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EEG Based Emotional Distress Analysis – A Survey

Prof. Shamla Mantri[1],Vipul Patil[2], Rachana Mitkar[3]
[1,2,3]*MIT College Of Engineering, Dept. Of Computer Engg., Pune 411038.*

Abstract—*This paper presents a novel approach for mental stress detection using EEG signal. Recently various research and techniques have been developed for analyzing the EEG signal. According to previously proposed papers, EEG signals were captured from the scalp of the brain and measured in responds to various stimuli. The collected data was then used to extract a set of features using various techniques such as PCA and ICA. For classifying "stressed" and "relaxed" states SVM, K-Means algorithms have been studied. Results have shown the potential of using EEG signal to visualize different levels of stress. This paper discusses the techniques and transformations proposed earlier in literature for extracting feature from an EEG signal and classifying them.*

Keywords—*Electroencephalogram (EEG), Principal Component Analysis (PCA), Independent Component Analysis (ICA), Support Vector Machine (SVM), K-means Algorithm.*

I. INTRODUCTION

In today's world, stress is an unavoidable ogre. In every field, stress is related to human work in one way or the other.Signs of stress include being easily irritated by things over which you have no control, such as feeling frustrated or helpless because of not being able to keep up with the pace of life. Scientists consider human brain as the main source of stress [2]. And therefore, brain signal, EEG, is captured in order to detect stress and analyze it.There are two major types of stress, Acute and Chronic. Acute stress is the most common of the types of stress. It comes on quickly and is usually short-lived. It is the most intense stress. Chronic stress is the type of stress that arises out of long-lasting events and circumstances beyond your control. The hardest part of chronic stress is that people just get used to it.Electroencephalograph (EEG) signal can be used in order to detect whether the person is in stressed or relaxed state. EEG is generated from central nervous system. Electroencephalography is a method used in measuring the electrical activity of the brain from cerebral cortex. This activity is generated by neurons. There are two methods to capture EEG signal, invasive and non-invasive. Using EEG, the summed activity of nerve cells in the brain can be recorded using electrodes attached temporarily to the scalp surface. Recordings can therefore be both cost-effective and with no risk of side effects.The steps for stress analysis using EEG signal are as shown in Fig. 1:

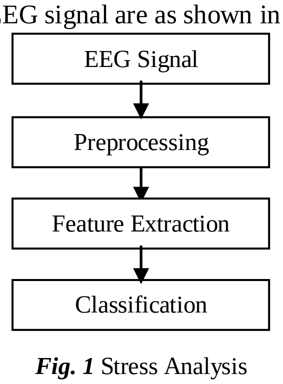

Fig. 1 Stress Analysis

A. EEG Signal Acquisition

First EEG signal will be collected using the 10/20 internationally recognized placement system. This system is based on the relationship of various position of electrode placed on scalp and the underlying area of cerebral cortex [4].

B. Preprocessing

In the case of EEG signal preprocessing it is necessary to filter out the 50Hz noise and also it is desirable to filter frequencies bellow 1Hz and above 60Hz, that does not contain any important information [5].

C. Feature Extraction

Feature extraction is used for representing and classifying different patterns of brain activity. In this phase, techniques such as ICA (Independent Component Analysis) and PCA (Principal Component Analysis) are used [6].

D. Classification

The features extracted are further classified into different classes. Classification process will be performed to show whether the person is in stress or relaxed mode for which we can use SVM (Support Vector Machine) and K-means algorithm.

II. LITERATURE REVIEW

The electrodes are placed on the scalp by an EEG technician. This system uses four anatomical landmarks from which measurements can be made. The names of the electrode sites use alphabetical abbreviations that identify the lobe or area of the brain to which each electrode refers:
F = frontal
Fp = frontopolar
T = temporal
C = central
P = parietal
O = occipital
A = auricular (ear electrode).

Whenever a neuron is active, its voltage changes. Million of neurons fire together. Each mental state produces a distinct pattern of electrical activity. Here, we identify areas of the brain that match with different thought processes or behaviors [7].

