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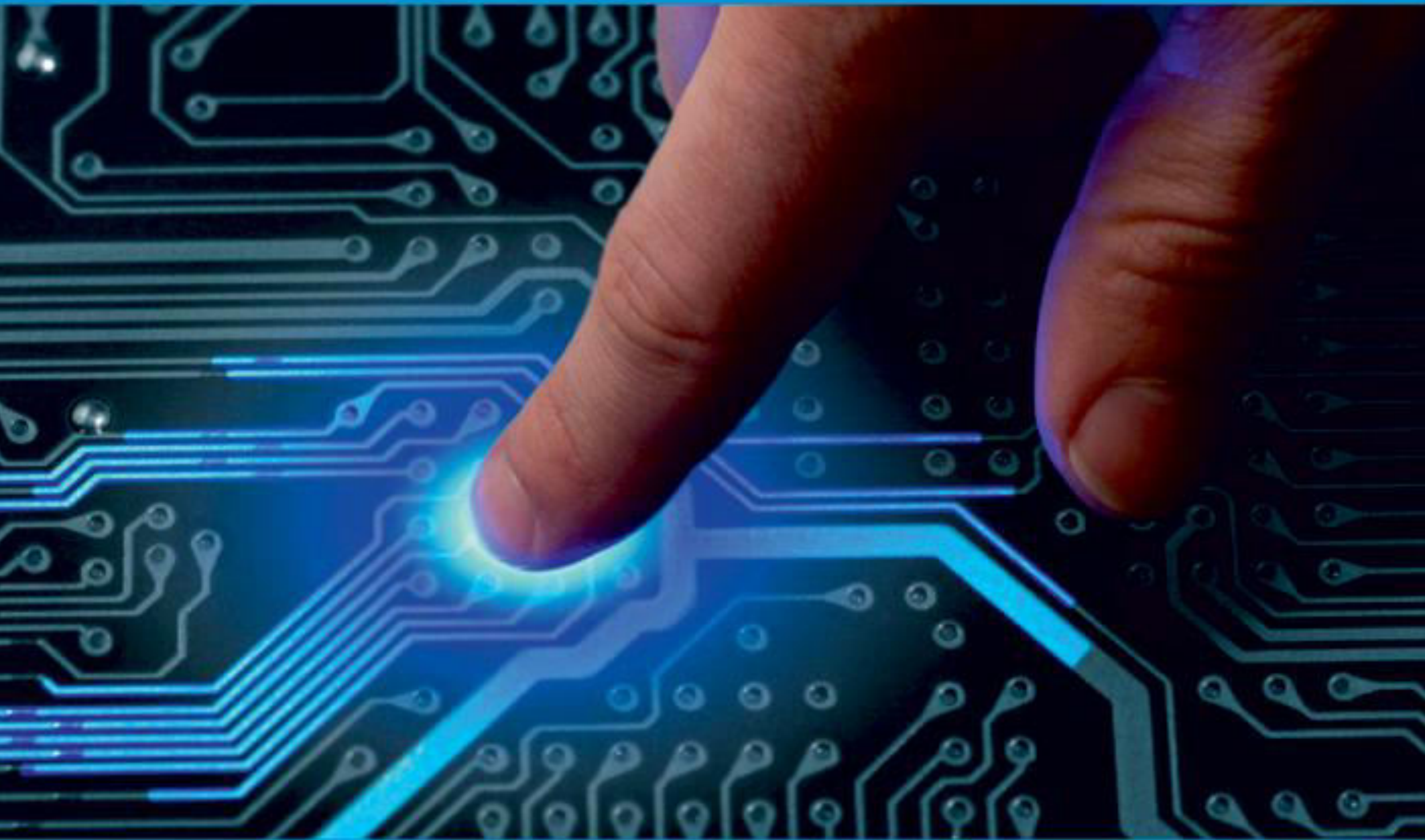

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Emotion Classification and Simulation of EEG Signal using KNN Mathematical Model and MATLAB

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ABSTRACT: In everyday human communication, emotion is essential. Emotions are crucial in fostering more natural human-machine connection. Personal well-being depends on emotional balance. This study will use EEG to identify the emotional state of individuals who have been burned. The electroencephalograph (EEG) can be used to correlate the brain's dynamics with emotional states. Happy, angry, sad, and disgusted are the four emotions. An apparatus that converts neural data into orders that may operate external software or hardware, like a computer or robotic arm, is known as a brain–machine interface (BMI). People with motor or sensory disabilities frequently utilize BMIs as supported living devices.

It is an effective mixture classification method that employs electroencephalography (EEG) signals to create a channel of communication for people who are immobile or physically handicapped. We present a method for emotion recognition based on the generalized mixture distribution model to recognize the expressions of an immobilized person's emotions. With MAT Lab's assistance, the processing is completed.

