International Journal of
Science and Engineering Investigations vol. 7, issue 78, July 2018
ISSN: 2251-8843

EEG-Based Emotion Recognition through Nonlinear Analysis

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Abstract- Emotion recognition has become a very controversial issue in Brain Computer interfaces (BCI). Moreover, numerous studies have been conducted in order to recognize emotions. Also, there are several important definitions and theories about human emotions. Considering low cost, high time and spatial resolution, EEG has become very common and is widely-used in most BCI applications and studies. Due to EEG's nonlinearity and complexity, most traditional methods fail to describe EEG while emotion elicitation. In other words, new approaches based on EEG phase space have recently gained a great deal of attention. In this paper we try to cover important topics related to the field of emotion recognition. We review several studies which are based on analyzing electroencephalogram (EEG) signals as a biological marker in emotion changes. First, we state some theories and basic definitions related to emotions. Then some important steps of an emotion recognition system are described. After that, most popular databases are explained. Finally, recent and most important studies are reviewed.

Keywords*- Emotion Recognition, Affect Assessment, Human Feelings, Nonlinear Analysis, Arousal, Valence*

I. EMOTIONS; DEFINITIONS, THEORIES AND MODELS

Everyone knows original and basic emotions such as happiness, fear, anger, disgust, sadness and surprise. But neuroscientists and researchers have no consensus about the nature of emotions. There are two opinions about emotions: one approach considers emotions as general states of individuals and the other one knows emotions as physiological interactions [1]. Imagine a person driving a car while another car approaches and causes him to deviate from the road. At first that individual probably experiences fear and anger. According to the first view, fear comes from the inference that one might be in anger and that anger is because of the driver who has just put him in danger. Thagard [1], Oately [2] and Nussbaum [3] believe in the first approach. Oately demonstrated how original emotions have a strong relation with executing goals. In other words, people become happy while approaching their goals and sad when they fail. Therefore, we can consider emotions a general representation of our problems [1]. In contrast to the first view, the second approach emphasis on physical and physiological interactions. When someone causes an individual driving a car to deviate off the road, their heart rate, blood pressure and respiration rate increase. Feelings (like fear or anger, etc.) originate from the brain's responses to these physiological changes and not from the interpretation of the situation. James introduced this approach for the first time in 1884 [4].

Researchers mostly consider two models for emotions in order to describe and classify them. There are two major views about emotion models; discrete and continuous. In the first model, emotions are considered different and separate phenomena. In contrast to the first view, the second model suggests that emotions are better described by some continuous variables such as arousal, valence, liking, dominance, etc. Both views are explained below. Psychologically speaking, in terms of emotion classification and based on the discrete model there are two basic theories: Plutchik's theory and Ekman's theory. The first theory classifies emotions into two different categories: basic emotions and secondary ones. These emotions are as follows: anticipation, joy, trust, sadness, fear, surprise, anger, disgust. Secondary emotions come from a combination of these elementary feelings. These emotions are love, optimism, aggressiveness, submission, contempt, awe, remorse and disapproval. Ekman's theory is known as a discrete model. He introduced six basic emotions: fear, sadness, happiness, surprise, disgust, anger [5]. After that, the number of these emotions increased to fifteen. James and Lange in the nineteenth century introduced another theory, James-Lange theorem [6]. In this theory environmental variations cause physiological changes in our autonomous nervous system and consequently cause different emotions. Besides the discrete model of emotions, there is the continuous model which Lang proposed and is also called valence-arousal model. Based on this model, valence and arousal values are assigned to each emotion. In other words, in this model emotions are a continuous spectrum of valence and arousal values and generally emotions are plotted in a 2D coordination called valence-arousal plane.

II. EMOTION RECOGNITION SYSTEMS AND DATABASES

In this section, a general emotion recognition system is explained and different aspects are taken into account. Also there are several rich databases in terms of emotion recognition which have been used in numerous studies. There are some important steps in an emotion recognition study. Figure 1 shows the emotion classification process. Physiological changes cause emotions. Therefore, researchers analyze signals and images related to these physiological changes in order to recognize feelings and classify emotions. However, physiological signals introduce some problems like noise, artifacts, etc. Another problem is that we cannot visually recognize emotions from physiological signals and computerized processes are required [7-10]. Also, there are other factors which affect emotions, such as sex, age and race. Usually, researchers consider these parameters while studying emotions.

