

Application and Development of Machine Learning Based Brain Computer Interface Technology in Emotion Recognition

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Abstract. Accompanied with advances in brain computer interface (BCI) technology, recognizing emotion through brain and electroencephalography (EEG) signals is becoming more and more popular and accurate. Models and algorithms to interpret brain signals are explored with different results, aiming at more accurately recognizing and in return effectively regulating emotions. In order to comprehend contemporary emotion recognition (ER) theories based on BCI, EEG, and deep learning, and this paper will review several commonly accepted emotion models and the experimental practice using EEG signals to measure various emotions. In the following, approaches to decipher EEG signals, including feature extraction in different domains, electrode selection, classification of emotions, and brain network, will be explained and compared in accuracy. The paper will also discuss future research direction, proposed application, as well as challenges of BCI-based ER. The results of review show a noticeable emergence in novel ER algorithms and increase in reliability and accuracy. This also reflects a higher and more meaningful application in future ER practices, possibly, and in large scale, improving people's living status, helping them understand themselves, regulating violence in society, and avoiding negative impacts of depression and related emotion pressure.

Keywords: Emotion recognition, BCI, EEG, Machine learning, Feature extraction.

1. Introduction

Emotion is widely considered as one's instinctive state of mind brought by neurophysiological changes under certain circumstance. It plays a fundamental role in daily and social practices since one's mood can influence how he interact with others, and thus in order to effectively avoid potential depression, mental disorders, and social conflicts, the process of efficient emotion recognition and regulation is needed.

Emotion recognition (ER) can be based on physical features, including facial expression, thermal facial images, tone variation and kinematics [1]. But nowadays, as neuroscientists begin to reveal the nature of human brain, brain activity is also gradually linked with assorted human emotions and cognitive abilities. Brain activity provides more direct, credible, and hard-to-conceal information to decipher, which outperforms factors of facial expression and gestures. Therefore, detecting brain activity using brain-computer interfaces (BCI), a technique functions as a bridge in the interaction of human and computer, and representing and filtering brain signals through electroencephalography (EEG) enables researchers in the field of ER an enhanced accuracy and timely feedback, and possibly has usage in regulating negative emotions.

Various models and approaches to recognize emotion using BCI and EEG signals are increasingly popular, yet they show widely different results and accuracy. They focus on extraction of features and means to classify EEG features into the closest type of emotion.

In the following, this paper will review the recent advances in BCI's usage on emotion recognition based on previous classification models and approaches to gather brain signals. Researchers' data on emotion recognition experiment, both experimental conditions and accuracy, will also be included. Finally, the paper will provide viewpoints on future research directions, accompanied by challenges of BCI to conduct emotion recognition.

2. Related works

2.1. Emotion model/emotion classification

In order to clearly recognize emotions, categorizing emotions is crucial at the first step. Since the concept of emotion was brought up in 1884, various models of classification have been raised by scientists to define emotions. Two main types of quantitative models proposed are the discrete model and the dimensional model [1, 2].

The discrete model clarifies that there are only 6 basic core emotions ranging from relaxation, happiness, and surprise to fear, anger, and sad, and that these primal and distinct emotions combine to generate other complicated emotions.

The dimensional model has emotions being represented by spots on a valence-arousal two-dimensional space, respectively representing the negativeness or positiveness of the emotion and the intensity of that emotion. The valence-arousal classification model is shown in Figure 1. At certain circumstances, a third dimension, usually dominance, may also be included in some dimensional model.

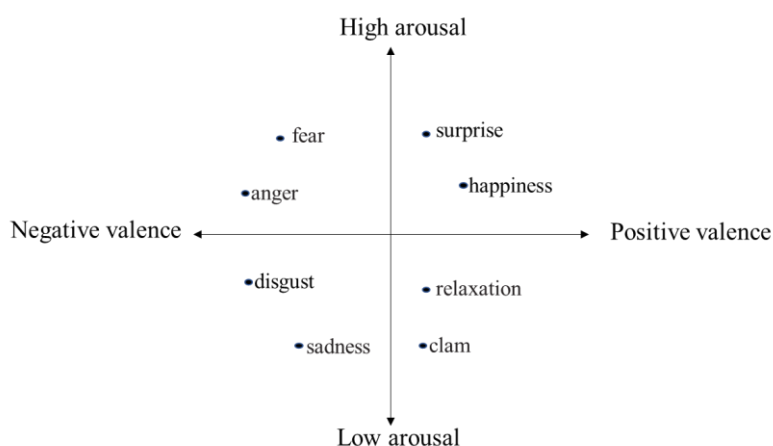


Figure 1. Two-dimensional valence-arousal model

Through time, researchers have formulated a number of classifying models but have not yet come to a conclusion of a best fitted emotion classification model. Most literature utilizes the dimensional model for further study due to its simplicity and needlessness to distinguish a complex emotion between discrete classes. A hybrid classification style, sorting emotions by eight core emotions differing in intensity is also applied.

