

Happy Emotion Classification based on EEG analysis

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Abstract—Emotion classification is one of the trending topic since a famous psychologist Plato, Aristotle and so on. Earlier it was a topic of interest in the field of psychology. Gradually, entered the field of Medical Sciences and now in Engineering domain. There are several methods through which emotion has been tried to classify, for example using gesture analysis, facial expressions, speech analysis and so on. This paper is one such an attempt to analyze the captured EEG signals by extracting the features of signals from the subject under expert supervision.

Keywords—EEG Analysis; Emotion; Emotion classification; k Nearest Neighbour;

I. INTRODUCTION

Human brain activity is used for calculating EEG signals and recognizing emotion, these signals are taken from the scalp of the brain. Kernel Density Estimation (KDE) is used for capturing features from EEG signals and classified via the artificial neural network classifier to recognize emotional condition of the subject under test. Proposed modified KDE gives better results in terms of accuracy, it also gives better estimation of the emotion of the subject from streaming EEG data by using the concept of cluster kernels [7]. Phase information is gained by detecting phase relationship between frequency components which is offered by bispectral analysis and it also offers characterizing the non-Gaussian information contained in the EEG signals [8]. EEG-based effective computing is a new research field that aims to find neural correlates between human emotions and the registered EEG signals. Typically, the discrimination models are subject-dependent. Due to the high EEG variability between individuals, building subject-independent models is harder problem. A proposal of unified system for efficient discrimination of positive and negative emotions. The users were exposed to high arousal affective images and the recorded brain signals differentiated according to their positive and negative valence. Major challenge in building subject independent affective models is to identify the most discriminative features between subjects. Spatial and temporal features are extracted from the EEG signals. The feature selection strategies explored are consistent in selecting parietal and occipital channels and late waves as better encoder of the emotion valence state and less variable across subjects [9]. Classification system is introduced based on Multilayer Extreme Learning machine to improve the accuracy. ML-ELM is used to classify and the combination of PCA and LDA is chosen as the method of feature extraction, in this system. The ML-ELM as not only the advantage which ELM as but also better performance than ELM [10].

II. REVIEW OF LITERATURE

In recent technology automatic emotion recognition is an interdisciplinary research field that deals with algorithmic detection of human affect such as anger, sadness from a variety of sources. Here evaluation of human emotion is often done using oral feedback or questionnaires during doctor-patient sessions. The affect state of a person can be evaluated in a continuous non-intrusive manner using automatic emotion detection. Author provides a way of detecting emotion from brain waves, i.e, EEG data, which features, EEG channel location and frequency bands are best suited for is an issue of ongoing research [1]. Author explains recognition of emotions by hidden Markov models using image of a human face. There are two methods in hidden Markov models, based on determination of the maximum of the likelihood functions and based on multi-level hidden Markov Models [2]. It presents an analysis of the possibility of recognizing speaker's emotions from speech signal in polish language. The most important step was to determine which of the previously extracted features were the most suitable to distinguish emotions and with what accuracy emotion could be classified. Two feature selection methods –sequential forward search (SFS) and t-statistics were examined. Emotion classification was implemented using k-nearest neighbor, linear discriminate analysis (LDA) and support vector machine (SVM) classifiers [3].

Sleep analysis primarily depend on EEG waveform features assessed in concert with eye movements, respiration and muscle tone. “Complexity domain” approach based on Multiscale Entropy(MSE) analysis of EEG signals and to that based on ECG-derived CPC. Author observed that progressive decrease arousability as measured by both conventional sleep scoring and CPC analysis. It supports that stage 2 non REM sleep has distinct sub-phases, that map to CPC high and low frequency coupled

dynamics [4]. The author tried to develop an automatic system for identification of drowsiness level of driver which leads to the major accidents in the traffic. The EEG signals help to know the various changes in the characteristics of a person. By using these signals the various bands are to be analyzed. There are mainly six EEG pulses like delta, theta, alpha, mu, beta and gamma, but alpha and beta are the best particular pulses in the drowsiness state inspection. The Fast Fourier Transform method is used to check the signals features like arousal, valence and dominance. By these signals we can create the fuzzy rules to determine drowsiness level [5]. A system for the neuro-motor rehabilitation of limbs was validation in three-sub-acute post-stroke patients. The system allows cortical and kinematics measures by integrating high-resolution EEG, passive robotic device and virtual reality. Here the patients underwent 13 rehabilitation sessions and all patients showed increased participation in the process. The proposed system is suitable to monitor the Neuro-motor functional recovery of post-stroke patients. At the end of session the patient able to perform or take care of himself [6].

