EMOTION RECOGNITION FRAMEWORK USING EEG SIGNALS FOR MUSIC PERSUADED ACTIVITY

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Abstract - Music is known as emotional expression. The mind is emotionally evoked by sound. These feelings are responsive not only to genre styles but also to an individual's vulnerability to music. Unlike songs like relaxation, patriotism, gladness, whimsy or depression, various brain activity can generate EEG signals. EEG is used for the measurement of electrical brain function. This EEG signal contains valuable data on the different subject emotions. In this study, it has been suggested an EEG signal of song induced behaviour for a mood detection system. The key aim is to study the happy EEG signal pattern connected with the left and right hemispheric areas of the brain. In the 30-40 age range, were picked, 15 men. Electrodes mounted under the Global Standard 25-75 on the scalp of the subject. Each evaluation lasted 15 minutes with eyes shut, and each participant was asked to focus on the work. We generated an EEG statistical model with data from four cognitive abilities of ten different subjects in this sample. In the left-hand hemisphere, we decide the happy rhythms for feelings over the temporal lobe. So we infered that the prefrontal cortex reacts more to feelings instead of the correct part. This research also reveals valuable details on mood identification in the alpha power frequency.
Keywords: Brain-Computer Interface, EEG signals, Music, Emotion recognition, Voice activity detection.

1 INTRODUCTION

In the case of brain injury or late-stage amyotrophic, lateral sclerosis (ALS), people gradually get crippled despite otherwise being cognately intact [1]. The only way to recover a degree of connectivity for these patients is to test the neuroactive pathway via the brain-computer interface (BCI) [2, 3]. Current BCIs based on EEG are primarily dependent on visual or attention comparisons for the screen-based letter collection, which results in a sluggish pace of contact (in just a bunch of words per second) [4]. The latest research investigated this topic by linking nerve impulses to script (cognitive voice decoding) or voice acoustics (neural speech synthesis). The model of sound extraction will lead to faster BCIs of the next decade. Many experiments have shown that neural speech decoding is feasible [5–9]. Scientific investigations have shown the likelihood of an electroencephalographic (EEG) or electrocorticographic (ECoG) classification of the phoneme, syllable and letter, and a magnetoencephalographic (MEG) term classification [10-12], stated for example. Recently, BCI neural voice decoding was further enhanced in two experiments on direct mapping of neural speech signals to ECoG [13,14].

The lack of meaningful voice/speech start-up and offset identification for potential BCIs is a significant challenge in improving the dialogue system's neural speech encoding. Manual marking of the speech behaviour segments inside the neural records is the majority of recent work on the encoding of neurological language. The decoding procedure needs to be fully automated in real-time, including automated identification of speech-engine operation fragments in sensory neurons, to apply speech-BCI development to real-world implementations. That means that the new experimental protocol for manual voice activity markings needs to be replaced by voice activity recognition systems (VAD), capable of automatically distinguishing the times at which the subject begins and finishes. Voice activation identification (voice activities) (VAD) was commonly used to determine voice/speech activity onsets and offsets in automated speech recognition (ASR)[15].

Current ASR systems will continue to talk to users with VAD (speakers). Here, we extracted the word 'VAD' and referred to the neuronal signals as 'NeuroVAD' as speech movement identification. The hypothesis is that the rhythms of neural activation during speech will be different from those during silence. A VAD device (NeuroVAD) may be applied to assess automated initiation of voice motor functions in a neural signal and then feed into a voice BCI for retrieval.

The remainder of this paper is organized as follows. Section 2 describes the associated research on VEC. In Section 3, the workload arrival framework for VEC has been provided. Section 4 provides simulation results and discussion. Section 5 provides the conclusion and an overview which describes possible future studies.

