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Human Emotion Recognition using Brainwave Patterns

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Abstract: Emotions play an important role in everyone's life. The brain waves tell the difference in the emotions a person is going through. The electroencephalogram (EEG) signal contains valuable information related to the different emotional states, which helps to understand physiology and psychology of the human brain. The parameters extracted from EEG signals are useful for recognition and classification of emotions. The aim is to use the EEG data to develop an efficient brain computer interface (BCI) system which recognizes human emotions using brain activity. The system also assesses the quality of emotion recognition in practice. The proposed system makes use of machine learning concepts to achieve the required objectives. Initially the pre-processed data downloaded from widely used dataset (DEAP) is loaded and serialized for feature extraction, which is done by using Welch Power Spectrum Density Estimation Method and the emotions are classified using classifiers such as Multiclass Support Vector Machine, Support Vector Machine, Artificial Neural Network, K-Nearest Neighbors, Random forest and Classification and Regression Tree (CART). The analysis of this BCI system finds application in patient monitoring systems, psychological therapy and rehabilitation centers in the medical sector. Its commercial applications range from gaming industry to automation and user personalization.
***Keywords**: Electroencephalogram (EEG) signal, Multiwavelet transform, Classification of emotions, Multiclass least squares support vector machines (MC-LS-SVM, Welch Power Spectrum Method.*

I. INTRODUCTION

Emotion is an important aspect in the interaction and communication between people. Even though emotions are intuitively known to everybody, it is hard to define emotion. In spite of the difficulty of precisely defining it, emotion is omnipresent and an important factor in human life. People's moods heavily influence their way of communicating, but also their acting and productivity. A large part of communication is done nowadays by computer or other electronic devices. But this interaction is a lot different from the way human beings interact. Most of the communication between human beings involves non-verbal signs, and the social aspect of this communication is important. Humans also tend to include this social aspect when communicating with computers.

Electroencephalography (EEG) is the recording of electrical activity along the scalp using a pair or multiple electrodes that detect signals correlated to neural activity. Depending on the frequency range the brain waves have been categorized the following way [3]: a) beta waves (greater than 13 Hz), b) alpha waves (8-13 Hz) c) theta waves (4-8 Hz) and d) delta waves (0.5-4 Hz). All the bands are differently affected by various inputs from the outside world and thus can be used to judge mental state of a person. The objective of this project is to create a system for emotion recognition using brain activity and assess the quality of this emotion recognition in practice. This project will design, build and test a system for the offline recognition of emotions from EEG signals. An EEG data-set is to be created by collecting brain signals which would be cleaned to use it for feature extraction and training classification. Using this data- set we will also investigate the quality of different parameters for our project.

II. LITERATURE SURVEY

In spite of the notable advancements in this field, a common language has yet to emerge, and existing BCI technologies vary, which makes their comparison difficult and, in con- sequence, slows down the research. Factors contributing to increased difficulty in traditional BCI technology are Limited resolution and reliability of information that was detectable in the brain, high variability and the fact that BCI systems require real-time signal processing which was earlier expensive or inefficient. The major focus in this field demands greater and enhanced applicability with maximum ease to disabled. Features based on multi-wavelet-transform for classification of human emotions are discussed in paper [1]. These features have been used as input features set for multiclass least squares support vector machines (MC-LS-SVM) together with the radial basis function (RBF), Mexican hat wavelet and Morlet wavelet kernel functions for classification of emotions for better accuracy. The paper [2] proposes a statistical based system for human emotions classification by using electroencephalogram (EEG).From the EEG data, a total of six statistical features are computed and back-propagation neural network is applied for the classification of human emotions. The paper [3] discusses about brain waves. Brain waves tells the difference in the emotions the person is going through. Alpha brain wave in both happy and sad state is studied. This research studies the alpha brain waves in happy and sad emotion.

