Review on Emotion Recognition using EEG Signals

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Abstract: In this paper, emotion recognition using EEG signals has been reviewed. The methods applied, dataset used for simulation, the results obtained along with the limitations and future work/gap is summarised in this review paper. This paves a way for the upcoming researchers to focus on the problems to be solved and the methods to be proposed as a novel new method or could be an integration or hybrid of the existing techniques or algorithms, along with the dataset to be used.

Keywords: Emotion Recognition, EEG, Arousal, Valence.

1. INTRODUCTION:

Emotion is a state of affectiveness of all human beings that encompasses cognition as well as consciousness. It plays a very vital role in social, safety and cultural interactions of the humans. Hence, emotion recognition of humans has become a prominent research area focusing many applications such as computer science, neuroscience, artificial intelligence, cognitive science and psychology.

An EEG signals can be obtained from the human brain by contacting electrode to the scalp of the head which non-invasively capture the activity of electricity of brain unlike implanted electrode into the brain and other methods. Since the human responses can be linked to the cortical activities so the EEG can act as a source to classify the emotions. The emotion of a person can be recognized by analysing multiple electrodes at the same time, where when multiple electrodes are receiving the electricity signal spikes, then the bundling behaviour of human emotion can be modeled accordingly [1].

Human emotion is extremely complex where it is not only the psychological reaction toward the external world but also the physiological reactions towards the psychological reactions [2]. The emotion of human was categorised by different researchers into various discrete types and categories, and the most common and recognised emotion model is the valence-arousal scale by James A. Russell as shown in the Figure 1, which is a 2D model. The 4 prominent emotions can be divided by the quarters of the scale, where the rest of the emotions are between the quarters which is to be positive, negative or neutral [3]. The emotion categorise by the valence-arousal scale can be understand as a compass where the horizontal (east to west) dimension represent the pleasant to unpleasant or known as the negative to positive. On the other side the vertical (south to north) dimension is the sleep to arousal or the low to high activation. The emotion will be coordinated onto the valence-arousal scale based on the activation level and the pleasantness of the emotion [4].

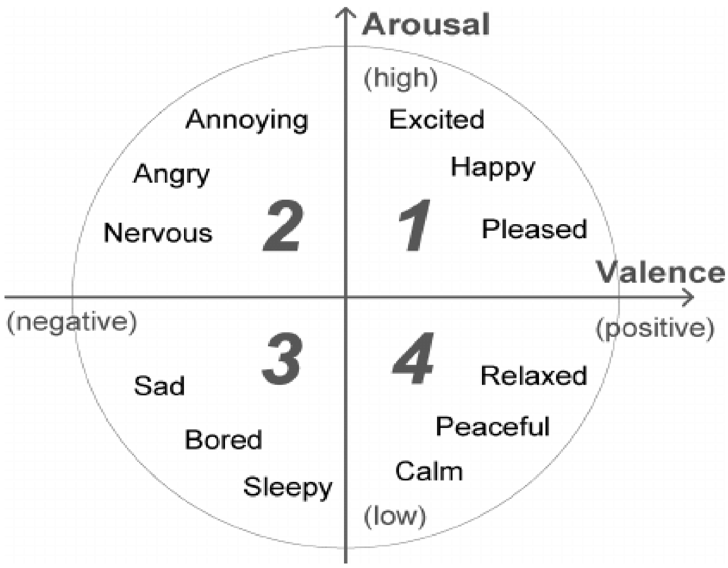

Figure 1: 2D Valance-arousal emotion space [4]

2. LITERATURE REVIEW

Researchers [5] proposed EEG based Emotion recognition using Deep Learning Network (DLN) with Principal Component Based Covariate Shift Adaptation (PCBCSA). In this research work, the DLN was used to explore the unknown feature correlation that exists between the inputs signals that is important for the learning task done. The DLN has been implemented with the help of a Stacked Auto Encoder (SAE) with hierarchical based feature approach. Thus, a stack of 3 autoencoders with two softmax layers were implemented and the emotion classification was estimated in terms of valence and arousal, one softmax layer for valence and another one for arousal. DLN performs a feedforward propagation, where the features derived from the first hidden layer of the feedforward propagation, will be used in order to perform the unsupervised pretraining in the 2nd hidden layer. Further, the algorithm computes the features in a similar way from the features learned from the other previous hidden layers. Next, network will be allowed to learn weights and bias parameters in both the softmax classifiers, fine tuning process will be done.