Topographically speaking, the asymmetry of brain hemispheres is also related to valence and arousal level.

Research carried on ten-month-old infants exposed to videotapes discovers a greater association between positive emotions with the left frontal brain area than the right counterpart, showing a potential connection in valence and left hemisphere. However, recent studies have found exception to this hypothesis, stating that the asymmetry theory is not established universally than personally.

2.2. Framework of contemporary ER by EEG

Neurophysiological changes in brain areas are closely related to elicitation of emotions, perception, and cognition. (e.g., the amygdala to interpret emotion of incoming signals and fear conditioning, the prefrontal cortex for reward system, the insular cortex for conscious feeling, etc.) Therefore, understanding how brain signals are related in various emotions are fundamental for ER. The most commonly exploited technology is electroencephalogram (EEG) through BCI, which is non-invasive and easy to use. BCI and EEG gathers, filters, and reconstructs the original brain signals to obtain certain features for emotion recognition. After preprocessing the EEG signals, algorithms are applied

to extract useful features for later model assessment and classification. Figure 2 shows this process virtually.

In order to regulate emotions, methods of emotional regulatory stimulus take place after recognition.

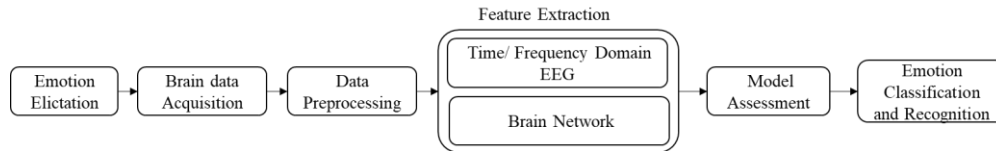


Figure 2. EEG Emotion Recognition Framework

2.3. Emotion interpretation through EEG signals

2.3.1 Feature extraction

There are several attributes' researchers focus to explore in ER by EEG: time domain, frequency domain, and a combination of time-frequency analysis [1-4]. Currently, brain network construction is also regarded as a promising way of extraction, as shown in Figure 3.

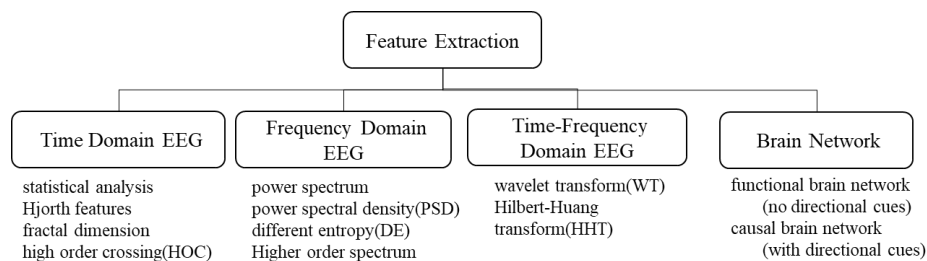


Figure 3. Feature extraction method of EEG

1) Time domain EEG

In terms of time domain, figures including common statistical value of EEG signals (e.g., maximum, minimum, median, mean, first and second difference, zero crossings, skewness coefficient, etc.), fractal dimension (FD), Hjorth features and high order crossing (HOC) are deployed to further transform brain signals into emotions [1, 4].

Scientists focus on the maximum, minimum, mean value and standard deviation of the event-related potentials (ERP) responses. They have successfully proposed an EEG-based method to detect negative emotional responses to neutral face expressions using a FD-based algorithm. Experiments exhibit a relatively stable relationship between arousal level and FD 6 area, as well as valence level and AF3-F4 area with 90% consistency. A real-time subject-dependent algorithm to perform ER tasks with credible results also gains attention.

2) Frequency domain EEG

Analyzing EEG signals from frequency features evaluates EEG bands and delta, theta, alpha, beta, and gamma spectrum to capture and distinguish brain signals of different emotions. Power spectral density (PSD), different entropy (DE), and all EEG frequency spectrum are commonly explored.

Alejandra Martínez-Tejada et al observed strong relation between the theta, alpha and beta bands with arousal level when studying subjects whose emotions are stimulated by video games. Valence level shows less correlation compared to arousal [5].

3) Time-frequency EEG

Time-frequency analysis was implemented to explore the pattern of frequency variation through time, and thus provides a more comprehensive view to investigate brain signals. The most commonly exploited time-frequency analysis methods include WT (wavelet transform) and HHT (Hilbert-Huang transform) [2].