For doing the research EEG machine is used and to elicit the happy and sad emotion move clips are used. The result shows there is difference in the Alpha waves in happy and sad emotions. This work[4] studies and implements several measures of EEG signal complexity and then compares the complexity features measured or extracted from EEG signals. Time do- main analysis of EEG signals is performed using several signal processing techniques such as higher order moments, entropies and fractal dimension calculation using fractal analysis. Frequency domain analysis of EEG signals is performed using signal processing techniques such as Welch Power spectrum and Discrete Fourier Transform (DFT). EEG signal analysis using Wavelet Transform was also performed.

III. METHODOLOGY

A. Loading Pre-Processed Data

Pre-processing is a step to process raw EEG signals in such a way that they are ready to be used. The measured EEG signal is a combination of brain activity, reference activity and noise. EEG software first subtracts a baseline, the average potential before the stimulus occurs from each trial, then finds and eliminates electrodes at which potential values exceed some defined threshold. The retained electrodes usually include central scalp placements which may contain record brain activity, parietal placements that may contain temporal muscle artifacts and frontal electrodes that may contain blinks and eye movement artifacts. It is critical to detect such artifact contaminating event-related EEG data for several reasons. First, artifactual signals often have high amplitudes relative to brain signals. Thus, even if their distribution in the recorded EEG is sparse, they can bias evoked potential or other averages constructed from the data and, as a consequence, bias results of an experiment. Independent Component Analysis (ICA) applied to a concatenated collection of single-trial EEG data has proven to be efficient for separating distinct artifactual [8] processes, ranging from eye artifacts to muscle and electrical artifacts. The data set that is used in this project is DEAP (Database for Emotion Analysis using Physiological signals) which is already preprocessed. These files contain a down sampled (to 128Hz), preprocessed and segmented version of the data in pickled python/numpy formats. Each zip file contains 32 .dat (python) or .mat (matlab) files, one per participant. Each participant file contains two arrays: data whose dimension is 40 x 40 x 8064 consisting of video/trial x channel x data and labels whose dimension is 40 x 4 consisting of video/trial x label (valence, arousal, dominance and liking).

B. Feature Extracton

The second step in the operation is the feature extraction scheme which is meant to determine a feature vector from a regular vector. A feature is a distinctive or characteristic measurement, transform, structural component extracted from a segment of a pattern. Statistical characteristics and syntactic descriptions are the two major subdivisions of the conventional feature extraction modalities. Feature extraction scheme [4] is meant to choose the features or information which is the most important for classification exercise. Wavelet Transform plays an important role in the recog- nition and diagnostic field: it compresses the time-varying bio-medical signal, which comprises many data points, into a small few parameters that represents the signal. As the EEG signal is non-stationary, the most suitable way for feature extraction from the raw data is the use of the time-frequency domain methods like multi-wavelet transform [1] which is a spectral estimation technique in which any general function can be expressed as an infinite series of wavelets. One of these methods is Welchs method. The data sequence is applied to data windowing, producing modified periodograms. The information sequence x (n) is expressed as:

1) $x_i(n) = x(n + iD)$, n = 0,1,2,….., M -1

while i = 0,1,2,…..., L-1

take iD to be the point of start of the i^{th} sequence. Then L of length 2M represents data segments that are formed. The resulting output periodograms give:

2)

$$\tilde{\tilde{P}}_{xx}^{(i)}(f) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n)w(n)e^{-j2\pi fn}\right|^2.$$

Here, in the window function, U gives normalization factor of the power and is chosen such that :

3)

$$U = \frac{1}{M}\sum_{n=0}^{M-1} w^2(n),$$

where w(n) is the window function. The average of these modified periodograms gives Welchs power spectrum as follows:

4)

$$P_{xx}^{W} = \frac{1}{L}\sum_{i=0}^{L-1} \tilde{\tilde{P}}_{xx}^{(i)}(f)$$

C. Classification

1) *Support Vector Classification:* The multiclass classification task is solved by dividing M classes to L binary classification tasks. The various coding algorithms such as one verses all and one verses one are used to represent the output of this SVM classifier.