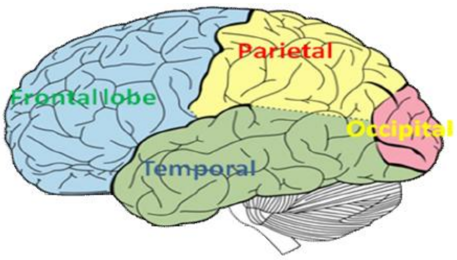

Fig. 2 Brain Partition

- The right hemisphere is responsible for negative emotions (disgust, fear, stress)
- The left hemisphere is responsible for positive emotions (Happiness, joy)

EEG power decreases during sadness and increases during happiness (frontal lobe). The region that shows the difference between sadness and happiness is the frontal pole with left CBF being higher during sadness and lower during happiness.

In order to use EEG signals, they used a band pass filter to remove both technical and physiological artifacts. In order to stimulate the emotion of interest, the user is seated in front of a computer and is viewed an image to inform him/her which type of emotion she has to think of. The signals from 64 different channels that cover the whole scalp are captured. The reason why 64 channels are used is to capture signals in all the rhythmic activity of the brain neurons. As for feature extraction, they simply transformed the signal into the frequency domain and use the power spectral as the EEG features [7].

Table I: **EEG Rhythms**

Rhythm	**Frequency Range**	**Location**	**Reason**
Delta	(0-4)Hz	Frontal Lobe	Deep Sleep
Theta	(4-7)Hz	Midline, temporal	Drowsiness and meditation
Alpha	(8-13)Hz	Frontal, Occipital	Relaxing, closed eyes
Mu	(8-12)Hz	Central	Contralateral Motor acts
Beta	(13-30)Hz	Frontal, Central	Concentration and thinking
Gamma	(30-100+)Hz		Cognitive functions

III. FEATURE EXTRACTION

For feature extraction we will study PCAand ICA techniques.

A. PCA (Principal Component Analysis)

PCA is a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension. There are few mathematical concepts those are used in PCA [9]. Those are as follows:

1) Statistics.
2) Standard deviation.

$$\mathrm{X} = \frac{\sum_{i=1}^{n} \mathrm{Xi}}{n}$$

The symbol X (said "X bar") to indicate the mean of the set X.

$$s = \sqrt{\frac{\sum_{i=1}^{n}(X_i - X)^2}{(n-1)}}$$

Now, 's' is the standard deviation.

3) Variance

$$s^2 = \frac{\sum_{i=1}^{n}(X_i - X)^2}{(n-1)}$$

4) Covariance

$$\mathrm{cov}(X, Y) = \frac{\sum_{i=1}^{n}(X_i - X)(Y_i - Y)}{(n-1)}$$

5) Covariance Matrix

$$C^{n\times n} = (c_{i,j}, c_{i,j} = \mathrm{cov}(\mathrm{Dim}_i, \mathrm{Dim}_j))$$

So, the 3 dimensional matrix is: $C = \begin{pmatrix} \mathrm{cov}(x,x) & \mathrm{cov}(x,y) & \mathrm{cov}(x,z) \\ \mathrm{cov}(y,x) & \mathrm{cov}(y,y) & \mathrm{cov}(y,z) \\ \mathrm{cov}(z,x) & \mathrm{cov}(z,y) & \mathrm{cov}(z,z) \end{pmatrix}$

6) Matrix Algebra
7) Eigen vectors
8) Eigen values

Steps to be carried out for Principle component analysis are as follows [10]:

1) Collect data.
2) Subtract the mean.
3) Calculate the covariance matrix.
4) Calculate the Eigenvectors and Eigen values of the covariance matrix.
5) Choose the correct generated components and generate new feature vector.
6) Plot these values with the eigenvectors of covariance matrix on top.
7) Derive a new data using: Final data=Row feature vector × Row Data Adjust.
8) Plot new data.

B. ICA (Independent Component Analysis)

ICA is a feature extraction method that transforms random multivariate signal into a signal having components that are independent of each other. ICA based artifacts correction can separate and remove a wide variety of artifacts from EEG data. This independence denotes the information carried by one component cannot be inferred from the others. Independent components can be extracted from the mixed signals by using this method [12].