WT refers to a special way of decomposing EEG signals, transforming original waves into bands of variable length and then analyzing the frequency-based features of each portion of bands to examine EEG signals.

The discrete wavelet transform method was applied to extract features in EEG signals. Results in accuracy of valence (84.05%) and arousal level (86.75%) have supported the reliability of WT in emotion recognition. High frequency gamma bands yield more noticeable accuracy.

HHT, on the other hand, is a nonlinear feature extraction based on empirical mode decomposition (EMD), and intrinsic mode functions (IMF). Compared to traditional methods, HHT is more competent in dealing with non-stationary signals [3].

Anandhi and Jeritta use HHT analysis to explore children's the emotion with Autism Spectrum Disorder (ASD), a sort of aggressive and sudden emotional outbursts, and results in ER have averagely 74.5% accuracy in patients [6].

4) Other methods in EEG

a. Channel selection

Recently, a research team including Sofen Gannouni innovated a novel channel selection method to improve the effect in emotion recognition. Feature extraction is based on the zero-time windowing (ZTW) method, and electrodes are then selected according to a ZTW-based epoch selection approach in which EEG trials are separated into short fragments to find epoch location. This result shows a surprisingly credible average accuracy rate above 89% in recognizing 9 emotions, surpassing previous models of lower accuracy and less emotions in distinguishing [7].

b. Brain network

Current feature extraction focuses on a single perspective and region in brain, and may thus miss information comprehensively. In order to solve this problem, researchers build up brain network to examine the correlation of various brain regions. Typically, there are two kinds of brain network: functional brain network (no directional cues) and causal brain network (with directional cues). After construction of brain networks, analysis and emotion recognition is based on features and parameters of networks [3].

2.3.2 Classification

Apart from feature extraction of EEG signals, a proper way to classify the extracted features is also crucial.

Support vector machine (SVM) is frequently used to provide accurate recognition. SVM is a kind of linear classifier used to build a hyperplane with optimal difference between 2 classes going to be chosen from [2, 6].

Shahabi et al take advantage of SVM to differentiate emotions (joyful, neutral, melancholic, familiar, unfamiliar) triggered by music with a best performance of 93.7% [8].

Mehmood et al use SVM in accomplishing an innovative LPP-based feature extraction experiments and SVM helps reach an improved accuracy, above 80% in three of four types of valence-arousal trial [9].

K nearest neighbor (KNN) is another commonly used and relatively simple classification model. It works by comparing and finding the closet k data to classify the new data [3].

Nawaz et al apply this method, as well as SVM, in emotion recognition after watching a 1 min long videotape. The emotion model researchers choose is a three-dimensional (valence, arousal, dominance) model. Results in accuracy show a maximum in KNN classifier in analyzing valence and dominance (77.54% and 79% respectively) [10].

2.3.3 Machine learning's application in research

Compared to conventional ER, ER by machine learning can greatly enhance a dynamic accuracy. Contemporary machine learning methods encompass logistic regression (LR), decision tree, artificial neural network (ANN), naive Bayes, random forest, etc. [3]. There are several machine learning models in the field of emotion recognition.

1) Convolutional neural network (CNN)

CNN has been proven to be a valid and reliable machine learning approach in recognizing images, and therefore has been frequently used in recognizing EEG images [3].

Li et al deploy and train hierarchical CNN(HCNN) with features to recognize positive, negative, and neutral moods. Results have proved CNN a potent candidate on beta and gamma waves [11].

2) Deep belief network (DBN)

DBN consists of stacked Restricted Boltzmann Machine (RBMs) and can be used in supervised and unsupervised learning tasks [12].

The emoF-BVP multimodal database is studied with 23 different emotions generated by actors. Four DBN models are used for analysis and contribute to the improved recognition results than current state of art methods. A convolutional deep belief network (CDBN) is also proposed, presenting higher accuracy (79.2%) in subtle emotion recognition.

3) Recurrent neural network (RNN)

RNN is another advanced deep learning algorithm which perform better in time series data. Long short-term memory (LSTM) belongs to RNN and has its benefits in memory processing and sequential contexts [13].

Salma et al apply this method to DEAP data set for classifying low/high valence, arousal, and liking status from EEG features. Results have shown an average accuracy of 85.65% in arousal, 85.45% in valence, and 87.99% in liking, surpassing previously proposed methods [14].

4) Artificial neural network (ANN)

Besides methods described above, artificial neural network is also regarded as a promising direction for accurate emotion recognition. ANN is composed of connected artificial neurons to imitate natural brain. It can play a part in handling complex situations. Studies using ANN have highlighted its reliable performance, some reaching over 90% of accuracy in emotion recognition and outperforming other methods.