Subjects were allowed to watch a 40 one minute videos which are music oriented and the DEAP dataset was used. Thus, 32 subjects have been used for testing and the Power Spectral Densities (PSD) from the 32-channel EEG signals are given as the input features for the DLN. Next, Principal Component Analysis (PCA) is applied to the outcome of the DLN in order to extract the very important components of the input features. Further, PCBCSA is implemented in order to minimize the non-stationary effects of the EEG signals given as input. Here, PCA extracted the most 50 important features from the 230 input initial features fed. Then, these extracted features were given as input to the DLN with 50 hidden nodes in each of the layers.

Experimentally investigated results show that the DLN is good in classifying into 3 various levels of arousal and valence with utmost accuracy of 46.03% and 49.52%, respectively, while the PCBCSA has enhanced to obtain 6.53% and 5.55%, more as compared to DLN, respectively.

It is observed that there is a very strong relation between the autoencoder and PCA. One of the most important limitation of the DLN is the high computational time required, which is around 20-25 minutes on a laptop if i5 Core.

Researchers [6] faced challenges of accurately interpreting the thought of the subject or person, from the raw brain signals analysed, as these raw brain signals suffer from low fidelity and noise. Further, the pre-processing that is done usually as a first step is time consuming. Thus, the researchers have proposed Unified Deep Learning [UDL] that enables the Human-Thing Cognitive activity.

The proposed framework was intended to measure the one's brain activity using EEG, although the other methods to be used are FNIRS and MEG. The raw brain signals were sent through the internet to be stored in the cloud server, which uses the pretrained deep learning model and this model is person dependent which is used to analyse the raw signal. The analysed results were used to interpret to actuate various IoT applications such as smart home, smart city and smart hospital.

Here, a Selective Attention Mechanism (SAM) learning approach was used to explore the distinctive features of the given input brian signals. Also, proposed a Modified Long Short-Term Memory (MLSTM) which is used to differentiate the inter dimensional information as fed by the SAM. Finally, two case studies were done, one was brain typing system and the other was a cognitive robot. The cognitive robot was trained to take an IoT object from one room to another of a house. The desired object was associated with an RFID tag and thus, the robot grasps the object, then turns backs, further walks along the predefined or trained path to the destination with the house and puts back the object on to the place. A 100% simulation based result was achieved in performing this task. The robot controlling was done using the Robot Operating System (ROS) and one user's EEG raw data was used as the simulation input. Thus, this has paved way for other researchers to test and implement in real time.

Researcher's [7] used the EEG signals to undergo the bispectral analysis, where the phase information was obtained by the phase signal detection which gives the relationship between the frequency components and characterizes the non-Gaussian components. A Valence-Arousal model was used to derive the bispectrum quantification emotion features. A 2 channel EEG signal machine was used to collect the EEG signal and were preprocessed to remove any artifacts due to EOG and filtered using the Butterworth filter. The derived features of the bispectrum was obtained using Higher Order Spectral Analysis (HOSA) toolset of the MATLAB, which extracted into 3 frequency bands, namely, 4-8 Hz theta, 8-12 Hz alpha and 12-30 Hz beta.

