A Review on Analysis of EEG Signal

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Abstract

The electroencephalogram (EEG) popularly known as brain waves represents the electrical activity of the brain. The scalp EEG represents a combination of the multifarious activities of many small zones of the cortical surface beneath each electrode. The signal changes its characteristics in relation to mental tasks, external stimuli and physiological processes. By studying and analysing these change in characteristics and the pattern of electrical activity is useful for diagnosing a number of conditions that affect the brain. The conditions may be epilepsy, dementia, brain tumor etc. By analysing the EEG signal we can also categorise the brain signals generated by brain for different emotions like happy, sad, anger etc. Numerous research and techniques have been developed for processing, feature extraction and analysis of EEG signals. Each having their advantages and limitations. In this proposed paper various techniques and transformations that have been described in earlier literatures for processing and analysis of EEG signals is discussed.

Keywords: *EEG, brain waves, processing, feature extraction, analysis.*

1. Introduction

The electroencephalogram (EEG) is a recording of the electrical activity of the brain from scalp [11] .The waveforms recorded reflect the activity of the surface of the brain, the cortex. This activity from the brain structures underneath the cortex. The nerve cells in the brain produce signals that are called action potentials. These action potentials move from one cell to another across a gap called the synapse and special chemicals called neurotransmitters help the signals to move across the gap. Physiological control processes, thought processes and external stimuli generate signals in the corresponding parts of the brain that may be recorded at the scalp using surface electrodes [11]. The brain wave is extracted and the signal undergoes various processes like data acquisition, filtering, feature extraction and then analysis for analysing the signal in any of the aspect, as illustrated in figure 1 [12]. In data acquisition the recorded signals are converted in the form that can be further processed [12]. Any signal other than that of interest could be termed as noise. These are removed using filters. The EEG is a non-stationary signal the feature extraction from the filtered data is done either in time domain or in frequency domain [12]. Ones the feature is extracted the signals are studied and compared with the normal EEG signal. After undergoing the above processes the brain waves can be compared and detected in any of the perspective.

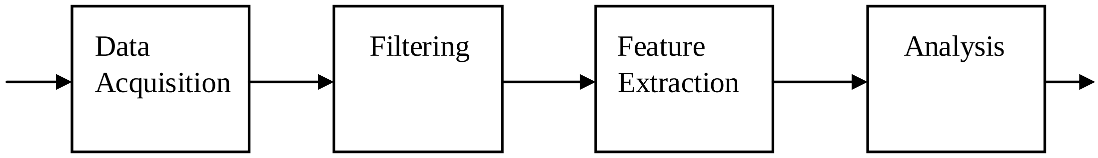

Fig 1: Steps in analysis of EEG signal

2. Literature Survey

The literature survey describes various methods for analysing the EEG signal. A brief description of various processes given by different authors is given below:

Dan Nie et al. (2011) authors aims at finding the relationship between EEG signals and human emotions. In this study EEG signals are used to classify two kinds of emotions, positive and negative. First, features from original EEG data was extracted and a linear dynamic system approach was used to smooth these features. At an average test 53% was obtained by using all of the features together with a support vector machine. Next, the dimension of features was reduced through correlation coefficients. The top 100 and top 50 subject-independent features were achieved, with average test accuracies of 89.22% and 84.94%, respectively. Finally, a manifold model was applied to find the trajectory of emotion changes.

Kwang-Eun ko et al. (2009) proposed an emotion recognition system for human brain signals using EEG signals.They measured EEG signals relating to emotion, divide them into five frequency ranges on the basis of power spectrum density, and eliminate low frequencies from 0 to 4 Hz to eliminate EEG artifacts. The resulting calculations of the frequency ranges are based on the percentage of the selected range relative to the total range. The calculated values are then compared to standard values from a Bayesian network, calculated from databases. Finally, we show the emotion results as a human face avatar.

Murugappan Murugappan et al. (2010) have summarised the human emotion recognition using different set of electroencephalogram (EEG) channels using discrete wavelet transform. An audio-visual induction based protocol has been designed with more dynamic emotional content for inducing discrete emotions (disgust, happy, surprise, fear and neutral). EEG signals are collected using 64 electrodes from 20 subjects and are placed over the entire scalp using International 10-10 system. The raw EEG signals are preprocessed using Surface Laplacian (SL) filtering method and decomposed into three different frequency bands (alpha, beta and gamma) using Discrete Wavelet Transform (DWT). The authors have used “db4” wavelet function for deriving a set of conventional and modified energy based features from the EEG signals for classifying emotions.