KEY WORDS: MAT LAB,EEG, BMI,HHI

I. INTRODUCTION

Human being interacts with different machines throughout their life. Similarly, emotions are vital and inevitable in every human‟s life. Most interactions between machines and humans are discrete and overt events where machine knows about human only when explicit command are sent, like by pressing button. Hence, interaction between machines and humans is less autonomous and less intelligent. Scientists have come up with the evidence that emotional skills are a basic component of intelligence. Reeves and Nass [21] have shown that replacing one of the humans in Human-Human Interaction (HHI) with a machine follows the same fundamental rules of HHI. Hence, it has become essential to come up with the system where it can detect the human emotion it is working with, i.e. to induce the machine with the emotional intelligence so that the system can emulate the property of implicit communication which exist in human interaction. Affective computing is the study and development of system that can recognize and act accordingly to the human affects or emotions. Picard who is a pioneer working in the field of Affective computing states that "Emotion plays the vital role in rational decision making, understanding, learning and other various cognitive function". Therefore, development of aforementioned system would open the gate for more meaningful, robust, natural, and reliable interaction between machines and humans.

Different kinds of methods have been devised to recognize the underlying emotion of a person. Notably, emotion recognition (ER) from facial expression [22], voice intonation [23], gesture, and signal from Autonomous Nervous System (ANS) like heart rate and Galvanic Skin Response (GSR) had been being carrying out [24][25]. ER from Electroencephalography (EEG) signals is relatively new in the field of affective computing. ER from EEG signals overcome some of the drawback that arises while using the technique of ER from facial expression, GSR, heart rate, like facial expression can be easily faked, for example a person might be really feeling pain inside but he might show the expression of happy. Signal from ANS are more susceptible to noise, for example, GSR signals might not only originate from emotional influence but may also from physical influence. On the contrary, signal from central nervous system like EEG is captured form the origin of emotional experience. Moreover, EEG signals which have fine resolution are easy to record with affordable cost.
Different techniques and step are needed to classify the emotion from EEG Signals. These steps includes the recording

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of Signals, pre-processing of recorded raw signals to remove the artifacts from it, extracting the most suitable feature from processed signals, formatting the dataset and evaluating it with the use of machine learning tool.

II. LITERATURE REVIEW

Real-time brain signal acquisition, analysis, and translation into output commands is accomplished by a computer-based system called a Braine Computer Interface (BCI) [3]. The first kind concentrates on the fundamental emotions, which are composed of a limited number of emotional constructions, including fear, rage, sadness, and happiness. The second method concentrates on how emotions are characterized by the arousal and valence models. In order to discover the two main aroused emotional states that are associated with good and negative emotions, neurophysiology researchers employed algorithms that used wavelet transform to identify and experiment with eye blinks [1].

Body and face mirroring is a basic mechanism suggested by embodied-emotion explanations [16]. For instance, boredom denotes the absence of a goal, melancholy denotes the loss of hope for achieving a goal, anger denotes the response to a goal that has been unsuccessful, and pleasure denotes the ful fillment of achieving a goal. The majority of BCIs rely on motor imagery or visual attention, while a range of mental tasks have been investigated for BCI control [9]. In order to regulate the ANS alterations brought on by any facial movement, the non-emotional expression consisted of actions that were not part of any of the emotional expressions [15].

According to several theories, particular emotions like happiness, fear, sadness, hostility, guilt, surprise, and interest are considered discrete in that they are assumed to be unique experiential states that stem from distinct causes [11].

Emotion plays an important aspect in the interaction and communication between people. In particular, peoples moods may heavily influence their way of communicating, acting and productivity. For example, there are two car drivers, one being happy and the other being very mad. The aim of this study is to present a package including standard software for the electroencephalographic (EEG), electro-oculographic (EOG) and electromyographic (EMG) preliminary data analysis, which may be suitable to standardize the results of many EEG research centres studies (i.e. multi-centric studies) especially focused on event related potentials. [4].

A new feature extraction method for a user-independent emotion recognition system, namely,HAF-HOC, from electroencephalograms (EEGs). A novel filtering procedure, namely, Hybrid Adaptive Filtering (HAF), for an efficient extraction of the emotion-related EEG-characteristics was developed by applying Genetic Algorithms to the Empirical Mode Decomposition-based representation of EEG signals[14].Patients with severe brain injury may suffer from disorders of consciousness (DOC), including coma, vegetative state (VS) and minimally conscious state (MCS).An EEG-based BCI system for the detection of consciousness in patients with DOC [10]. The emotions computational models have been applied to the recognition of affective states through physiological measures, such as Heart Rate Variability (HRV), Blood Volume Pulse (BVP), Skin Temperature (SKT) ,Electrocardiogram(ECG), and Electrodermal Activity (EDA) [12].To build a physiological emotion database, a key problem to be considered is the partition of emotional space, which is commonly divided into two categories, i.e., dimensional emotion model and discrete emotion model. Dimensional emotion model is expressed using multiple dimensions or scales to categorize emotions [19].