The derived bispectrum features are the normalized bispectral entropy, normalized bispectral squared entropy, mean-magnitude of bispectrum, first order and second order spectral moment. Lastly the classification of the pre-defined emotional states was done using the LS-SVM Linear and RBF classifier, long with the Artiifical Neural Network (ANN) which included Error Back Propagation Network (EBPN). The emotion classification was done into Low/High Arousal and Low/High Valence and an accuracy of 64.84% and 61.17% was obtained. But this accuracy has been increased as compared to Kolestra et al [8] using the DEAP dataset achieved 62% and 57.6% only.

Thus, the accuracy percentages that are obtained by the researchers in this work are valid only for the offline emotion classification. So, there is a gap for future researchers to perform for online classification. Further, a higher accuracy can be obtained by combining the time frequency domain with the bisepctrum features from various channels along with the ensemble classifiers such as Adaboost, Random Forest, etc.

Researchers [9] identified the problems in the classification and recognition of EEG signals that the automatic recognition is usually restricted with small number of emotion classification. This is due to the issues in the signal features, noises, subject based issues and constraints with EEG. Researchers tried to overcome these by proposing a novel featured based recognition of emotion using BCI and EEG.

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Researchers [9] have proposed a system which used a wider sets of emotion recognition and included additional features while pre-processing and emotion classification recognition and is based on the dimensional model. The researcher achieved to improve the accuracy because of the proposed combination of the mutual information along with the feature selection and kernel classification methods.

Researchers [10] proposed human emotion recognition using a Hybrid Deep Neural Networks (HDNN), with the help of Electroencephalographic multidimensional features. The researchers have contributed in two steps, where in the first step spatial and temporal characteristics is integrated with the frequency domain of the EEG signals and mapped into a two dimensional image. With the help of these two dimensional images, a series of the EEG based multi-dimensional features were used to represent the image which in turn represents the EEG signal emotion variation. Secondly a HDNN was constructed by integrating DNN with LSTM Recurrent Neural Network (RNN) in order to identify the human emotional state. The researchers tested the proposed HDNN using DEAP data set, which included EEG signals from 32 subjects using a 32 channel EEG system. Each subject was taken around 40 trials with each of them lasted for 60s. The results proved that there is a significant improvement made in the accuracy achieving 75.21%.

The results obtained by the HDNN method was compared with some selected baseline methods, such as SVM, k-NN and Random Decision Forest (RDF). There were five features trained namely, power spectrum entropy, C0 complexity, PSD, correlation dimension and Lyapunov index. PCA was used to reduce feature dimensionality and all training was done using the MATLAB R2016a version. The test results showed that the average accuracy of emotion classification is 75.22%, 69.58%, 67.45%, 45.47% and 62.84% with CLRNN, CNN+RNN, SVM, RDF and k-NN, respectively. In literature, most of the researchers classified emotions generally into two as pleasant or unpleasant and Positive or negative, while some of them have classified into three such as pleasant, unpleasant and neutral. But in this study, researchers have classified into four types, such as HVLA, HVHA, LVHA and LVLA.

The proposed method was intended to be used in various fields such as mental related health care systems, entertainment behavior system relating to safety, social and cultural aspect. Thus, the emotional variations of any subject can be analysed.

Researchers [11] mentioned the current problems faced in emotion recognition, that the conventional methods do not consider the complementarity of the time domain, frequency domain and the time-frequency domain characteristics of the EEG signals and fail to capture the correlation between them. Researchers currently have proposed an integrated framework using DLN based on Deep Belief Networks-Glia Chains (DBN-GC). Here, DBN-GC is used to extract the intermediate features of the input raw EEG signals from various domains and by mining the inter-channel based correlated information using GCs. Finally, the time domain, frequency domain and time frequency domain characteristics which describe the high level features are fused by the Restricted Boltzmann Machine (RBM) in order to classify or recognize the emotion. DEAP dataset was used for testing and the EEG signal was recorded with 512 Hz frequency for sampling and then down sampled to 128 Hz and the filter used for pre-processing was a band-pass filter with cutoff frequency ranging from 4 to 45 Hz. The results averaged to have an accuracy of 76.83% and 75.92% of Valence and Arousal.