Suppose there are c independent scalar source signals $x_i(t)$ for $i = 1, \ldots, c$. For convenience we group the c values at an instant into a vector $x(t)$ and assume that the vector has zero mean. Because of our independence assumption, and an assumption of no noise, the multivariate density function can be written as follows [11].

$$p\big(x(t)\big) = \prod_{i=1}^{c} p\big(x_i(t)\big)$$

IV. CLASSIFICATION TECHNIQUES

For classification we will study Support Vector Machine and K-means Algorithm.

A. SVM (Support Vector Machine)

The Support Vector Machine is a very effective selective classifier which maps the input onto a dimensional space and then finds an optimal plane to separate the data in that space. This new space is more commonly known as feature space. SVM seeks to maximize the margin between the two classes by finding the separating plane which lies halfway between the data classes. When the information is modified by some non-linear transformation, they 'spread out' allowing a separating plane to be found in the feature space. In general the SVM is computed by using the kernel trick [13].

$$f(x) = \sum_{i=1}^{N} a_i y_i K(s_i, x) = b$$

where K is some kernel function, such as, $K(x_i, x_j) = \Phi(x_i).\Phi(x_j)$

What makes SVM different is its strong foundation on statistical learning theory which establishes a bound on the generalization error (the error rate of a learning machine on unseen data) thus improving the classification results for unseen patterns. Maximization of margin is used to minimize this bound.

SVM, however, comes with its share of limitations. Determining the most appropriate choice of kernel for a particular task can be very tough. SVM is mainly designed for binary classification which can limit its applicability to multi-class classification. Although effective, the process of classification using SVM can be very slow especially as the size of the data increases. This is limitation applies to both the training and test phases [14]. In the past, authors have suggested that there might be a possibility for limiting the computational load of SVM by reducing the data dimensionality which would decrease the number of computations that have to be performed within the SVM.

B. K-means Algorithm

K-means is a simple algorithm to classify or to group various objects based on their features or attributes in K number of groups. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters [16]. The main idea is to define k centroids, one for each cluster. The objective function is,

$$\mathrm{J} = \sum_{j=1}^{k} \sum_{i=1}^{x} \| \mathrm{X}_i^{(j)} - \mathrm{C}_j \|^2$$

where $\| \mathrm{X}_i^{(j)} - \mathrm{C}_j \|^2$ is a chosen distance measure between a data point $\mathrm{X}_i^{(j)}$ and the cluster centre C_j, is an indicator of the distance of the *n* data points from their respective cluster centers [17]. Flowchart for K-means algorithm is shown in Fig. 4 [15].

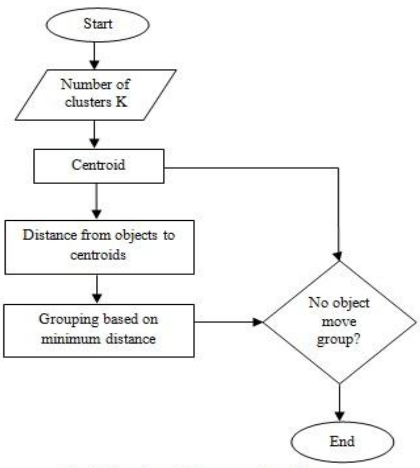

Fig. 3 Flowchart for K-means Algorithm

V. CONCLUSION

The study of EEG has been comprehensively used for detection of stress levels. Feature extraction and classification techniques of EEG signals have been suggested earlier in literature by many researchers. This paper provides a review of the most efficient techniques developed in the past. The efficiency of a technique can be judged upon its level of accuracy and the speed at which the features are extracted and classified. The future work mainly concentrates on developing an even more efficient algorithm that can be used for various diagnostic activities to reveal stress levels. The diagnosed conditions can then be acted upon appropriately and at the earliest stage. Therefore, the future work has scope for improvement in identifying and acting upon the revealed stressed condition.

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