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Improving Accuracy of Emotion Detection using Brain Waves and Adaptive Swarm Intelligence

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Abstract: In recent year, Authors had been attempting to find or detect the feeling of human by recorded brain signal for example, EEG (electroencephalogram) alerts. Because of the unnecessary degrees of unwanted signal from EEG recording, a solitary feature alone can't accomplish great execution. Distinct feature is key for automatic feeling identification. Right now, we present an AI based scheme utilizing various features extricated from EEG recordings. The plan joins these particular highlights in feature space utilizing both managed and unaided component choice procedures. To re-request the joined highlights to max-importance with the names and min-repetition of each feature by applying Maximum Relevance Minimum Redundancy (MRMR). The produced highlights are additionally diminished with principal component analysis(PCA) for removing essential segments. Test report will be generated to show that the proposed work should outperform the condition of-workmanship techniques utilizing similar settings in real time dataset.

Keywords : brain signal, electroencephalogram, emotion recognition, PSO.

I. INTRODUCTION

EEG is the technique of electrophysiological monitoring. This records the electrical movements of the brain. EEG is noninvasive with electrodes placed near the human scalp. Electrocortocography is a term in which invasive electrodes are been used. Clinically, the signal from the brain that is electrical signal[2]. This electrical activity going on in the scalp is recorded by the EEG headset. EEG headset is placed on the head of the human. The movement of the electrodes on the scalp. The different signal is recorded from the scalp of the human for emotion identification.

EEG may likewise be useful for diagnosing or treating the scatters like mind dysfunction cerebrum harm from head injury, mind tumor that can have an assortment of causes encephalopathy, rest issue, stroke. EEG can likewise be utilized in top to bottom consideration gadgets for cerebrum highlight.

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Many types of methods are their to study brain function exist, including (FMRI) functional magnetic resonance imaging, PET positron emission tomography, (MEG) magneto encephalography, NMR or MRS , (SPECT)single-photon emission computed tomography, (ECOG) electrocorticography and near infrared spectroscopy (NIRS). Notwithstanding the especially negative spatial affectability of EEG, it has two or three gifts over a portion of these methodologies:

1. Hardware costs is lower than that of many distinct methods [3].
2. EEG prevent constrained accessibility of technologists to give immediate care in over the top site hospitals[4].
3. EEG sensors can be utilized in more greater places than PET, fMRI, SPECAT, MEG or MRS as these techniques require bulky and unmoving gadget[4].
4. EEG is massively tolerant of issue movement, not like greatest different neuroimaging methods. System also exist for limiting, and in any event, taking out movement artifacts in EEG recorded data.
5. EEG takes to account higher see of responses to audio-related improvement, it is quiet.
6. EEG does no longer aggravate claustrophobia, unlike fMRI, PET, MRS, SPECT, and every so often MEG.
7. EEG does not contain exposure to excessive-depth (>1 tesla) magnetic fields, as in a number of the alternative techniques, specially MRI and MRS. These can reason a diffusion of unwanted issues with the data, and also restrict use of these techniques with members which have metal implants of their body [5], such as EEG does no longer contain publicity to radio ligands, in contrast to positron emission tomography.
8. ERP studies may be performed with rather easy paradigms, compared with IE block-design fMRI research.
9. Extremely uninvasive, in contrast to Electrocorticography, which clearly requires electrodes to be located on the floor of the brain.

In ordinary scalp EEG, Recordings is obtained by method for setting terminals at the scalp with a conductive gel or glue, generally in the wake of setting up the scalp place by utilizing light abrasion. Numerous structures generally use electrons, everything about is connected to an individual wire. Few system use caps or nets into which electrodes are implanted; this is particularly typical while high-thickness varieties of electrode are required.

II. RELATED WORK

For detecting emotion many authors has used different methods for analyzing different emotion states. Emotion states are of two type negative emotions and positive emotions.

Negative emotions includes stressed out, afraid, nervous, anger, sad, bored, tired out etc. Positive emotions includes alert, joy, excited, happy, relaxed, calm etc.

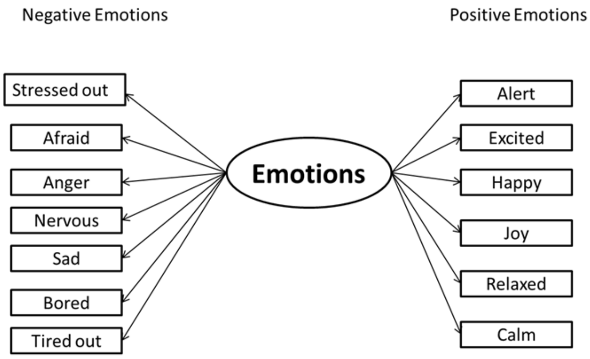

Fig. 1. Negative & Positive Emotions

Figure 1 show the diagram of positive and negative emotions of human being .Detection of this emotions can be obtained by using EEG signals. The choice of features is important in the study of emotion by machine learning. Authors has made utilize of many distinct features from EEG recordings. An ensemble learning calculation for consequently preparing the most discriminative subset of EEG channels for interior feeling acknowledgment[1]. Their strategy describe an EEG channel utilizing kernel based representations processed from the preparation EEG recordings. For ensemble learning and figure a chart inserting straight discriminant target work utilizing the kernel representations. Their target work is efficiently explained by sparse non-negative Principal Component Analysis (PCA) and the final classifier is picked up utilizing the sparse projection coefficients.