2 RELATED RESEARCH ON VEC

Various researchers have worked together to create a mood identification method for music and EEG signals. The authors suggested the EEG approach of analyzing it using the Fractal Analysis (FA) and Neural Network (NN) [16]. The attributes of the EEG were extracted using FA. These EEG data properties have been calculated with NN. Computer simulations were used to classify the EEG pattern. The EEG pattern was ranked according to four conditions: rock music, Japanese Schmaltzy ballad music, curative music, and classical music [17]. Authors of [18] also processed the EEG signal and discovered where an individual had various rhythms in his or her brain. With Phoenix Digital EEG 128 channels, they acquired the EEG signal.

Such indicators are related to the signals before the respondents receive music. They noticed substantial variations in these signals. The performance of various musical forms on the electroencephalogram (EEG) operation was classified as Karthick et al. [19]. They were studied with classical and rock music from Indian Carnatic. They investigated some 300 s of EEG data. The EEG statistical analyses were performed using the DFA and multiscale entropy (MSE) algorithms. They observed that the electrical encephalogram of either with or without tunes differed significantly from both approaches. Users mentioned that MSE shows greater entropy values for both musical forms, showing that with brain processes music, the complexity of the electroencephalogram increased[20].

Authors in [21] suggested a method of sensing mood using music. Substantial and intangible components were studied in EEG frequencies. These amplitude variations were encouraged to create the personality attributes of EEG. The distribution of these spectrum combinations rates that did not contain noise frequency components is measured under the proposed procedure. It was determined if the audio suited the mood by excellent outcomes of the thresholds. A genetic algorithm (GA) based approach has been used in [22]. In [23], authors examined an alternative to recognizing emotional reactions using electroencephalogram (EEG) signals during the multimedia presentation.

In principle, BCI includes brain function analysis (through brain imaging technology) and the detection of characteristic changes in brain designs that are regulated for communicating with the outer world (through computer signal processing algorithms) [24, 25]. The BCI contains messages and commands expressed in an electrophysiological signal inside the brain rather than by muscle contractions, as in traditional communication methods.[26, 27]. Thinking process communication should consider the working of the brain. It also refers to the understanding of electric signals generated by the thinking process in the brain. The brain can reach remotely through EEG signals by controlling them. The key challenge is to consider the thinking process utilizing EEG signals. If EEG signals can correlate the thinking mechanism, so electroencephalogram (EEG) signals can track the thought process.

Extensive analysis has taken place in the field of supervised thinking in various ways. The emotion perception device was developed with visual cues such as facial features [28] and video clips by several different researchers [29]. Music is a reminder of feeling. These sentiments concentrate not only on the kind of music but also on the musician's sensitivity. Various kinds of songs such as patriotism, optimism, romanticism and depression cause different brain work to produce multiple EEG signals [30]. Attributes may be derived from EEG signals to distinguish various music forms. Music is, therefore, a robust emotion creator that stimulates the multiple areas of the brain. Centred on this fundamental theory, a framework that provides a mood recognition system can be designed.

3 PROPOSED METHODOLOGY

Music emotionally triggers a feeling. Such sentiments rely primarily on music for the individual who is sensitive to music and responsiveness. Songs can be graded, however, according to their total mental impact. For this analysis, we distinguished patriotism, optimism, romanticism or depression depending on track popularity. Comprehension of triggered neural activity when listening to music is crucial for continuing education in identifying various music styles.

3.1 Emotion Recognition with music

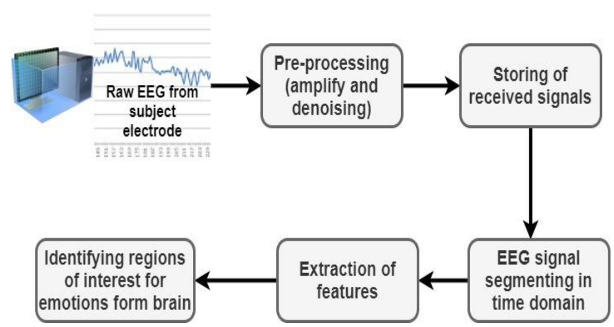

Figure 1 Outline of the proposed system for emotion detection from music using EEG signals.