Panagiostic C. Pentrantonakis et al. (2010) in this paper, a novel emotion evocation and EEG-based feature extraction technique is presented. In particular, the mirror neuron system concept was adapted to efficiently foster emotion induction by the process of imitation. In addition, higher order crossings (HOC) analysis was employed for the feature extraction scheme and a robust classification method, namely HOC-emotion classifier (HOC-EC), was implemented testing four different classifiers [quadratic discriminant analysis (QDA), k-nearest neighbour, distance, and support vector machines (SVMs)], in order to accomplish efficient emotion recognition. Through a series of facial expression image projection, EEG data have been collected by 16 healthy subjects using only 3 EEG channels, namely Fp1, Fp2, and a bipolar channel of F3 and F4 positions according to 10–20 system. Two scenarios were examined using EEG data from a single-channel and from combined-channels, respectively. Compared with other feature extraction methods, HOC-E Cap pears to out perform them, achieving a 62.3% (using QDA) and 83.33% (using SVM) classification accuracy for the single-channel and combined-channel cases, respectively, differentiating among the six basic emotions i.e. happiness, surprise, anger, fear, disgust, and sadness.

Panagiotis C. Petrantonakis et al. (2011) the proposed paper which aims at providing method for evaluating the emotion elicitation procedures in an electroencephalogram (EEG)-based emotion recognition setup. By employing the frontal brain asymmetry theory, an index, namely asymmetry Index (AsI), is introduced, in order to evaluate this asymmetry. This is accomplished by a multidimensional directed information analysis between different EEG sites from the two opposite brain hemispheres. The proposed approach was applied to three-channel (Fp1, Fp2, and F3/F4 10/20 sites) EEG recordings drawn from 16 healthy right-handed subjects. For the evaluation of the efficiency of the AsI, an extensive classification process was conducted using two feature-vector extraction techniques and a SVM classifier for six different classification scenarios in the valence/arousal space. This resulted in classification results up to 62.58% for the user independent case and 94.40% for the user-dependent one,confirming the efficacy of AsI as an index for the emotion elicitation evaluation. The classification-based evaluation of the efficacy of the AsI resulted in promising results, which pave the way for more robust emotion elicitation processes. Signals with higher AsI values seem to demonstrate better classification attitudes in contrast to other with lower AsI values.

Saadat Nasehi and Hossein Pourghassen (2012) proposed in this paper, an optimal EEG-based emotion recognition algorithm based on spectral features and neural network classifiers is proposed. In this algorithm, spectral, spatial and temporal features are selected from the emotion-related EEG signals by applying Gabor functions and wavelet transform. Then neural network classifiers such as improved particle swarm optimization (IPSO) and probabilistic neural network (PNN) are developed to determine an optimal nonlinear decision boundary between the extracted features from the six basic emotions (happiness, surprise, anger, fear, disgust and sadness). The best result is obtained when Gabor-based features and PNN classifier are used. In this condition, our algorithm can achieve average accuracy of 64.78% that can be used in brain-computer interfaces systems.

Suwicha Jirayucharoensak et al. (2014) proposed a study which describes the utilization of a deep learning network (DLN) to discover unknown feature correlation between input signals that is crucial for the learning task. The DLN is implemented with a stacked auto encoder (SAE) using hierarchical feature learning approach. Input features of the network are power spectral densities of 32-channel EEG signals from 32 subjects. To alleviate over fitting problem, principal component analysis (PCA) is applied to extract the most important components of initial input features. Furthermore, covariate shift adaptation of the principal components is implemented to minimize the nonstationary effect of EEG signals. Experimental results show that the DLN is capable of classifying three different levels of valence and arousal with accuracy of 49.52% and 46.03%, respectively. Principal component based covariate shift adaptation enhances the respective classification accuracy by 5.55% and 6.53%. Moreover, DLN provides better performance compared to SVM and naïve Bayes classifiers.

You-Yun Lee and Shulan Hsieh (2014) proposed a study which aimed to classify different emotional states by means of EEG-based functional connectivity patterns. Forty young participants viewed film clips that evoked the following emotional states: neutral, positive, or negative. Three connectivity indices, including correlation, coherence, and phase synchronization, were used to estimate brain functional connectivity in EEG signals. Following each film clip, participants were asked to report on their subjective affect. The results indicated that the EEG-based functional connectivity change was significantly different among emotional states. Furthermore, the connectivity pattern was detected by pattern classification analysis using Quadratic Discriminant Analysis. The results indicated that the classification rate was better than chance.

Yuan Pin Lin et al. (2010) proposed a study which applied machine-learning algorithms to categorize EEG dynamics according to subject self-reported emotional states during music listening. A framework was proposed to optimize EEG-based emotion recognition by systematically firstly, by seeking emotion-specific EEG features and secondly by exploring the efficacy of the classifiers. Support vector machine was employed to classify four emotional states (joy, anger, sadness, and pleasure) and obtained an averaged classification accuracy of 82.29% ± 3.06% across 26 subjects. Further, this study identified 30 subject independent features that were most relevant to emotional processing across subjects and explored the feasibility of using fewer electrodes to characterize the EEG dynamics during music listening. The identified features were primarily derived from electrodes placed near the frontal and the parietal lobes, consistent with many of the findings in the literature. The results of this study showed a spectral power asymmetry across multiple frequency bands, was a sensitive metric for characterizing brain dynamics in response to emotional states.