A regularized diagram neural system for feeling acknowledgment dependent on EEG signals was utilized by Peixiang Z. is biologically supported to catch both nearby and worldwide between channel relations. Furthermore, two regularizers, to be specific Node DAT and Emotion DL, to improve the robustness of our model against cross-subject EEG varieties and noisy labels. They assess their model in both subject-reliant and subject-independent classification settings on two open datasets SEED and SEED-IV and acquires preferable performance over a couple of serious baselines, for example, SVM, DBN, and BiDANN[7].

A fuzzy relational way to deal with human feeling acknowledgment from outward appearances and its control. The proposed plan uses over boost to energize specific sentiments in human subjects whose outward appearances are poor somewhere near partitioning and limiting the individual edges into districts of interest. Picked facial features, for example, illuminating, mouth opening, and the length of eyebrow narrowing are removed from the constrained zones, fuzzified, and mapped onto an inclination space by using Mamdani-type social models[8]. A plan for the approval of the framework parameters is likewise introduced and furthermore gives a fuzzy plan to controlling the progress of feeling elements toward an ideal state

A multimodal feeling acknowledgment frame work by joining outward appearance and EEG, in view of a valence-arousal passionate model. For outward appearance location, they followed an exchange learning approach for perform various tasks convolutional neural system (CNN) models to recognize the condition of valence and excitement. For EEG distinguishing proof, two learning targets (valence and energy) were perceived by different bolster vector machine (SVM) classifiers, independently[9]. Two decision level blend techniques reliant on the indicate weight rule or a flexible boosting methodology were used to combine outward appearance and EEG[9].

A deep learning structure dependent on a multiband feature matrix (MFM) & a capsule network (CapsNet) is proposed by Hao Chao. In the structure, the repeat space, spatial characteristics, and repeat band qualities of the multi-channel EEG signals are consolidated to build up the MFM[10]. At that point, the CapsNet model is acquainted with recognise feeling states as per the input MFM. Tests directed on the dataset for feeling analysis utilizing EEG, physiological, and video signals (DEAP) demonstrate that the proposed strategy outperform the majority of the basic models[10].

Hanieh Zamanian, Hassan Farsi[6] has done on feeling of human from electroencephalogram (EEG) signals. The framework infers an instrument of measurement of fundamental feelings utilizing. Up until now, a few techniques have been accounted for, which for the most part utilize distinctive grouping algorithms, developmental method, neural systems and handling algorithms. The point of paper is to build up a keen strategy to improve the exactness of feeling discovery by discrete sign handling strategies and applying advanced help vector machine classifier with hereditary transformative algorithm[6].

Table I: Feature Extraction method

Feature extraction method	Year	No. of classes	Accuracy(%)
Multiwavelet	2015	4	84.79
HOC, Statistical and fractal dimension	2014	4	80
Power of each frequency band, celebral asymmetry and coherence.	2013	3	66.3
Power Spectral Density	2012	3	52.2
Fractal Dimention	2010	4	81

Table II: Accuracy of different Algorithms

Authors	Year Publised	Classification Algorithm	Classification Accuracy
Bajaj & Pathori	2015	SVM	84.79
Zhang et al.	2016	SVM	69.67
Li and Lu	2009	LDA, KNN	83.79
Lin et al.	2010	SVM	82.29
Wang et al.	2011	SVM	66.50

The above tables show the accuracy of various algorithms used earlier.

To increase the accuracy of system, selection of method is very important to recognize the emotion of the person. PSO (Particle swarm optimization) uses global optimization, while SVM and other methods works on local matching.

III. METHODOLOGY

The existing work usually comes along with a lot of inefficiencies. Like kernel SVM requires a proper selection of kernel in order to perform accurate detection of emotions from the EEG sets. Thus, in order to tune the accuracy, we are planning to integrate an adaptive PSO based algorithm which will perform classification, and will learn from the outputs themselves in order to get the proper results of emotion classification. The problem identified by us is the issue of low accuracy given by the system, and how to improve it using the concept of particle swarm optimization, and its self-adaptive learning algorithm.

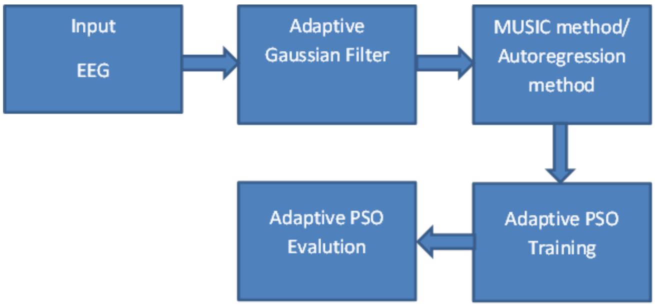

Fig. 2. Block Diagram of Emotion detection using PSO.

The following modules will be developed in our system,
1. Data collection module, in this module we will be collecting data from EEG headset for all kinds of emotions (happy, sad, neutral and excited).
2. Pre-processing using adaptive gaussian filter. The collected data will be pre-processed in order to obtain the noise free signals from the system.
3. Feature extraction: Once the signal is pre-processed, then with the help of wavelet and statistical features, the features will be extracted and the signals will be described as per requirement.
4. SVM and adaptive PSO for classification. The extracted features will be given for both training and evaluation purposes in order to obtain the final result.

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IV. RESULT AND DISCUSSION

We have compared the accuracy of the system used earlier for the identification of brain wave. We are using partial swarm optimization technique for improving the accuracy of the system and due to use of Adaptive filter the noise will be reduce.

V. CONCLUSION

The proposed system will have improved accuracy for classification because of high level feature extraction. The classifier will be trained with the most useful features for obtaining high accuracy. We represented channels using adaptive particle swarm optimization technique.

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