Mental Stress Detection in Humans Using EEG Signals

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***Abstract* --- The paper presents an experiment conducted to analyse a human subject for detecting their state of mind for any possible signs of mental stress. Electroencephalogram signals (EEG) were used in the experiment. The stress was induced in the subject via visual stimuli; images in International Affective Picture System (IAPS) dataset maintained and owned by "The center for the study of emotion and attention" -University of Florida were used. The main focus of this experiment is whether the subject is in stress or not rather than the cause of their stress.**

Stress being a very subjective to an individual we don't try to label different level of stress in scope of this experiment.

In process of this experiment to classify a clam state of mind from stressed state of mind numerous Machine learning algorithms were used at various stages of the experiment to analyse and classify the signals; Independent component analysis - lifting wavelet transform (ICA-LWT) were used for artifact removal. Discrete wavelets transform (DWT) and Principle component analysis (PCA) were used for feature generation and feature reduction respectively. The actual classification was done using two classifiers; Support Vector machines and Neural Network.

***Index Terms*--EEG (Electroencephalography), Support Vector Machine, Machine Learning, Neural Networks, Classification.**

I. INTRODUCTION

Stress and emotions are very complex phenomena's and they play an important role in the quality of a life of an individual. Scientists studied brain to analyse stress over many years [2] and therefore, EEG signals is the best way to study stress and as it can be rightfully said all the biological signals originate from brain so does stress. Some other signals have also been used to study stress in human subjects namely; Electrocardiogram (ECG), Skin Conductance etc. All been said stress is also very subjective in nature i.e. a situation which can put a person in stress may not necessarily have a similar effect on a third person. That's why analysing a subject to detect their state of mind is inherently a challenging task. The paper mainly focuses on offline implementation and creating a model for determining the mental state of the subject in terms of whether they are stressed or not and doesn't try to find causes of stress nor does it try to label the levels of stress. The paper discusses various prepressing, feature extractions and classification techniques used in the process.

The remainder of paper is arranged in the following sections- section II. Discussed the previous work in this field. Section III goes over the experiment setup and procedure. Section IV is analysis of the signal i.e. pre-processing, feature extraction techniques, and classification methods. Section V discusses the results obtained and future work to be done.

II. RELATED WORK

A lot of work has been undertaken in assessment of stress and emotions over past decade. Most researchers working in domain of stress analysis and cognitive science have used EEG signals, ECG signals or combinations of others signals like respiration rate, skin conductance as peripheral signals to conclude the state of human brain, author in [1] used Visual stimuli to conduct their experiment on 15 healthy subjects and collected EEG signals along with their Respiration rate, skin conductance, blood volume pulse, heart rate variability during the experiment and used these signals along with EEG to classify the subjects into clam or stresses states and obtained an accuracy of 78% using SVM and ENN. The researchers in [3] used EEG power spectrum and spectral centroids techniques to extract unique features for human stress. Similarly researchers in [4] used music and story as stimuli on 50 participants, to introduce a user independent system for emotions recognition using SVM as pattern classifier, the results showed close to 80% classifying accuracy of stress emotion. In [5] and [6] researchers used physiological sensors to detect metal stress, i.e. they collected ECG and galvanic skin response(GSR) and accelerometer data while participants performed 3 activities sitting standing and walking and compared to these when they were subjected to mental stressors and were able to achieve an accuracy of 92.4 % of mental stress classification.

In our experiment we used images to induce stress, papers [8] [9] [10] tries to discuss the cognitive model of emotional stress and different regions of the brain which show observable behaviour in stressed conditions. The studies also tried to explain how fear conditioning leads to emotional stress, result from these studies were used while selecting the electrodes placement in our experiment.

III. EXPERIMENT SETUP AND DATA COLLECTION

Collecting reliable and consistent data is very important in these kinds of studies and getting the right data depends on how what kind of procedure you follow. In this experiment we use Rapid serial visual presentation as the basis for our data collection process. The entire process and the steps involved are described below.

A. Stimuli

Labelled images (calm-neutral and negatively excited) form the IAPS database were used in the experiment. The Subject was showed these images using Psychophysics Toolbox – (*a* set of MATLAB and GNU Octave functions for vision research)

B. Experiment Setup

The experiment was conducted in an academic lab setup. The electrode placement for the experiment was in accordance with the 10-20 International standards [7]; Figure1 shows the 10-20 system of EEG electrode placement in our experiment signals from 5 electrodes at FP1, FP2, T3, T4 and Pz positions were recoded. The average of signals from the participants earlobe (A1 and A2) (Figure 1) was used a reference signal as these signals free from any brain activity. Conductive gel was used to keep the impedance below 5kΩ. The signals were collected at a sampling rate of 256Hz.

