the stress, relax and catnap state respectively. Table V shows that theta and alpha band are more effective for Hindi slow song and medium song and they were found 96.37% and 90.32% respectively. Hindi fast song shows the effectiveness of beta band which was 94.11%. So from this analysis it is observed that slow song detects the catnap state and medium fast song shows the relax state whereas fast shows the state at stress. So the cognitive state can be evaluated from the larger activity of alpha or beta or theta band.

The maximum power occurs at 5.7 Hz and 10.59 Hz for Hindi slow and medium song respectively as shown in Figs. 9(a) and 9(b) whereas at frequency 21.22 Hz for Hindi fast song which indicates the beta frequency band as shown in Fig. 9(c). So, the beta activity is more effective for fast song and the high frequency spectrum with fast bit of music leads human mind to stress.

VI. Conclusion

This work proposed an approach of cognitive state estimation based on the variations of brain activity and effective frequency bands of EEG signal while listening different types of music. The effective time domain and frequency domain features were extracted from spatial and temporal analysis. From the analysis, it was shown that θ band is more effective for soft song whereas the α band is effective for medium song and the β band activity is prominent for Bangla, Hindi and English fast song. The highest classification accuracy for soft song was 96.37% for θ band. For medium and fast song they were 90.32% and 94.11% for α band and β band respectively. Moreover, the maximum power spectral density occurs at θ band (4.8- 5.17 Hz) for slow song, α band (10.68- 11.32 Hz) for medium type of song, β band (19.76- 21.22 Hz) for fast type of song in this analysis. The α band activity indicates the positive emotion pleasant or the reduction of mental stress whereas β band activity shows the effect of mental stress. From this work, it can be concluded that the cognitive states depend on the functional activity of frequency bands while listening different types of songs. In our future work, cognitive state will be modeled for different types of music.

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