The proposed BCI mood recognition model is shown in Fig. 1. The suggested method for music emotion analysis with EEG signals has been seen in the figure. Both participants were taught the purpose of the research. The procedure was intended to be used for BCI as an emotion recognition device, they were instructed. It has been generated in this analysis that EEG datasets with data from 5 cognitive activities of 10 participants.

3.2 Pre-processing

The raw EEG data obtained from 15 individuals have been pre-processed. The pre-processing involves two significant steps: amplification of the incoming EEG signal followed by the filtering process. The Kalman filtering process based on equation (1) and (2) will be utilized to filter the noise from the raw EEG signal. The pre-processed EEG signals are stored in the device for further processing. Then, segmentation based on the mean location of the electrode will be done. Extraction of convenient features for the analysis has been carried, and regions of interest will be identified and based on the interpretation, emotion recognition has been carried out involves two significant steps: amplification of the incoming EEG signal followed by the filtering process. The Kalman filtering process based on equation (1) and (2) will be utilized to filter the noise from the raw EEG signal. The study data was collected based on the BCI system suggested. The sensitivity of sequencing was calculated associated with the input observations for an online BCI power Kalman filter BCI decoder. The Kalman filter decryption algorithm was used to convert historical dynamics to 2D vector controls with the sound and visual feedback formant in combination. The layout of the yield status represents the frequencies of the two-dimensional amplitude framework and is given by:

$$A(y)=XA(y-1)+j[y] \quad (1)$$

The regional condition determines the a priori probabilities of future amplitude levels A(y) is interpreted based on previous estimates A(y-1) and the autocratic paradigm of the first-order. The likelihood model represents ultimate functions, the relationship between forming rates and predicted predictability inflexions.

$$j(y)=PA(y)+l[y] \quad (2)$$

The likelihood matrix P is an exceptionally critical model of the relation between the practical familiarity j(y) and trajectory A(y). Equations (2) and (3) show a blunder of the Gaussian variables Y(0,j) and Y(0,A), and two matrixes of j are the optimal persistent factor in the state, while the MxM matrix of j is the most probable continuous battle.

3.3 Storing of Received Signals

The pre-processed EEG signals are stored in the device for further processing. Then, segmentation based on the mean location of the electrode will be done. Extraction of convenient features for the analysis has been carried, and regions of interest will be identified and based on the interpretation, emotion recognition has been carried out.

3.4 Feature Extraction

The initial EEG signal is the time domain signal, and the propagation of the signal energy is dispersed. The signal characteristics are turbulent. The EEG signal to describe the signal energy as a function of time or/and frequency is evaluated to obtain parts. Based on earlier research, frequency-domain extract features are best for recognizing mental tasks based on EEG[31]. Fast Fourier Transform (FFT) was the first measurement method by using the isolated FFT on the signal and finding its spectrum. EEG signal is non-stationary, which means its range varies over time; a series of individual stationary signal sections can be approximated as piece by sequence [31]. The Fourier functions are not sufficiently non-stationary. Therefore, the Fourier functions were implemented with sufficient windows, which give the STFT a sort of time-frequency depiction, a short time transformation (TFR). The discrete STFT equation is given by

$$Y_{FT}[o,p] = \sum_{l=0}^{M-1} y[l]x[l-n]e^{-j2\pi ol/M} \quad (3)$$

Where y[l] represents a signal and x[l-n] denotes an M-point window function. In STFT, the signal is separated into limited conditional, spanning and Fourier transform (FFT) frames. The feedback of consecutive STFTs will display the signal with a time-frequency. The signal is truncated into small data frames by multiplying it by a window to zero the signal built beyond the data framework. The window will be converted in time, and FT reapplied to each signal for analysis[32]. The STFT is added to a second EEG signal divided into 256 points, 40 per cent of which intersect each section.