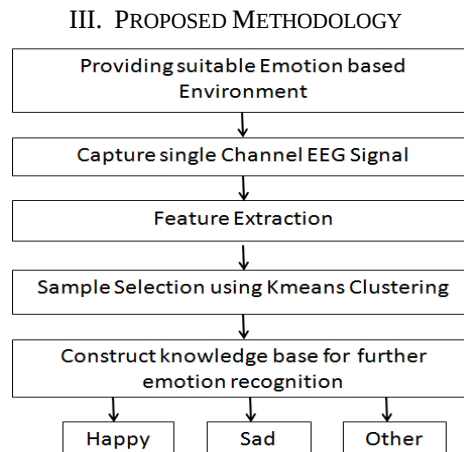


Figure1: Methodology for the phase 1 as Emotion dataset construction using EEG Analysis

Phase 1: Construction of Knowledge Base

A. Providing suitable Emotion based Environment:

Normally when we try to capture the signal from the person, the person mood may change rapidly. So creating the suitable environment to capture the brain signals makes easy and the person mood may remain constant. This could be better if the environment is happier while recording signals concerned to happy emotion class. It would also be better if the environment is sad while recording signals concerned to sad emotion class. It is true that these two feelings are mutually exclusive and cannot feel one way while feeling the other, that is a big reason to learn towards being happier more of the time. It can be nearly impossible to go from angry to happy, so we are just looking for the thought that eases you out of our angry feeling and moves we in the direction of happiness. It may take a while, but as long as we are headed in a more positive direction we will be doing yourself a world of good.

B. Capture single channel EEG signal:

MindWave Mobile Headset is used to capture single channel EEG signal. The headset should rest on the **head as shown with the sensor tip** touching the forehead, the ear loop behind the ear and the clip attached as shown in Figure 2. To operate the Mindwave with our computer system we need to achieve Bluetooth pairing with the device first and also get a good EEG signal with the Mindwave. If our device is properly paired and there is a fresh battery in the headset then MindWave starts sending signals to system.



Figure 2: Neurosky MindWave device mounted on head (Courtesy: Neurosky.com)

C. Feature Extraction:

Feature emphasizes the behavior and characteristics of the sample and its identity. These characteristics help us to differentiate or clusterize the samples or subjects depending upon the variance accounted. In this concerned, this proposal considers maximum & minimum amplitude, variance or standard deviation of each signal samples as features.

Variance: The difference between an expected and actual result. **Standard deviation:** A quantity expressing by how much the members of a group differ from the mean value for the group. **Minimum and Maximum Amplitude:** The amplitude of a periodic variable is a measure of its change over a single period.

D. Sample selection using kmeans clustering

The Algorithm 1 estimates the required collection of samples for the corresponding emotion.

1. Apply *kmeans* on the samples by considering $k = 2$
2. Count the samples of the clusters $v1$ (cluster1) and $v2$ (cluster2).
3. If $v1 > v2$ then
 Retain Cluster1 and discard Cluster2
 Else
 Retain Cluster2 and discard Cluster1
4. Repeat the steps from 1 to 2 for n (n depends on the similarity of the samples based on smaller distances) number of times

Algorithm 1: Valid sample selection for a particular emotion

E. Construct knowledge base for further emotion recognition

Several types of knowledge base construction models are available in the literature namely ANN, K-means, probabilistic models and so on. This proposal involves K-means algorithm to cluster collected features. This knowledge base may try to classify the sampled signals into happy, or other emotions.

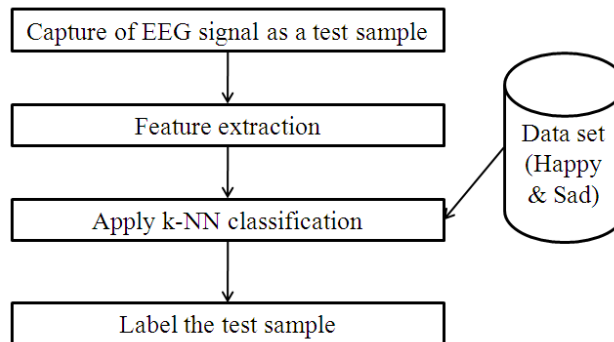


Figure 3: Testing phase of emotion classification

Phase 2: Classification of Test sample

Figure 3 depicting the test phase of the emotion classification. Similar steps are followed till the feature extraction of the test sample when compared to the phase 1. Later the features of test sample are merged with the data set constructed in the phase 1 for happy or other emotions. Apply k-NN classification technique to label the test sample either as happy or other.