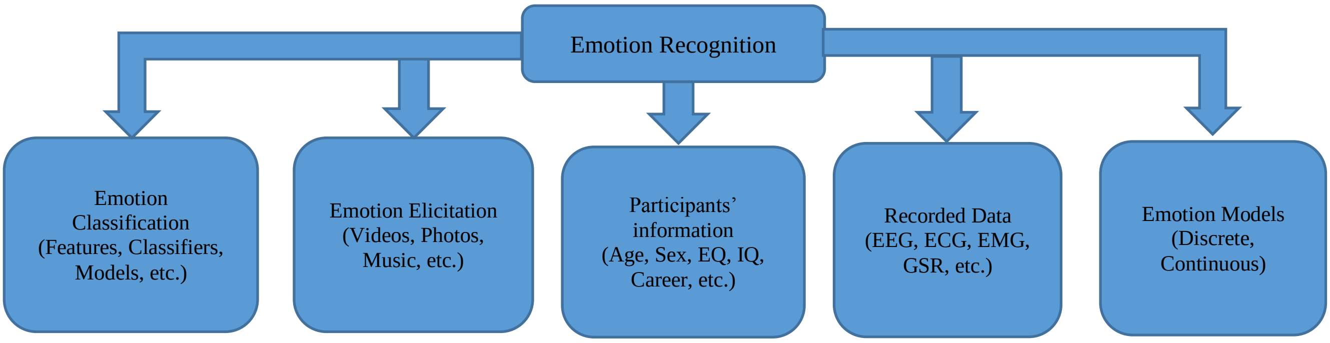

Figure 1. Important steps in a general emotion recognition syste

There are also other important factors in emotion recognition systems such as biological records, emotion stimulation, emotion models, number of participants and elicited emotions, online or offline recognition, classification methods and participants' recorded information. Emotion status is reflected by physiological changes, which is why biological signals and images are recorded in order to recognize emotions. Some biological signals which have been used in recent studies are Electrocardiogram (ECG), EEG, Galvanic Skin Response (GSR), Electromyogram (EMG), respiration rate and so on. EEG signals due to their simplicity to analyze and 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. The way emotions are evoked plays an important role in emotion recognition systems. 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 strong stimulation, emotion recognition is more likely to be performed with better results and higher accuracy. There are some types of stimulation like pictures [11-20], video clips [21-29], music [30-33], memories [34], self-induction [35-37] and games [38]. Recorded signals and information are processed through feature extraction and then classification methods. More information is provided in next section. In some studies, emotion recognition on the spot is really important such as monitoring patients while taking medicine. So online methods are of importance in those applications. For example, in [37], an effective, general and complete classification method for EEG signals was introduced. On the other hand, offline methods are more common and accurate in comparison with online studies. For example, Zhang and Lee in [40], recognized positive and negative emotions using neuro fuzzy method offline. Another problem in emotion recognition studies is the number of elicited emotions and the emotion model. Some studies, according to discrete model, consider a specific number of emotions and others according to the valence-arousal model suppose more emotions. For example, Koelstra et al. [23], Koelstra and Patras in [24], Hidalgo-Munoz et al. in [16], studied emotions according to the valence-arousal model. There are some public emotion databases which can be used by researchers for free. Table 1 represents most common and popular databases related to emotion recognition. Recorded signals and information, number of participants and stimulated emotions, emotion models and emotion elicitation are provided in this table.

III. PREVIOUS EMOTION RECOGNITION STUDIES

Emotion recognition has a wide usage in several fields in terms of normal and abnormal cases. Researchers have managed to detect and diagnose some mental disorders like depression, schizophrenia, etc. through emotions. Also processing signals leads to emotion recognition in normal cases. Since the number of studies in this field is quite large, we decided to explain and report studies in a comparative table. Table 2 describes recent studies including normal and abnormal cases. As mentioned above, due to some advantages emotion recognition based on EEG signals has become very controversial in BCI and other fields. So we limited Table 2 to emotion recognition studies through EEG signals.

TABLE I. EMOTION RECOGNITION DATABASES

Ref	Database	Emotion Stimulation	Participants	Recorded Signals	Emotion Model
[23]	DEAP	Video Clips	32	32 EEGs, 4 EMGs, 4 EOGs, 1 GSR, 1 Plethysmograph, 1 Temperature	Arousal-Valence Plane
[53]	MAHNOB	Video Clips and Pictures	30	16 EEGs, 3 ECGs, 2 GSRs, 1 Heart Rate, 1 Temperature	Happiness, Sadness, Disgust, Amusement, Fear, Surprise, Anxiety, Anger, Neutral
[54]	DREAMER	Video Clips	23	14 EEGs, 1 ECG	Arousal, Valence, Dominance
[55]	DECAF	Video Clips	30	MEG, ECG, EOG, EMG, NIR Facial Videos	Arousal-Valence Plane
[56]	SEED	Video Clips	15	15 EEGs	Positive, Neutral and Negative
[57]	ASCERTAIN	Video Clips	58	EEG, ECG, GSR and Visual	Arousal, Valence
[58]	AMIGOS	Video Clips	40	Audio, Visual, Depth, EEG, GSR & ECG	Arousal, Valence