A 256-point Hamming window multitudes each section, then each segment receives an FFT algorithm. It sums up and uses and normalizes 30 bands in 2 Hz of frequency range from 2 to 20 Hz. This results. This transforms every 2-second synaptic signal, through a spectral transformation, into 40 values later used to be an input in the neural network. The fundamental principle of the mechanism is seen in Fig. 3. For multi-channel EEGs representing the spatial dimension, the geometrical locations of the electrodes often popularize space-time-frequency (STF) measurement by multi-way processing techniques. To distinguish between activities and region of interest, based on the subject, we employ this approach by using the STFT by taking several electrodes. The data from an enlarged part of the skirt are used. Channel 14 is used, for example, as an input in the classification scheme on all other networks.

3.5 Classification and Identifying Regions of Interest

Generally, classification consists of finding the tag of a feature vector using a mapping that is cultured from a training set. The training stage aims to include pre-classified feature vectors in the algorithm (in this case, vectors with 320 functions) for the mapping process inability to forecast tags of new information. Neural networks are autonomic, self-organize, associated memory, operation concurrent and decentralized compared to conventional processes. With its high faults resistance, the recognition models based on neural networks are constant and can also be used repeatedly.

There are three stages to the creation, development and execution of artificial neural networks (ANN). The network architecture shall be specified at the design stage, namely the number of sources, exits and the neural stimulation mechanism. The training process involves the intensity of the network links through a training algorithm like backpropagation. The implementation stage is finally carried out using the set network parameters achieved in the training phase[32].

It can be done with training arithmetic and some non-linear function to relate input to the corresponding output pattern. In this research, the data were split between the learning portion and the evaluation part. The actual data will be given for training. There are feature vectors on each path. The choice of training patterns and testing conditions was randomly assigned. Training took place before the mean square error MSE was less than 0.0002, or the maximal occurrence limit of 19000 was met. The MSE indicates that NN instruction stops at the error point. The MSE is the mean NN value deducted from all training patterns by the designated target level. For the segment reflecting the role of the EEG pattern being learned, the optimal target output was set to 1.0.

3.6 Placing of Electrodes for Retrieving EEG Signal

The electrodes mounted on the participant's scalp are shown in Fig. 2 according to professional standards of 25–75. Each evaluation was performed with an eye closed for 15 minutes, and each participant has been requested to focus on specific activities. The respondents have been required to participate securely together with the headphones on a chair for both forms. They were instructed that changing their emotion by song is necessary. The subject was listening closely in a room to various kinds of songs.

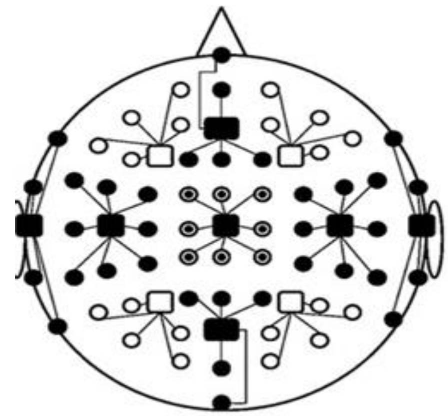

Figure 2 Electrodes placed in the scalp of the individual to obtain EEG.

3.7 Working Model for Experimentation

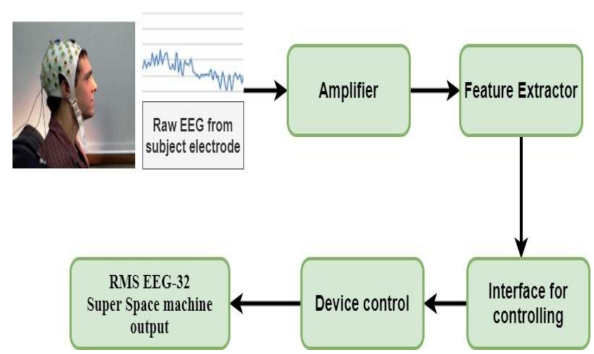

Figure 3 Working model of the proposed system for emotion detection from music using EEG signals

In an attempt to standardize language and practical models, a general architecture for the design of brain computers has been suggested to promote the benchmarking of BCI systems. In Fig. 3, they presented the generalized BCI machine functional model.