Zirui Lan et al. (2014) the authors have studied the stability of features in emotion recognition algorithms. An experiment to induce 4 emotions such as pleasant, happy, frightened, and angry is designed and carried out in 8 consecutive days (two sessions per day) on 4 subjects to record EEG data. A real-time subject-dependent algorithm with the most stable features is proposed and implemented. The algorithm needs just one training for each subject. The training results can be used in real-time emotion recognition applications without re-training with the adequate accuracy. The proposed algorithm is integrated with a realtime application “Emotional Avatar”. In this paper, stability of different EEG features for realtime emotion recognition was analyzed A novel real-time emotion recognition algorithm was proposed based on the most stable features such as FD, 5 statistics features, 1st order HOC and 3 band power features and it was compared with the previous algorithms. The proposed algorithm is a subject dependent one which needs just one training for the subject. The training results can be used in real-time emotion recognition applications without re-training with the adequate accuracy.

3. Conclusion

Electroencephalogram (EEG) opens a window for exploring neural activity and brain functioning. Changes in brain electrical activity occur very quickly and extremely high time resolution is required to determine the precision at which these electrical events take place. By analyzing the EEG signal we can get the knowledge about the kind of signals generated in brain for different emotions, in case of brain injury or in case of any brain disease and compare it from the normal EEG signal. Today’s EEG technology can accurately detect brain activity at a resolution of a single millisecond. Careful analysis of the EEG records can provide valuable and improved understanding of the brain electrical mechanisms.

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References

4.1 Journal Article

1) Dan Nie, Xiao-Wei Wang, Li-Chen Shi and Bao-Liang Lu Senior member IEEE, "EEG based Emotion Recognition during watching movies", SaC1.1, Proceedings of the 5th International IEEE EMBS Conference on Neural Engineering, 978-1-4244-4141-9/11 (2011) IEEE.
2) Kwang-Eun Ko, Hyun-Chang Yang and Kwee-Bo sim, "Emotion Recognition using EEG signals with relative Power values and Baseyian Network", Springer, International Journal of Control, Automation and Systems (2009) 7(5):865-870.
3) Murugappan Murugappan, Nagarajan Ramachandran and Yaacob Sazali, "Classification of human emotion from EEG using discrete wavelet transform", JBiSE, Biomedical Science and Engineering, (2010) 3, 390-396.
4) Panagiotis C. Petrantonakis, Student Member, IEEE and Leontios J. Hadileontiadis member IEEE, "Emotion recognition from EEG using Higher Order Crossings", IEEE Transctions on Information Technology in Biomedicine, Vol-14, No.2, March (2010).
5) Panagiotis C. Petrantonakis, Student Member, IEEE and Leontios J. Hadileontiadis member IEEE, "Novel Emotion Elicitation Index using Frontal Brain Assymetry for enhanced EEG based emotion recognition ", IEEE Transctions on Information Technology in Biomedicine, Vol-15, No.5, September (2011).
6) Saadat Nasehi and Hossein Pourghassem, "An optimal EEG based emotion recognition algorithm using Gabor Features", WSEAS Transactions on Signal Processing, Issue 3, Volume 8, July (2012).
7) Suwicha Jirayucharoensak, Setha Pan-Ngum and Pasin Israsena, "EEG based emotion recognition using Deep Learning Network with Principle Component based Covriate Shift Adaptation", Hindawi, Hindawi Publiction Corporation The scientific World Journal, Volume 2014, Article Id 627892.
8) You-Yun Lee and Shulan Hsieh, " Classifying different emotional states by means of EEG based functional connectivity patterns" , PLOS ONE, Volume 9, Issue 4, April (2014).
9) Yuan-Pin Lin, Chi-Hong Wang, Tzyy-ping Jung, Senior member, IEEE, Tien-Lin Wu, Shyh-kang Jeng, Jeng-Ren Duann, member IEEE and Jyh-Horng Chen, member IEEE, "EEG based Emotion Recognition in Music listening", IEEE Transactions on Biomedical Engineering, Vol. 57, No.7, July (2010).
10) Zirui Lan, Olga Sourina and Lipo Wang, "Stability of features in Real time EEG based Emotion Recognition Algorithm", CPS, International Conference on Cyberworlds, 978-1-4799-4677-8/14, (2014) IEEE.

4.2 Books

11) Rangaraj M. Rangayyan, Biomedical Signal Analysis A Case Study Approach, First edition, Wiley Interscience.
12) D C Reddy, Biomedical Signal Processing principles and techniques, First edition The McGraw-Hill Companies.