TABLE II. RECENT EMOTION RECOGNITION AND EVALUATION STUDIES FROM EEGS [59]

Ref	Emotions	Stimulation	Recorded signals	Method	Results
[17]	4 emotions from valence arousal model	Pictures (IAPS database)	EEGs	ICA, modified kernel density estimation (KDE), artificial neural networks	Improvement in recognition using modified KDE
[18]	Negative and positive	pictures (IAPS database)	EEGs from 26 women	Amplitude and latency of ERPs, Neural networks, logistic regression, naïve Bayes, linear discriminant analysis	P300 and P200 from parietal and occipital regions play role in emotion recognition
[19]	valence arousal emotions	Pictures (IAPS database)	EEGs from 26 subjects	Clustering and classification by Echo state networks (ESN)	Echo state networks were better than classic networks
[20]	Negative, positive, neutral	Pictures (Ekman emotion database)	EEGs from 16 depressed patients and 14 normal individuals	Sub band coherence, graph theory	-Higher coherence of depressed patients at gamma frequency band -higher coherence of normal individual in negative stimulation compared to positive
[25]	happiness, anger, fear, sadness, disgust, surprise	Video clips	forehead EEGs, SC, BVP, RR from 25 individuals	adaptive weighted linear model, KNN, SVM,	EEG forehead signals are sufficient for emotion recognition
[26]	valence arousal emotions	video clips	EEGs from 32 individuals (DEAP database)	Bispectrum analysis, LS-SVM, ANN (Linear and RBF kernels)	Sub bands had better results than EEGs
[27]	valence arousal emotions	video clips	DEAP database	minimum-Redundancy-Maximum-Relevance (mRMR), SVM, genetic algorithm-SVM (GA-SVM)	Preference of mRMR vs SVM and GA-SVM
[30]	Negative, neutral and positive	video clips	EEGs from 15 subjects (SEED database)	domain adaptation, subspace alignment auto-encoder (SAAE)	Effectiveness of SAAE in emotion recognition
[29]	valence arousal emotions	video clips	EEGs and face expression from 30 subjects (MAHNOB-HCI database)	multimodal approach, Spectral power difference, discriminant spectral power, KNN, ANOVA, fusion	Effectiveness of multimodal approach
[37]	disgust	Self- induction (remembering unpleasant smell)	EEGs from 10 men	Wavelet transform, PCA, SVM	right hemisphere and T8 play important role in emotion recognition
[41]	valence arousal emotions	video clips	EEG signals and peripheral signals (DEAP database)	Spectral and time features, multiple-fusion-layer based ensemble classifier of stacked auto-encoder (MESAE)	Preference of MESAE method vs classic methods
[49]	Anger, happiness, neutral	Pictures (Ekman and Friesen's collection)	EEG signals from 46 subjects	event-related spectral perturbations, ANOVA	-theta synchronization lead to increase in low depression patients following happiness stimulation -increase of theta synchronization due to anger elicitation in high depression patients
[50]	sad, disgust, fear, anger, happy and surprise	Pictures (IAPS database), sounds (IADS[3] database), video clips	EEG signals from 57 subjects	wavelet packet transform, Hurst exponent, K-nearest Neighbour (KNN), Probabilistic Neural Network (PNN)	-Beta as the most discriminative frequency band -sad emotion had higher accuracy (82.32%)
[51]	valence arousal emotions	Video clips	EEG signals and peripheral signals (DEAP database)	reinforcement online learning (ROL), support vector regression (SVR), least square regression (LS)	Reduced learning time for Least square reinforcement learning and support vector reinforcement learning methods
[52]	Positive and negative	Pictures (GAPED database)	EEG signals from 12 subjects	Power Spectral Density (PSD), Signal Power (SP) and Common Spatial Pattern (CSP), Linear Discrimination Analysis (LDA)	Higher accuracy for finding better electrode arrangement