In the primitive phase of every BCI, the model and cognitive ability must be examined to provide differentiated influences. This involves logging several activities or information tests so that differentiated functionality can be checked afterwards. An average test or the frequency domain is initially performed to observe a general characteristic pattern. The biggest problem is determining if this type of operation can be triggered by one experiment or a limited section of persistent EEG data. Feature extraction techniques must describe EEG features by a set of principles that differentiate between the various cognitive processes and the corresponding constraints in offline or virtual methods. This human-controlled EEG behaviour modification may be used to build a BCI device to provide power.

4 RESULTS AND DISCUSSION

Fifteen male individuals were chosen from 30-40 years of age. Concepts without behavioural disorders were shown to be safe. They had no trouble with communicating. They had a good vision, too. All subjects had to sit comfortably in the research laboratory on an armchair in front of the projector. To eliminate noise effects, the lab was electromagnetically protected.

The parameters for experimentation in emotion recognition with music are shown in table 1. Machines for EEG have been recorded on the available commercial EEG machines, i.e. the EEG-32 Super Space machine RMS (Recorders and Medicare Systems). The sample rate was 300/s, which means the sample time between two samples was 5ms. Each retrieval trial was reported 15 min. The other EEG system parameters have been described as follows: Factor: 2 Hz, filter height: 75 Hz, sensitivity: 10 V, channel number: 20, speed sweeping: 45 mm/s. The experiment was carried out on 15 individuals.

Table 1 Parameters considered for the experiment of emotion recognition using music

Parameter	Value
Recording machine	RMS (Recorders and Medicare Systems) EEG-32 Super Space machine
Recording time of the experiment	15 min
Sampling rate	300 samples/s
Sampling interval	5ms
Sensitivity	10V
Lowest frequency	2Hz
Highest Frequency	75Hz
Mean location of electrodes	13
Total electrodes	75

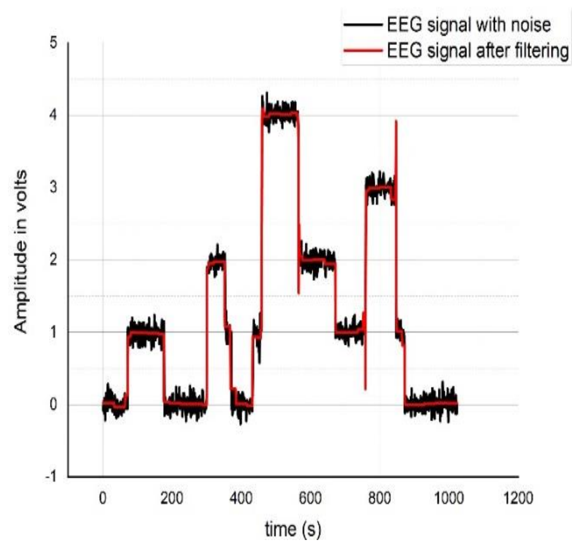

Figure 4 Comparison between raw EEG signal with noise and the pre-processed signal after filtering

Fig. 4 shows the comparison between raw EEG signal with noise and the pre-processed signal after filtering. The original EEG signal acquired from the subject using the electrode will contain noise added to the signal. This noise is removed in the pre-processing step using the appropriate filtering technique.

Four modes, namely: Relieved, depressed, cheerful, and patriotic, has been denoted as Emotion 1 (E1), Emotion 2 (E2), Emotion 3 (E3), and Emotion 4 (E4), respectively. The Electrodes are separated into the Left Hemisphere, the Right Hemisphere and the middle Hemisphere by the brain area.

