A REVIEW ON TECHNIQUES FOR EMOTIONS CLASSIFICATION USING EEG SIGNALS

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ABSTRACT

Emotion detection has been a topic of interest for various areas like health care, social security, decision making etc. There are several important definitions and theories of human emotions. There have been a number of advancements in human-computer interaction. The papers were reviewed based on Electroencephalogram (EEG) signals as a marker for emotional states as it has become popular in many brain-computer interfaces (BCI) applications and studies. Several successful attempts have been made to classify these emotions using machine learning. In this paper, some of the popular machine learning algorithms for classification of these emotions are covered. The algorithms that we came across the most were Support vector machine (SVM), K-nearest (KNN), Logistic regression (LR) and decision tree (DT).

Keyword : - *Machine Learning, Emotions, Electroencephalogram, Brain-computer interfaces, Artificial Intelligence, Support vector machine (SVM), K-nearest (KNN), Logistic regression (LR) and decision tree (DT).*

1. INTRODUCTION

Emotions are a very important and necessary part of human being. Our emotional state affects our health and working conditions. When a person is in a positive state of mind, the efficiency of doing work increases as compared to when a person is in a negative state of mind. Everyone is aware of a few main emotions like anger, sadness, happiness, fear etc. There are numerous opinions on how emotions occur and can be detected: one approach considers emotions as general states of individuals and the other one knows emotions as physiological interactions. The general states of individual include the situations that they face in their daily lives to with we connect the emotions. For example, when watching a horror movie, a person feels scared. Here we connect the feeling of being afraid of the situation in front of us which is the horror movie. Considering the same above example when a person watches a horror movie his/her heart rate, blood pressure, respiration rate increases. Emotional status of a person is recognized by these physiological changes. Another way of recognizing emotions is by physical signals such as facial expressions, gestures, posture etc. But this method is often not very reliable as it is easy for a person to control his/her facial expression and posture. Physiological interaction, on the other hand from the brain’s responses. These brain activities are simulated by the situation in front of us and therefore a largely involuntary.

One of the ways is by detecting brain activity using EEG. Electroencephalography (EEG) is the measurement of electrical activity in the living brain. EEG signals due to their simplicity to analyze and a good time and spatial resolution have become common and useful in most BCI applications such as emotion recognition.

2. PHYSIOLOGICAL SIGNALS

Psychological changes reflect the emotional status of a person which is why biological signals and images are recorded in order to recognize emotions. Some biological systems in the human body and their indexes are described as follows: 1-Cardiovascular system: electrocardiogram (ECG), heart rate variability (HRV), cardiac output, blood pressure, etc. 2- Respiratory system: respiration rate, etc. 3- Muscular system: electromyogram (EMG) signals, etc. 4- Brain activity: EEG signals, etc. The other category is using the internal signals—the physiological signals, which include the electroencephalogram (EEG), temperature (T), electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), respiration (RSP), etc. The nervous system is divided into two parts: the central and the peripheral nervous systems (CNS and PNS). The PNS consists of the autonomic and the somatic nervous systems (ANS and SNS). The ANS is composed of sensory and motor neurons, which operate between the CNS and various internal organs, such as the heart, the lungs, the viscera, and the glands. EEG, ECG, RSP, GSR, and EMG change in a certain way when people face some specific situations. The physiological signals are in response to the CNS and the ANS of the human body, in which emotion changes according to Cannon’s theory [1]. One of the major benefits of the latter method is that the CNS and the ANS are largely involuntarily activated and therefore cannot be easily controlled. EEG signals due to their simplicity to analyze and a good time and spatial resolution have become common and useful in most BCI applications such as emotion recognition. Also, EEG recording systems are cheap and accessible. Previous studies show that by recording and processing EEG signals we can achieve very good results in terms of emotion classification. So a decision was made to explain and review some previous studies related to emotion classification through EEG signals.

3. EMOTION SIMULATION

For emotion recognition, it is very important to know how these emotions were evoked. In the past few years the simulation of emotions using music, videos etc have been very popular. Some believe that video clips can stimulate human emotions the best while others find music or memories the most effective way. What is clear is that the stronger the stimulation is the richer the database will be. By using good and strong stimulation, emotion recognition is more likely to be performed with better results and higher accuracy.

Once these emotions are elicited, the next problem is of emotion model. One way is to think of these emotions as distinct. Paul Ekman supported that emotions are discrete, measurable, and physiologically distinct. His research led him to classify 6 emotions as basic: anger, disgust, fear, happiness, sadness, and surprise[2].

On the other hand, the other way is to describe emotions in a continuous dimension. For example, sad can be very sad or less sad. Lang [3] investigated that emotions can be categorized in a 2D space by valence and arousal. In his theory, valence ranges from unpleasant (negative) to pleasant (positive), and arousal ranges from passive (low) to active (high), which indicate how strongly human feels [4] studied emotions using the valence arousal model.