III. METHODOLOGY

An effective method for classifying mixtures that makes use of electroencephalography (EEG) signals to create a channel of communication for individuals who are immobile or physically handicapped. We present a method for emotion recognition based on the generalized mixture distribution model to recognize the expressions of an immobilized person's emotions. The suggested approach is especially well-suited for the high EEG signal variability, which enables the proper identification of the emotions. DWT is used to extract the brain signals' characteristics. MATLAB (Math works Inc.) was used for data processing and visualization. The KNN classifier is being used and which is presented below.

K-NN Classifier

The EEG test feature vectors are compared with trained feature vectors by using distance and similarity measure. The unidentified test sample is recognized as the one that belongs to the closest sample in the training set. The smallest value is considered if distance measure is used and largest value is used if similarity measure is used. This process is simple and less accurate. The accuracy can be increased by considering nearest neighbors by considering group of close feature vectors instead of selecting just a nearest training set sample. This is referred as K-Nearest Neighbor technique.

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K number of best matching neighbors are selected to classify the unknown sample to the given class. The value of K ranges from one to total number of images in the training set. The recognition accuracy depends on the chosen K value. As the value of K increases, we are considering matching neighbors to not matching neighbors in the training set.

Mathematical model for K-NN

For a given query instancex_t, K-NN algorithm works as follows:

$$y_t = \underset{c\epsilon\{c_1,c_2,\ldots\ldots c_m\}}{\arg\ \max} \sum_{x_i \epsilon\ N\ (x_t,k)} E(y_i, c)$$

Wherey_t, is the predicted class for the query instance x_t , c is the class number and m is the class number present in the data. N (x_t, k) Set of k nearest neighbors of x.

$$E(a,b) = \begin{cases} 1 \text{ if min ED} \\ 0 \text{ if max ED} \end{cases}$$

Where

Euclidean distance ED $= \sqrt{\sum_{i=1}^{n}(a_i - b_i)^2}$between query instance vector a and trained vector b.

IV. EXPERIMENTAL RESULTS

Figure 1 below displays the signal processing generic block diagram. Pre processing is the broad category into which signal processing can be separated. Classification and feature extraction. Since EEG signals are extremely complex, many signal processing techniques have been applied either singly or in combination to extract the best features for the relevant application. Techniques such as wavelet Among the prominent approaches are autoregressive coefficients and transforms. The raw brain signals are obtained from http://bnci-horizon-2020.eu/database/data-sets and are used as an input in this case.

We don't need to pre process the data because the raw date signal is already pre processed. The feature extraction algorithm then makes use of the pre processed data. The discrete wavelet transform (DWT) coefficient is used to extract features. The collected signal is then categorized using a classification algorithm. The accuracy and computational complexity of the results can be increased by selecting the classification method that is most appropriate for the feature vectors. KNN, or K-Nearest Neighbor classification. The results are obtained from the simulation and are presented and compared with some state of art work are an those are presented in the table 1.

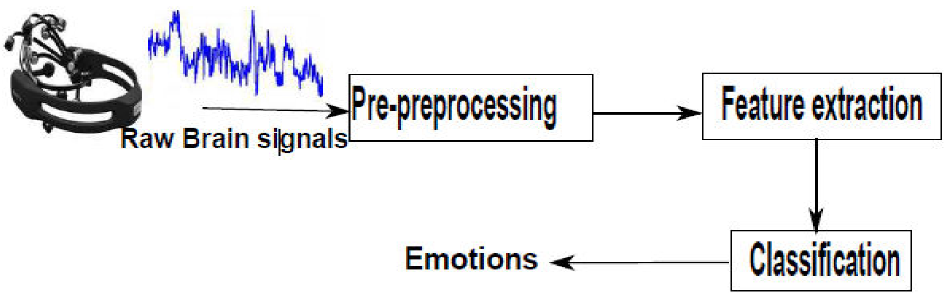

Figure 1 Block Diagram Signal processing.

Table 1: Comparison of the results

Ref.no	Methods	Channels	Classifiers	Accuracy
[13]	Sparse Bayesian method	14	LDA	72.74%
[14]	HAF-HOC to EEG	3	QDA SVM	77.66% 85.17%
Proposed Method	DWT	4	KNN	84.02%

V. CONCLUSION

In the paper, it is evaluated the feasibility EEG signals for the classification of emotional states. For this, we were given the data previously collected in controlled environment.

These data were pre-processed to remove the artifacts. Each dataset was formatted in acceptable format for the classification software MATLAB. The classification was carried out with the use of KNN as the selected technique yielding us the accuracy 84%.

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