Deep sleep is linked to the E1 wave. The pulse is of both high and low frequency. Rest and head trauma are corresponding to emotion E2. E3 is relief and vigilance. If the frequency E3 is lower, the further operation has been suggested. The level of alertness is inversely proportional. During problem-solving, the E4 rhythm is more involved. We focus on E3 rhythms in this study. In Fig.5 and Fig.6, it's said that in sad song mode, it's calm and in national song mode, more caution. Participant in tragic song mode is more peaceful and in national song mode more alert. This demonstrates that the EEG signal provides insightful knowledge about an individual's various emotions. Signal EEG includes vast amounts of data. By seeking more active area for emotions, one can reduce this information.

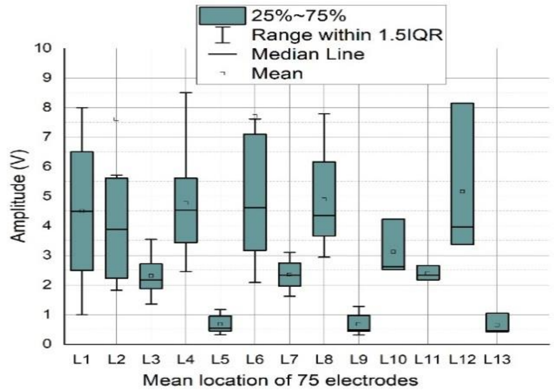

Figure 5 Statistics of Emotion 1 (E1 – Relieved) recognized with music input from EEG signals

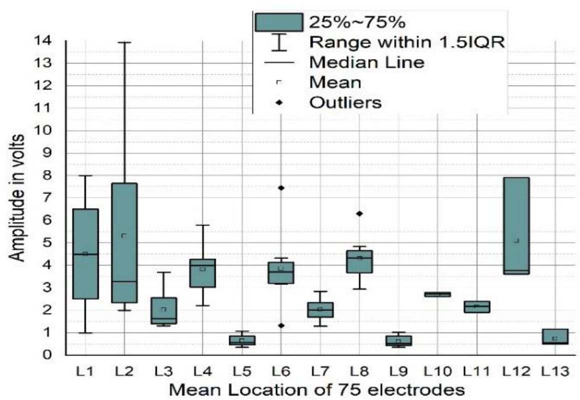

Figure 6 Statistics of Emotion 2 (E2 – Depressed) recognized with music input from EEG signals

As we understand that happy rhythms are reciprocal to cognitive function, which means decreased processes in the brain. The joyful rhythm is higher than happy emotion, and if they are less, they mean more brain activities.

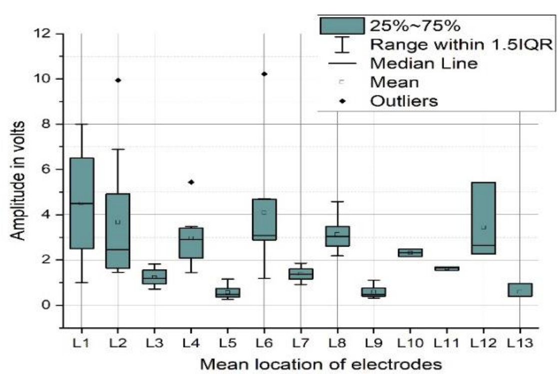

Figure 7 Statistics of Emotion 3 (E3 – cheerful) recognized with music input from EEG signals

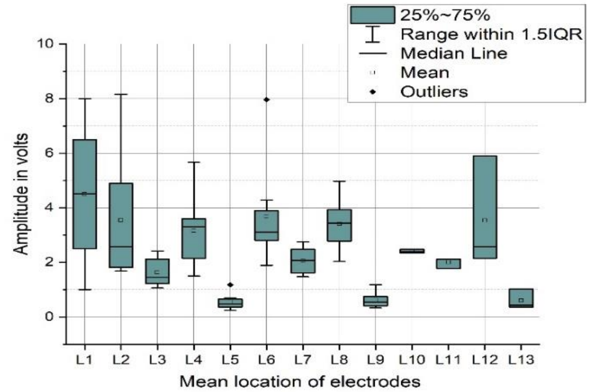

Figure 8 Statistics of Emotion 4 (E4 – Patriotic) recognized with music input from EEG signals