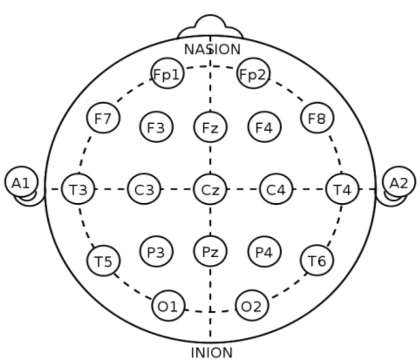


Fig.1: 10-20 Electrode placement system [15]

C. Procedure

Once the initial step was over, the subject were shown emotion specific images on the computer screen using Psychophysics Toolbox and were asked to analyse what they see. The experiment consisted of 8 trails for each emotion (clam and stressed) and each trial consisted of 8 images shown for 3 seconds each making the total time per block to be 12 seconds. Prior to displaying the images sequence, a dark screen for 5 seconds followed by an asterisk in the center of the screen for 3 seconds was shown to separate each trail and to attract the participant's attention respectively. The trail ended with a white screen for 10 seconds to capture the post stimuli emotion of the subject. The breakup for a specific trail is shown in Figure 2.

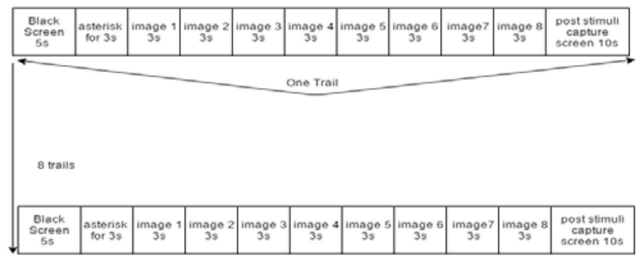


Fig.2 Timeline breakup of each trail.

IV. ANALYSIS OF EEG SIGNALS

Before applying the signal for classification there a various steps that needs to be taken to condition the signal for good and reliable classification. The section below describes each step in the process in detail.

A. Pre-processing

EEG signals are bound to be contaminated noise which may be due to eye blinks, muscle moments, power line noise etc. So before analysing the signal for feature basic pre-processing was done to get rid of the mentioned noise/ aritifacts in the signal.

The data collected was filtered using a band pass filter in the frequency band of 0.5 to 64 Hz. Although the prominent EEG signals characteristics are observed in the frequency range 0.5-30 Hz the 0.5-64Hz band was considered keeping in mind that if required in later stage of the experiment, Higher order spectrum analysis of the signal might be helpful in the feature extraction and to analyse the signal in higher order spectrum we would need double the frequency content of the signal. MATALB filtfilt function which is a part of MATALB signal processing toolbox was used for filtering the signal [16]. In addition to the band pass filter a notch filter at 60 Hz was applied to discard the effect of power line noise. After filtering the obtained data was zero meaned to reduce loses due to DC components. Figure 3 shows the filtered and zero mean output. After the initial filtering and zero meaning of the data it was applied to the artifact removal scheme shown in Figure4.