Algorithm-1:
”One VS One” coding for multiclass classification Initialize class [] = 0;
For each L1 from 1 to 5 do
    For each L2 from 1 to 5 do if (L1 L2) then
    L = classify (L1, L2); class [L]++;
    end
end

The learning step of the classifiers [6] is done by the whole training data, considering the patterns from the particular class as positives and all other examples as negatives. In validation phase, a pattern is presented to each one of the classifiers and then classifier which provides a positive output indicates the output class.

2) *Artificial Neural Network:* An artificial neural network is made-up of many artificial neurons which are linked together according to specific network architecture. The aim of the neural network is to transform the inputs into meaningful outputs to match the specific target values as closely as possible. An ANN is defined by three types of parameters: The interconnection pattern between the different layers of neurons, learning process for updating the weights of the interconnections and activation function that converts a neuron’s weighted input to its output activation. In ANN, the number of neurons in the input layer and hidden layers varies according to the feature types used, whereas the number of neurons in the output layer is nothing but the four emotional states.
3) *Random Forest:* A random forest is a meta estimator that fits a number of decision tree classifiers on various sub- samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement.
4) *K-Nearest Neighbours:* kNN is a non-parametric method used for classification and regression. The input consists of the k closest training examples in the feature space. The output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.
5) *Decision Tree:* Decision Trees (DTs) are a non- parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features.

Decision Tree Classifier is a class capable of performing multi- class classification on a dataset. As with other classifiers, Decision Tree Classifier takes as input two arrays: an array X, sparse or dense, of size holding the training samples, and an array Y of integer values, size, holding the class labels for the training samples. Decision Tree Classifier is capable of both binary classification and multiclass classification.

D. Results

1) *SVM:* SVM classification technique does give an accuracy of 63.66%. This can be improved by using multiclass classification as given below.
2) *Multiclass SVM:* The proposed features extracted from sub-signals obtained by decomposition of EEG signals and classification by MC-SVM classifier provides 68.02% accuracy for classification of emotions.
3) *Artificial Neural Network:* Using the data collected, the emotion recognition accuracy obtained with ANN as the classifier is 61.86%.
4) *Random Forest:* Random forests show very robust results even when adding all up to 900 features which is indication of the robustness of RFs to non-relevant features. Overall, standard deviations of measurements were smaller for Random Forests than for SVMs.
5) *k Nearest Neighbour:* kNN does give a good accuracy of 64.54% which is optimistic
6) *Decision Tree (CART):* Out of all the classifiers that are used in this project, Decision Tree’s CART has the highest recognition rate of 70.09%.

The results are formulated as a Table

TABLE I. Classification Results

Classification Methods	Accuracy
SVM	63.27
Multi-class SVM	68.04
ANN	61.86
Random Forest	68.57
KNN	64.54
CART (DT)	70.9

IV. CONCLUSION

During this project we have focused on the construction of a program to recognize emotion from brain activity, using EEG signals. We have used the widely known DEAP dataset for the EEG signals. Electroencephalography (EEG) seems to be the most practical way of measuring brain activity, because it is cheap and easy to use. Several researchers have shown that it is possible to measure emotional cues using EEG measurements. After gathering knowledge about the subject, various method are studied for signal processing, feature extraction and classification and appropriate method is chosen to be implemented.

V. FUTURE WORK

In future research, the application approach presented in this project can be further improved in the following ways:

A. Until now, to our best knowledge there is no real-time EEG-based emotion recognition algorithms. The task of real time classification of emotions can be done to be used in medical domain.
B. Until now, to our best knowledge there is no real-time EEG-based emotion recognition algorithms. The task of real time classification of emotions can be done to be used in medical domain.
C. There is still room for the improvement to get even better result. Such improvement can be achieved by adding more subjects which will result in increase in dataset size. Other technique like Peak detection, thresholding can be used for EEG data processing EEG signals can also be isolated into separate frequency band of Alpha and Beta to check if that gives some interesting result.
D. An optimal fusion algorithm for multimodality system e.g., the use of EEG signals and facial images, is not present in the literature. Various fusion techniques, in both the feature level and the decision level, should be investigated.
E. The current implementation is very slow and there is a great need for the computational improvements for near real- time analysis. In particular, the parallel calculation of different projection directions to boost computation time should be studied to shorten processing time especially if real-time processing is required or a large number of EEG channels will be utilized.