Fig. 7 and Fig. 8 show that the person has done more action in the brain than the depressed and romantic Song mode for Happy and National Song. The joyful importance of the national song mode is much lower than that of other moods so that topics provide more brain activation for the patriotic model. So it has been suggested that the matter is national song mode more warning. The figure shows that the level of emotion negligible compared to the joyful pattern is more of patriotic feeling and is reduced from national, loving, pleasant, and unhappy. This information can again be reduced by seeking a more active electrode location. We now analyze the data according to various electrode locations in multiple areas. The graph shows that the left emotions are more involved than the right hemisphere of the brain.

5 CONCLUSION

This paper aims to design a framework that offers a database that can be used to develop an emotion detection system. We demonstrate in this analysis that the various emotions of people using EEG signal can be recognized. Alpha power can be used for one of the variables. Larger alpha power values signify patriotic, Joyful, Loving songs-induced emotions, whereas lower value is equivalent to unhappy feelings. Thus these emotions can be distinguished with alpha power values. To understand the importance of particular humour, different brain positions have been observed, as the left hemisphere and the right hemisphere. In the temporal lobe, it has been found that signalling is more emotional in the prefrontal cortex. In the left field, the mood EEG signals are more potent than in the right areas. So we infer that the left area of the brain gives more emotional responses instead of the right.

References

[1] Laureys. S, et al., "The locked-in syndrome: What is it like to be conscious but paralyzed and voiceless?", Prog. Brain Res, Vol. 150, pp. 495–511, 2005.

[2] Brumberg, J.S., Nieto-Castanon, A., Kennedy, P.R., Guenther, F.H, "Brain-computer interfaces for speech communication", Speech Commun., Vol. 52, no.4, pp. 367–379, 2010.

[3] Wolpaw, J.R., Birbaumer, N.., McFarland, D.J., Pfurtscheller, G., Vaughan, T.M, "Brain computer interfaces for communication and control", Clinical Neurophysiology, Vol. 113, no.6, pp. 767–791, 2002.

[4] Birbaumer, N., "Brain-computer-interface research: Coming of age", Clin. Neurophysiol., Vol. 117, no.3, pp. 479–483, 2006.

[5] Formisano, E., De Martino, F., Bonte, M., Goebel, R, ""who" is saying "what"? brain-based decoding of human voice and speech", Science, Vol. 322, no.5903, pp. 970–973, 2008.

[6] Herff, C, Heger, D, de Pesters, A, Telaar, D, Brunner, P, Schalk, G, Schultz, T, "Brain-to-text: Decoding spoken phrases from phone representations in the brain", Front. Neurosci, Vol. 9, 2015.

[7] Dash, D, Wisler, A, Ferrari, P, Wang, J., "Towards a Speaker Independent Speech-BCI Using Speaker Adaptation", Interspeech, pp. 864–868, 2019. Available online: https://www.isca-speech.org/archive/Interspeech_2019/pdfs/3109.pdf

[8] Dash, D, Ferrari, P, Wang, J., "Decoding Imagined and Spoken Phrases from Non-invasive Neural (MEG) Signals", Front. Neurosci, Vol. 14, no. 290, 2020.

[9] Wang, J, Kim, M, Hernandez-Mulero, A.W, Heitzman, D, Ferrari, P, "Towards decoding speech production from single-trial magnetoencephalography (MEG) signals",IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 3036–3040, 2017.

[10] Dash, D, Ferrari, P, Heitzman, D, Wang, J., "Decoding speech from single trial MEG signals using convolutional neural networks and transfer learning", Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2019.

[11] Kellis, S, Miller, K, Thomson, K, Brown, R, House, P, Greger, B., "Decoding spoken words using local field potentials recorded from the cortical surface", Journal of Neural Engineering, Vol. 7, no.5, 2010.

[12] Rezazadeh Sereshkeh, A, Trott, R, Bricout, A, Chau, T., "EEG classification of covert speech using regularized neural networks", IEEE/ACM Trans. Audio Speech Lang. Process, Vol. 25, no. 12, pp. 2292–2300, 2017.