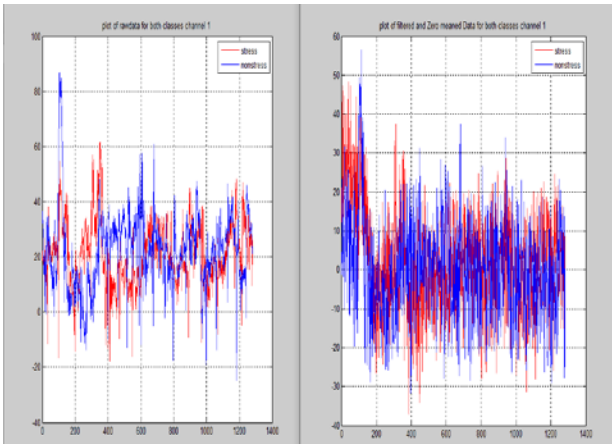


Fig.3 Filtered and zero mean output

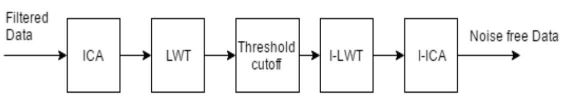


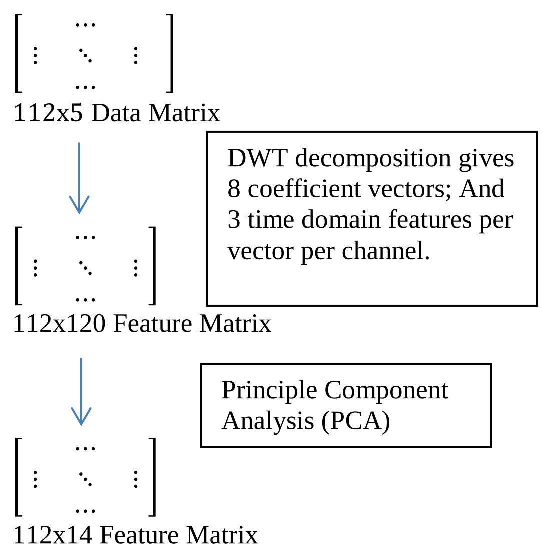
Fig.4 Artifact removal scheme

In this scheme the Independent Component Analysis ICA and Inverse Independent Component Analysis I-ICA were implemented using open source software Fast ICA [17] while the lifting wavelet transforms and inverse lifting wavelet transform was achieved using MATLAB wavelet Toolbox [16]. When the filtered data is applied to ICA; ICA decomposes the EEG signal into individual components consisting of essential brain activities and other non-neural artifact. After the signal is broken into individual components lifting wavelet transform decomposes the individual components into set of coefficients in order to identify ocular and muscular aritifacts. Followed by LWT we do power spectrum analysis of the signal in frequency range 0-5 and 15-35 to identify the ocular and muscular aritifacts, and if the power spectrum was above the certain level (threshold) the coefficients for that band of frequency was set to zero and then the individual components were reconstructed using I-LWT. The original noise free signal was then reconstructed back from individual components using I-ICA. The threshold level for this experiment was chosen by visual inspection of power spectrum as eye blinks are pretty prominent with high power content but a more effective way of thresholding will be utilizing adaptive learning algorithms.

B. Feature Extraction and Feature Reduction

Feature extraction is a very important step in any classification problem. We used discrete wavelet Transform to generate our features. The feature can be looked upon in time or frequency domain. In this experiment we focused on time domain features. The detailed process is described in the section below.

Discrete wavelet Transform (DWT) based feature extraction has been successfully applied with promising results in physiological pattern recognition applications. [13]. In this experiment we used Daubechies wavelet function of order 4dB and a 4 level of decomposition. All the 8 sets of coefficients vectors generated in the process (4 detailed and 4 approximate) we considered so as to extract maximum features from the signal. MATLAB Wavelet Toolbox [16] was used for this operation. For each coefficient vectors generated we applied 3 time domain operations; root mean square, standard deviation, means resulting in 3 features for each coefficient vector. Thus 24 features for a single channel (8 coefficients vectors x 3 features). We applied this to each channel which resulted in 120 features per sample (5 channels x 24 features/channel). For each class we generated 56 samples; 7 samples from each trail and we had 8 trails per class. The resultant was 56x120 feature matrix for each class and 112x120 feature matrix for the entire system. This feature matrix was fed to PCA for dimensionality reduction; the output of the PCA gave us 112X14 feature matrix which was then fed to the classifier. The flow of matrix dimensionality is more clearly shown in the graphical representation below.



C. Classification

After extracting the desired good features the entire data was randomly divided into 3 parts: Training set (50%), validation set (25%) and performance set (25%). And then applied to Support vector machine classifier and neural network classifier. The performances of both the classifiers were compared with their ability to classify calm and stressed emotion

Support vector machine is widely used classifier for various classification problem (binary classification & and multiclass classification) [11] [12]. In our experiment we used MATLAB SVM function [16] for the implementation of the algorithm and Radial basis function kernel to map the feature matrix to a higher dimensional space. During the training stage of the classifier default values (1 &1) were used for parameter C and sigma respectively. The parameter C corresponds to the cost function while the sigma to the kernel. Once the initial model was learned the model was optimised further using the validation set to find the right value of C and Sigma so as to find an optimal hyper plane (i.e. There is no under or over fitting) between the two classes. Once the final model was ready we applied the 25% performance set data which was never used in any state of the model learning to test the accuracy of the system. We also used Neural Network with forward and back propagation as classifier. The number of nodes was chosen to be 14 which correspond to the number of inputs /dimensionality of the feature matrix. The neural network with only one hidden layer was used. The implementation of the neural network and the optimization functions were done with help of Coursera Machine Learning Tutorials [14]. The result of classification averaged over 5 runs is shown in Table 1.

Classifier	Training Accuracy	Validation Accuracy	Performance Accuracy
SVM	100%	91%	82%
NN	96%	92%	80%

Table 1: Accuracy of classification process.

V. RESULTS AND CONCLUSIONS

The results show reasonable accuracy of classification of stressed and clam emotions. Both the classifiers were close enough in terms of the classification. The accuracies were close to expected. The offline model was tested multiple times and the average accuracies in range of 77-82% for both the classifiers.

Further scope of improvement can be achieved in terms of the experiment setup as well as the techniques utilised. For this experiment we have chosen the images based on the closeness of its assessment to our aims, to best of our understanding, which can be considered as a limitation because as stated earlier emotions of individual subjected to certain stimuli is not the same. The real-time implementation of the model with reasonable accuracy is a challenge too. As an extension of this project we would look into experiment setup where the data collection from the participants independent of any stimuli in a real world scenario. The feature extractions process can also be improved upon using non-linear feature extraction techniques and frequency domain analysis.

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