IV. CONCLUSION

Emotions, which are subjective activities pertaining to brain physiology, affect substantial processes such as memory, concentration and etc. Emotions play a crucial role in human relations and can be expressed by either verbal indication such as emotional terms and words or non-verbal cues like facial expressions and body language [61]. So, this means that emotion recognition as a decoder of these cues is of importance. During recent years, emotion classification has been receiving a great deal of attention from numerous researchers in different fields. Thanks to emotion recognition systems, physicians and psychologists are now able to diagnose and treat people’s mental disorders like depression, autism and etc. Many scientists have tried to design a precise and fast emotion recognition system employing biological signals with the aim of controlling robots or recognizing emotions online. Emotion states are key to designing video games and e-learning [59]. A lot of studies have been conducted in order to help researchers to distinguish the real feelings of a person. Almost all people suffering from mental and neurological disorders like Autism, Parkinson and depression have trouble expressing their emotions. Emotion estimation would provide computers and robots with the possibility of interaction with human beings in a better way. So by classifying emotions computers are more likely to understand humans’ feelings [63-67]. These are just some interesting aspects of emotion recognition. Although emotions play a significant role in people's day to day life, findings about human emotion detection is still limited and doubtful. For example, many Human-Machine interaction systems do not have the ability to recognize and translate the human emotional information. In other words, they cannot recognize human emotion states and cannot use this complex though rich information. The purpose of computation for recognizing human emotion is filling this lack with detecting emotional cues that occur during human-computer interaction [61]. Also, there is no clear definition for feelings and different types of emotions exist [68]. There are numerous studies, models and theories but in most studies it has been claimed that emotions and human feelings are subjective and difficult to understand and classify. It suggests that there is a lot to know about human feelings. Based on what was mentioned, we can easily conclude that emotion classification is important in our world. This motivated us to conduct the current study with the aim of understanding more about emotions.

In psychology various theories and models are suggested to indicate emotions. Based on the previous studies, there are two major models to represent emotions: discrete model and dimensional model. The first one states that there are some universal basic emotions with unique physiological characteristics, though their number and type vary from one theory to another [69, 70]. The most popular example of the discrete model is the classification of emotions into six main emotions: anger, disgust, fear, happiness, sadness, and surprise. This is also agreed by cross-cultural studies such as [72]. The disadvantage of the discrete view is that this model cannot distinguish the scope of emotions which are expressed in natural communication [61]. In contrast, in the dimensional theory, emotions are described in terms of dimensions. These dimensions include evaluation, activation, control, power, etc. Evaluation and activation are the two main dimensions to describe the principal facets of emotion. The evaluation dimension (valence) measures human feeling from pleasant to unpleasant, while the activation dimension (arousal) runs from active to passive, and measures the likeliness of the human taking action under the emotional state. Dimensional model indicates emotions by at least two factors: arousal (calm/exciting) and valence (positive/negative) which result in the arousal-valence plane. Considering the dimensional model, there are two dimensions to indicate feelings which results in the arousal-valence plane. Russell in [71] proposed emotion distribution in these two dimensions. The first quadrant (high arousal-high valence or HAHV) consists of happiness, pleasure, excitement, and satisfaction; the second (high arousal-low valence or HALV) consists of anger, disgust, hostility, and fear; the third quadrant (low arousal-low valence or LALV) contains sadness, boredom, shame, and depression; and the fourth (low arousal-high valence or LAHV) consists of relaxation, contentment, hope, and interest. The advantage of dimensional representation is that it helps out researchers to label the range of emotions which means that emotions can be represented by arousal and valence quantitative values in the dimensional model [69-74]. Figure 2 demonstrates the dimensional or arousal-valence based model. Some major emotions are shown in the corresponding quadrants. A lot of studies have used the dimensional perspective as it can describe emotions better than the other models.

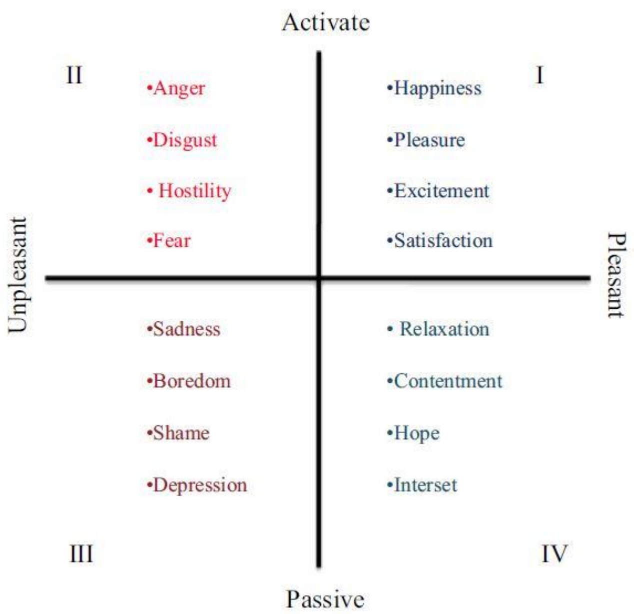

Figure 2. Distribution of emotions in the dimensional model [70]