[13] Angrick, M, Herff, C, Mugler, E, Tate, M.C, Slutzky, M.W, Krusienski, D.J, Schultz, T., "Speech synthesis from ECoG using densely connected 3D convolutional neural networks", Journal of Neural Engineering, Vol. 16, no.3, 2019.

[14] Anumanchipalli, G, Chartier, J.F, Chang, E, "Speech synthesis from neural decoding of spoken sentences", Nature, Vol. 568, pp. 493–498, 2019.

[15] Tong, S, Chen, N, Qian, Y, Yu, K, "Evaluating VAD for automatic speech recognition", 12th International Conference on Signal Processing (ICSP), 2014.

[16] Ito, S., Mitsukura, Y., Fukumi, M., Akamatsu, N, "Feature extraction of the EEG during listening to the music using the factor analysis and neural networks", International Joint Conference on IEEE Neural Networks, 2003.

[17] Jasper, H.H, "Report of the committee on methods of clinical examination in electronic photography", 1957. Available Online: http://asenic.ru/fishka/austral/jasper1957.pdf

[18] Huisheng, L., Wang, M., Hongqiang, Y, "EEG model and location in brain when enjoying music", 27th Annual International Conference on IEEE Engineering in Medicine and Biology Society, 2005.

[19] Karthick, N., Thajudin, A.V., Joseph, P.K, "Music and the EEG: a study using nonlinear methods", International Conference on IEEE Biomedical and Pharmaceutical Engineering (ICBPE), 2006.

[20] Ito, S. I., Mitsukura, Y., Fukumi, M., Jianting, C, "Detecting method of music to match the users mood in prefrontal cortex EEG activity using the GA", International Conference on IEEE Biomedical and Pharmaceutical Engineering (ICBPE), 2007.

[21] Khosrowabadi, R., Quek, H.C., Wahab, A., Ang, K.K., "EEG based emotion recognition using self-organizing map for boundary detection", 20th International Conference on IEEE Pattern Recognition (ICPR), 2010.

[22] Klimesch, W, "EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis", Brain Research Reviews, Vol. 29, no. 2–3, pp. 169–195, 1999.

[23] Klimesch, W., Doppelmayr, M., Russegger, H., Pachinger, T., Schwaiger, J., "Induced alpha band power changes in the human EEG and attention", Neuroscience Letters, Vol. 244, no. 2, pp. 73-76, 1998.

[24] Kwon, M., Kang, J.-S., Lee, M, "Emotion classification in movie clips based on 3D fuzzy GIST and EEG signal analysis", 2013 International Winter Workshop on IEEE Brain Computer Interface (BCI), 2013.

[25] Levine, S.P, "A direct brain interface based on event related potentials", IEEE Transactions on Rehabilitation Engineering, Vol. 8, no. 2, pp. 180–185, 2000.

[26] Mason, S.G., "A general framework for brain-computer interface design", IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 11, no. 1, pp. 70–85, 2003.

[27] Millan, J.R., Hauser, A., Renkens, F., "Adaptive brain interfaces—ABI: simple features, simple neural network, complex brain-actuated devices", 14th International Conference on Digital Signal Processing Proceedings, 2002.

[28] Millan, J.R., Mourino, J, "Asynchronous bci and local neural classifiers: an overview of the adaptive brain interface project", IEEE Transactions on Neural Systems and Rehabilitation Engineering, Vol. 11, no. 2, pp. 159-161, 2003.

[29] Morrison, J.H., Patrick, R.H, "Life and death of neurons in the aging brain", Science, Vol. 278, no.5337, pp. 412–419, 1997.

[30] Reza, F.-R, "P300-based speller brain-computer interface", Recent advances in biomedical engineering, In Tech, 2009. Available Online: https://www.intechopen.com/books/recent-advances-in-biomedical-engineering/p300-based-speller-brain-computer-interface