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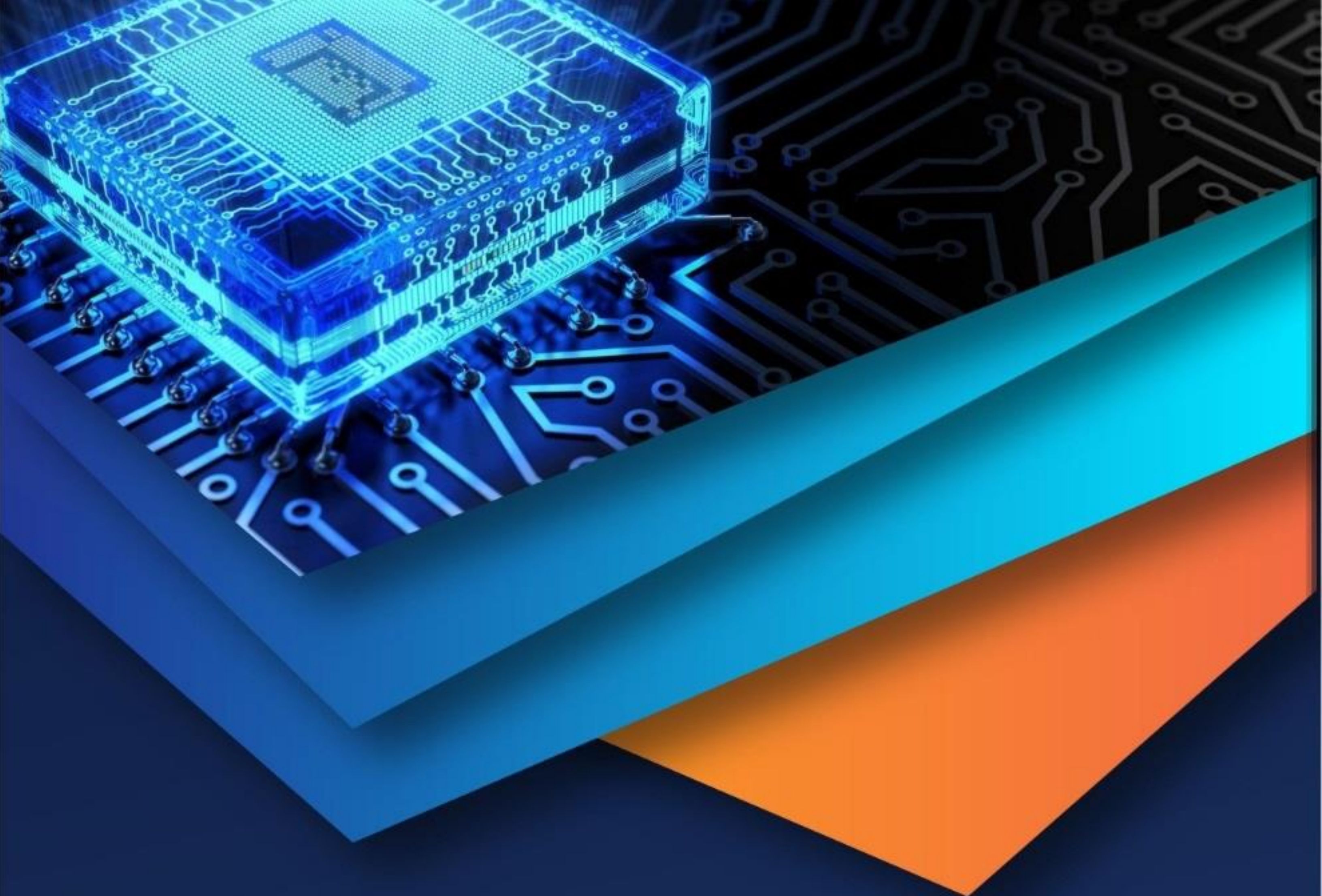

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