Researchers have come to a conclusion that emotions are not exactly what arise. This means that there is a boundary between what arises and what is felt by individuals. In other words, there are two fundamental perspectives of emotions which are called the outer and inner aspects. Changes in the voice or body gesture are good examples for the outer aspect of feelings. While activities in our physiological systems such as brain are considered the emotional inner aspect [61]. In recent years, most studies have focused on analysis of the outer aspect like voice or facial expression to detect emotional states, however these ways did not give enough information to the scientists about human feelings. So they decided to concentrate on the inner aspect i.e. physiological activities. Biological signals which are a very picture of physiological activities include emotional information that can be used to assess emotions, but less attention has been paid to them [75-78]. We can distinguish emotions through biological signals such as EEG, Electrocardiogram (ECG), Electromyogram (EMG), body temperature and etc. These signals can be considered information sources whereby we can classify emotions. Among these sources EEG has very high spatial and temporal resolution. In addition EEG signals are easily available and price effective. As it was mentioned before, several studies and databases have recorded and used EEGs in order to classify emotions. Results show that EEG can simply reflect emotional changes. High classification accuracy was achieved by previous works in this field. There are also reliable databases with appropriate number of samples of EEG recordings in different emotional statues. This shows the importance and efficiency of studying and analyzing EEG in emotion recognition.

Most emotion assessment methods consist of three main steps including the biological signal which is processed, extracted features and the classification model. Extracted feature may come from traditional approaches or modern ones which are more related to nonlinear analysis. We can see that both traditional and modern processing approaches have been employed to classify emotions. But common traditional methods which focus on time domain statics, frequency or frequency-scale domain are mostly useful for analyzing linear signals with specific mathematical characteristics such as linear, stationary and Gaussian distributed [68]. However, it is obvious that biological systems such as brain are inherently complex, non-Gaussian, nonlinear, and non- stationary [79]. That is the reason why nonlinear analysis has gained a lot of attention as a novel methodology over the past years. Nonlinear analysis makes it possible to extract more meaningful information and features from the recordings of brain activity [80]. Recent theories of complex systems and nonlinear dynamics have suggested strategies where the focus shifts from the traditional methods such as simple power spectra to the study of the pattern in the fluctuations of physiological signals using nonlinear methods [79]. Although phase space of a complex and nonlinear signal is estimated in most real world applications, it is the most practical, efficient tool to process such signals. Signal processing through trajectory analysis in the phase space results in a better understanding of the dynamics of underlying signals. Trajectory analysis provides us with valuable information about the attractor and signal behavior. Several studies have been carried out to propose some quantifiers like approximate entropy, sample entropy, correlation dimension, fractal dimension, lyapunov exponents and recurrence quantification analysis (RQA) [80-86]. All of these features quantify major properties of trajectories and also the attractors in a phase space [87]. Based on what was mentioned, nonlinear analysis can better describe changes and characteristics of complex signals like EEG in practical and real world applications such as emotion recognition. Since this kind of processing has resulted in higher accuracy and more valuable information about human feelings in recent years, it is suggested that researchers try to introduce new methods in this field.

In this paper, we reviewed several emotion recognition studies from EEG signals. First, we stated some emotion approaches and theories. Then we described different components of emotion recognition systems: different kinds of biologic measurements (EEG, ECG, etc.) offline vs online recognition systems, different types of emotion stimulation, and the specific emotion models which have been used in studies (valence-arousal model and discrete model). Although numerous studies have used audio or visual elicitation, researchers have come for the conclusion that multi-modal elicitation (audio–visual stimuli) is the most effective elicitor comparing to the other modalities [60]. That is why most recent studies have employed video clips in their experiments. Since EEG has become more and more common in emotion recognition applications in recent years, our main focus was on the subject of emotion recognition through EEG signals. So different papers and studies were reviewed in order to cover this issue. Based on what was mentioned, nonlinear analysis plays a crucial role in EEG-based emotion classification systems. Higher accuracy has been achieved by representing phase space of EEG. Also valuable information about brain function and interactions between brain lobes in emotion elicitation has been obtained by these studies. This paper suggests researchers employ more nonlinear methods to study and know emotions better. Attempts were also made to support recent, valid and reliable studies for young researchers who are interested in this field.

ACKNOWLEDGMENT

We would like to thank Science and Research Branch, Islamic Azad University due to their support.

COMPETING INTERESTS

The authors declare that they have no conflict of interest. The authors declare that they have no competing interests. The authors declare that there is no conflict of interest regarding the publication of this paper.

ETHICAL APPROVAL

This article does not contain any studies with human participants performed by any of the authors.

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