4. EMOTION MODELS

There are two unique models for signifying emotions:

1) Emotions are discrete and fundamentally different constructs: The discrete emotional model either makes use of six basic emotion classes namely anger, disgust, fear, joy, sadness and surprise or uses domain-specific expressive classes such as boredom, confusion. Each emotion acts as a discrete category rather than an individual emotional state[5].

2) Dimensional emotion models: A second method for recognizing emotions is a dimensional model. It denotes emotion in a dimensional form. A common set of dimensions link the various emotional states in this model. They are defined in a two(valence and arousal) or three (valence, arousal, and dominance) dimensional space. Each emotion occupies a position in this space. Valance defines the positivity or negativity of an emotion. Arousal denotes the excitement while dominance gives a sense of control. The two-dimensional models that are most prominent are the circumplex model, the vector model, and the Positive Activation – Negative Activation (PANA) model[6].

4.1 Circumplex Model

James Russell developed the circumplex model of emotion[7]. According to this model, emotions are distributed in a two-dimensional circular space, containing arousal and valence dimensions. Arousal is represented on the vertical axis and valence is represented on the horizontal axis, while the center of the circle represents a neutral valence and a medium level of arousal[6]. Circumplex models have been used most commonly to test stimuli of emotion words, emotional facial expressions, and affective states[8].

4.2 Vector Model

Vector model is a two-dimensional model that consists of vectors pointing in two directions, representing a "boomerang" shape. The model assumes arousal as an underlying dimension, and that valence determines the direction in which emotion lies. For example, a positive valence would shift an emotion to the top vector and a negative valence would shift the emotion down the bottom vector[6]. Vector models have been most widely used in the testing of word and picture stimuli[8].

4.3 Positive activation – negative activation (PANA) model

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4.4 Plutchik's model

Plutchik's model is a three-dimensional model that is a hybrid of both basic-complex categories and dimensional theories. The emotions are arranged in concentric circles where inner circles are more basic and outer circles more complex. Outer circles are also formed by blending the inner circle emotions. Plutchik's model, like Russell's, derives from a circumplex representation, where emotional words were plotted based on similarity[10]. There are numerous emotions, which appear in several intensities and can be combined in various ways to form emotional "dyads"[10]–[12].

5. ONLINE AND OFFLINE RECOGNITION

Real-time emotion recognition is essential in various situations where monitoring patients are needed. This is where online methods are of importance. Iacoviello et al [13] an effective, general and complete classification method for EEG signals was introduced. This study used self-induction as emotion elicitation. Wavelet transform (WT), principal component analysis (PCA) and support vector machine (SVM) were used to process and classify EEG signals. Also, Sourina et al [14] introduced an online emotion recognition study which used spatial time fractal to characterize brain states. A quintessential requirement in online recognition systems is that processing must be fast and precise. A fractal transform is one of these methods that was used in several related studies.
The other type of emotion recognition systems is offline. In offline recognition, the processing is not done real-time, instead, a database of past signals are used. Zhang and Li[15] recognized positive and negative emotions using neuro-fuzzy method offline. In this study, an unsupervised clustering method and adaptive neuro-fuzzy inference system (ANFIS) were used. Clustering was used in early steps for creating primary information related to emotions. Emotions were elicited by the International Affective Picture System (IAPS) images. In this study, EEG signals and visual information were recorded.

Table -1: Publicly available datasets

Dataset	Dataset Description
DEAP[16]	Includes 32 subjects, each watching 1-min long excerpts of music-videos, rated by users in terms of arousal/valence/like-dislike/dominance/familiarity, and frontal face recording of 22/32 subjects.
Enterface'06[17], [18]	Enterface'06 Project 07: EEG(64 Channels) + fNIRS + face video, Includes 16 subjects, where emotions were elicited through a selected subset of IAPS dataset.
Imagined Emotion[19]	31 subjects, subjects listen to voice recordings that suggest an emotional feeling and ask subjects to imagine an emotional scenario or to recall an experience in which they have felt that emotion before.
NeuroMarketing[20]	25 subjects, 14 electrodes, Like/Dislike on commercial e-commerce products over 14 categories with 3 images each. Article for the dataset: Analysis of EEG signals and its application to neuromarketing.
SEED[21]	15 subjects were shown video clips eliciting positive/negative/neutral emotion and

	EEG was recorded over 62 channels.
SEED-IV[22]	15 subjects were shown video clips ellicity happy/sad/neutral/fear emotions and EEG was recorded over 62 channels (with eye-tracking) for 3 sessions per subject (24 trials per session).
SEED-VIG[23]	Vigilance labels with EEG data in a simulated driving task. 18 electrodes and eye-tracking included.

6. CLASSIFICATION METHODS

Psychological Machine learning(ML), an application of artificial intelligence(AI), is a study of various different algorithms and models used to learn and improve from experience without using explicit instruction. The key feature of machine learning is self-learning. That is it focuses on making computer programs which can access data and use it for self-learning. The process of learning includes: Data, model, and output. Thus for ML application, we need to give in the input data, then train our machines by building ML "models" using different algorithms order to produce an action (output). The primary aim is to allow the computers to learn automatically without human intervention or assistance and adjust actions accordingly.