Researchers [12] proposed a new method to classify the emotions using CNN model based on the multimodal data. The performance classification was improved by integrating EEG and Galvanic Skin Response (GSR) signals, which are first preprocessed with the help of zero crossing rate. Here, DEAP dataset was used to test where data were collected from the 32 subjects with 1 minute for each with 40 selected various music videos. The system was recorded with 48 channels with 512 Hz of sampling frequency and downsampled at a rate of

128 Hz. The preprocessing is done using a Band Pass Filter (BPF) whose frequency ranges from 4 to 45 Hz. Emotions classified into four namely, HAHV, HALV, LALV and LAHV. First k-means was used to implement for comparison purpose with different values of k. So the preprocessed signal reflected the frequency and temporal based EEG characteristics. Then, GSR based preprocessing was done with the help of Short Time Zero Crossing Rate (STZCR). Finally GSR features was fused with the CNN to improve the accuracy rates. Training of CNN was done using Maximum Likelihood Estimation (MLE). The model proved to be over fitted beyond a certain number of 400 iterations. Thus, the proposed method achieved an accuracy of 73.4%.

Further research work can be carried in order to improve the concatenation of the convolution layers. Thus, the convolution layers need to be constructed for each of the data characteristic and thereby improving the classification performance.

Researchers [13] proposed an automatic emotion detection system in order to overcome the high level noise associated with the EEG signal when it is recorded. Further detection with the help of single feature is not sufficient to achieve a very good performance.

Hence, the researchers proposed a hybrid system, which combined the features of supervised and unsupervised learning network. A total of 14 various features was extracted. These features were re-ordered with the help of Maximum Relevance Minimum Redundancy (MRMR) to obtain the maximum relevance and minimum redundancy from each of the features. Finally, PCA is applied to reduce the dimensionality.

The researchers extracted five different types of features such as time, frequency, time-frequency domains, connectivity and multi electrode features and reduced using PCA. Final classification was done as HA, LA, HV, and LV. SVM was used as the classifier, although kNN, Naïve Bayes Classifier (NBC) and Random Forest (RF) were used in the literature. The proposed method achieved 74.3% and 77.2% classification accuracy for arousal and valence, respectively.

Researchers [14] proposed an EEG based emotion recognition usually done using CapsNet (Capsule Network). As the name implies, it is used to capture very special spatial characteristics of the analysed EEG signals that are neglected by the conventional or traditional methods. This method used the 10-20 international electrode position system in the scalp to extract the frequency and spatial characteristics, which are combined to form the Multiband Feature Matrix (MFM).

In this method, the PSD's extracted from one of the each frequency bands was normalized to a value that is between 0 and 1 and is in turn mapped into the four sub matrices that were combined to form the MFM. The capsule network was designed to consist of four major parts, the first component is the Rectified Linear Unit (RLU) which is used to detect the local features. The second component is the capsule primary, responsible for convolution process and used to feed the data to the capsules. The next component is the emotion capsule which recognizes the emotion part and includes the active routing process. The final component is the reconstruction of the 18x18 matrix which is the input to the system.

The outcome of this method indicated that the arousal and valence accuracy are 0.6628 and 0.6673 respectively. One of the major limitations of this proposed method was the matrix construction, which included more null values and this would increase the negativity during the accuracy classification.

3. CONCLUSION

Thus, it can be seen that many journal and conference papers have been reviewed for emotion recognition using EEG signals. Human emotion is a complicated signal analysis and the recognition of validation is always challenging in today's current day scenario. The current level methods, techniques used to recognise the emotion using EEG signals were reviewed. Different datasets used for testing were reviewed and based on the review, it must be noted that most of the researchers have used the DEAP dataset as a standard reference. Furthermore, the results obtained under the classification accuracy in terms of Arousal and Valence was validated for performance evaluation. Thus, this paper paves a way for the upcoming researchers to apply or integrate various exiting techniques to achieve an improved classification accuracy in near future.

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