IV. RESULTS AND DISCUSSIONS

Table 1 has listed around hundred samples of around ten subjects (10 sample signals from each subject) along with their features.

Table 1: Centroids at each iterations of data set construction process

Slno	Max Amplitude	Min Amplitude	Variance
1	0.12	0.025	0.23
2	0.22	0.03	0.24
3	0.3	0.031	0.34
4	0.32	0.023	0.146
5	0.4	0.086	0.32
...	...	...	...
95	0.567	0.123	0.844
96	0.999	0.843	0.7373
97	0.5423	0.768	0.818
98	0.888	0.312	0.719
99	0.648	0.622	0.4822
100	0.748	0.654	0.549



Figure 4: Distance between centroids vs iterations

Table 2: Centroids at each iterations of data set construction process

Iteration no	Range	centroid	max amplitude	min amplitude	Variance	Distance
1	1-100	centroid 1	0.506303	0.0843628	0.57843	0.7112
		centroid 2	0.664382	0.7712	0.67401	
2	1-74	centroid 1	0.321456	0.0645534	0.44581	0.3789
		centroid 2	0.631795	0.0892454	0.66202	
3	1-44	centroid 1	0.757712	0.0940666	0.50710	0.2618
		centroid 2	0.516820	0.0848443	0.80348	
4	1-23	centroid 1	0.5196	0.06212	0.73171	0.1504
		centroid 2	0.520083	0.1054333	0.87575	

Clustering of data is a method by which large sets of data are grouped into clusters of smaller sets of similar data.

It is a type of unsupervised learning, which is used when unlabeled data is considered for classification (that is data without defined categories or groups). The goal of this algorithm is to find groups in the data, with the number of groups represented by the variable K. The algorithm works iteratively to assign each data point to one of the K groups based on the features that are provided. Data points are clustered based on feature similarity. The results of the K-means clustering algorithm are:

1. The centroids of the k clusters, which can be used to label new data.
2. Labels for the training data (each data point is assigned to a single cluster) rather than defining groups before looking at the data.

The K-means Clustering method starts with K initial Clusters as specified. At each iteration, records are assigned to the cluster with the closest centroid. At the end of each iteration, distance between centroids of two clusters is estimated. The same is compared with the previous distances and decide to terminate the process of clustering. Finally the cluster with the higher variance is kept as a data set for further classifications.

Consider the test sample whose features Max amplitude, Min amplitude and variance as 0.515, 0.176 and 0.792 respectively. K Nearest Neighbor is applied on the Table 2 including the test sample. Resulted as follows

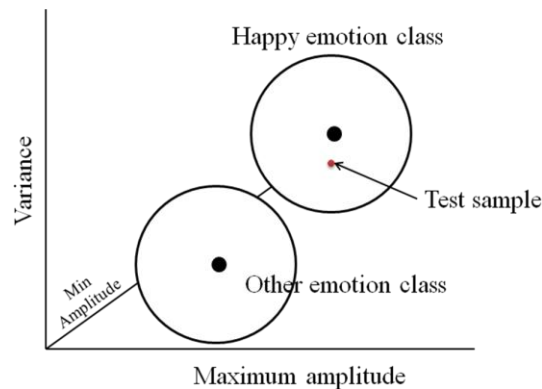


Figure 5: test sample classified as happy emotion

Figure 4 is clearly shows that the classification of the data set along with the mentioned test sample using k-NN classifier and test sample is classified as happy emotion class.

V. CONCLUSION

This paper has tried to analyze the captured EEG signal samples from around ten subjects and introduced a new and a robust algorithm for knowledge base construction. Also it has shown the classification of the test sample using constructed knowledge base. This is an attempt using certain features of a signal like minimum amplitude, maximum amplitude and a variance. It has tried with four test samples, here around 3 samples were tested successfully out of 4 samples. Hence the success rate is almost around 70 to 80% of the classification. Further efficiency can be met, when more number of samples are added to the data set.

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