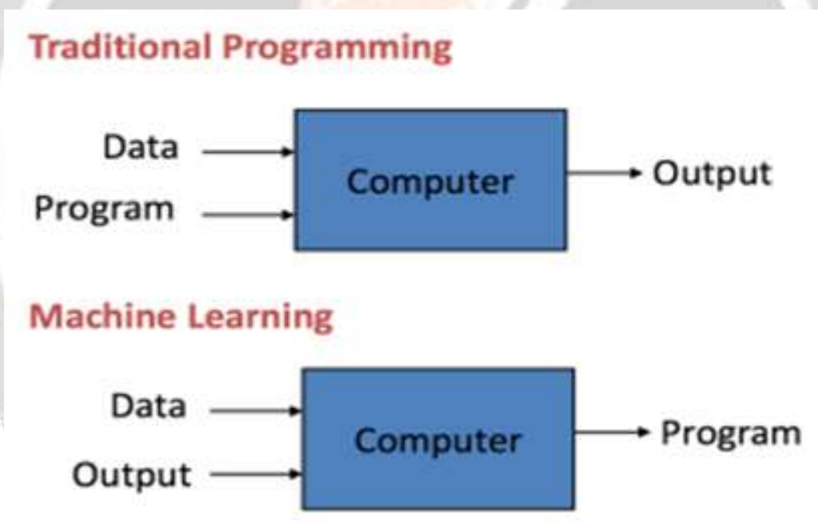

Fig -1: Machine learning flow

Machine learning allows us to analyze massive data. There are various approaches in literature in the processing steps to estimate the emotional state from the acquisition signals. Principal component analysis(PCA), Independent component analysis(ICA), discrete wavelet transform and Linear discriminant analysis(LDA) are some of the feature extraction techniques to reduce the dimensionality of data. Support vector machine (SVM), artificial neural network(ANN), K-nearest neighbor (KNN) are some of the commonly known and used machine algorithms for emotion classification.

The following paper [24] uses discrete wavelet transforms for feature extraction support vector machine and K-nearest neighbor classifiers have been used for classification. On 10-channel EEG signal, results show a classification accuracy of 86.75 % for arousal and 84.05 % for valence.

Murugappan et al.[25] in their paper also summed up emotion recognition using different set of electroencephalogram (EEG) channels using discrete wavelet transform. The EEG signals are collected using 64 electrodes from 20 subjects. The raw EEG signals are preprocessed and decomposed into three different frequency bands (alpha, beta, and gamma) using Discrete Wavelet Transform (DWT). Two simple pattern classification

methods, K Nearest Neighbor (KNN) and Linear Discriminant Analysis (LDA) methods are used. The results indicate that classification rate of 83.26% using KNN and 75.21% using LDA is achieved.
For emotion detection in listening to music, a framework was created in order to optimize EEG-based emotion recognition by systematically 1) seeking emotion-specific EEG features and 2) exploring the success of the classifiers. Support vector machine(SVM) was used to classify four emotional states (joy, anger, sadness, and pleasure) and obtained an averaged classification accuracy of 82.29% ± 3.06% across 26 subjects[26].

Ishino and Hagiwara [27]proposed a system that estimated feelings using neural networks to categorize emotional states based on EEG signals. It was reported that an average accuracy range from 54.5% to 67.7% for each of the four emotional states was obtained. Takahashi [28] proposed an emotion-recognition system using multimodal signals (EEG, pulse, and SC). The results showed that the recognition rate using a support vector machine (SVM) reached an accuracy of 41.7% for five emotions. Chanel et al. [29] showed that the maximum accuracy of 58% for three emotion classes could be obtained for arousal assessment of emotion. The classification was performed using the Na¨ıve Bayes classifier applied to six EEG features derived from specific frequency bands at particular electrode locations. Heraz et al. [30] established an agent to predict emotional states during learning. The best classification in the study was accuracy of 82.27% for distinguishing eight emotional states, using k-nearest neighbors as a classifier and the amplitudes of four EEG components as features. Chanel et al.[31] reported an average accuracy of 63% by using EEG time-frequency information as features and SVM as a classifier to characterize EEG signals into three emotional states. Ko et al.[31], [32] demonstrated the feasibility of using EEG relative power changes and Bayesian network to predict the possibility of a user's emotional states. Also, Zhang and Lee [33] proposed an emotion understanding system that classified users' status into two emotional states with the accuracy of 73.0% ± 0.33% during image viewing.

7. CONCLUSION

In this paper, we reviewed several different emotion recognition studies for EEG signals. First, we stated some emotion approaches and theories. Then different components of emotion recognition systems were described: different kinds of biologic measurements (EEG, ECG, etc) offline vs online recognition systems, different types of emotional stimulation. To scientifically assess emotions various emotion models were also covered. Russell circumplex model and vector model are the most commonly used dimensional model for emotional signals. Also different EEG datasets were described for emotion recognition. As EEG has become very popular for emotion recognition applications in recent years, our main focus was on the subject of emotion recognition through EEG signals using machine learning models. So different papers and studies were reviewed in order to cover this issue.

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