3. Experimental design and data

The following table 1 compares and analyze recent studies related to emotion recognition. The data set used, methods of feature extraction, options of classifier, classified emotions, accuracy, and further results are compared.

Table 1. Comparison of experiment data.

	Data set	Feature Extraction/Classifier	Emotions being classified	Accuracy	Further results
Asadur Rahman et al[15]	SEED	Spatial and frequency domain(PSD), CNN	Negative/positive/neutral	89.056 (trained by 25% data) 94.63 (trained by 50% data) (Highest accuracy with SEED so far)	
Yu et al[16]	VREED (created by researchers using 3D virtual reality videos)	Frequency domain (theta, alpha, beta, gamma waves)	Negative/positive	Average of 73.77±2.01%	Occipital and frontal brain areas are crucial in processing emotions.
Doma et al[17]	DEAP	SVM, KNN, LR, decision tree	Valence, arousal, liking,	Highest accuracy achieved: kNN> SVM>	

			dominance, familiarity	Decision trees > Logistic Regression	
				Between 55%-75% in accuracy and 70%-86% in F1 score	
Gannou ni et al[7]	DEAP	ZTW-based algorithm/RNN	Happy, pleased, relaxed, excited, calm, distressed, miserable, depressed, neutral	Average above 89% in all emotions	
Ayata et al[18]	DEAP/ Galvanic Skin Response(GSR) signals	Time domain, time-frequency domain (DWT), EMD &HHT /SVM, kNN, decision tree(DT), random forest (RF)	Valence, arousal	Time domain: 71.53% for arousal, 71.04% for valence; EMD: 81.81% for arousal, 89.29% for valence Classifier accuracy: RF> SVM> kNN> DT	
Zhuang et al[4]	DEAP	EMD&IMF(proposed method), FD&DWT(classical method for compare/ SVM	Valence, arousal	Valence accuracy: EMD(69.10%)> DWT> FD Arousal accuracy: EMD(71.99%)> DWT> FD	Three components of the proposed IMFs are analyzed. IMF1, the most rapidly changing element, corresponds to the highest accuracy and researchers therefore hypothesize that emotion

				has a stronger relationship to high frequency component.
Kumar et al[19]	DEAP, SEED-IV	DWT(on extracting 5 frequency bands), time domain features/ SVM	Four emotional classes(1:HAHV, 2:HALV, 3:LALV, 4:LAHV) in which categorize emotions into high/ low valence/ arousal levels	DEAP: 1: 74%, 2: 86%, 3: 72%, 4: 84% SEED-IV: 1: 79%, 2: 75%, 3: 77%, 4: 74%
Zhang et al[20]	SEED, DREAMER	Graph Convolutional Broad Network(GCB-net), DE in frequency domain,	Valence, arousal, dominance	Valence: 86.99% Arousal: 89.32% Dominance: 89.20% In SEED, this proposed method outperforms other contemporary method(highest accuracy of 94.24%). In DREAMER, this method also robustly improves accuracy than other models.

DEAP and SEED are the most frequently used and publicly available data set for emotion recognition.

DEAP was created by Koelstra et al [21] in 2011. It is a multimodal data set including features in EEG signals as well as peripheral physiological signals. Data are collected through 32 electrodes by 32 volunteers watching 40 1-min music videos. 22 volunteers' facial expression and videos were also recorded. Arousal, valence, liking, dominance, and familiarity levels are rated and documented in DEAP.

SJTU emotion EEG dataset (SEED) only contains EEG signals and no other physiological features as reference. EEG signals are obtained through 62 electrode channels while 15 subjects were watching 4-min long video clips containing positive, negative, or neutral emotions. Subjects were also required to finish a mood-related questionnaire [3].

On the basis of SEED with EEG signals, SEED-IV adds eye movement into the physiological features. A total of 45 subject results are collected in SEED-IV by 64 electrode channels. Participants are shown with 2mins videos in three sessions and then provides feedback of negative, positive, or neutral emotions [19].

Apart from the data base described above, DREAMER is also an accessible set with EEG and electrocardiogram (ECG) signals. Data in DREAMER consists of records after 23 participants received visual and auditory stimulus. Emotions are classified according to valence, arousal, and dominance [3].

As the graph shows, researchers also created novel and open database for future research currently. Yu et al [16] created database VREED using 3D videos as mood induction procedures (MIP), attempting to bridge the gap between potentially inaccurate 2D MIP and 3D world.

4. Discussion

Despite the fact that ER by BCI and EEG signals has been greatly augmented with the help of accurate feature extraction methods and classification models, problems still emerge.

For the process of gathering brain signals, researchers have not reached on a conclusion of the best electrode mapping and channel selection system. Though [10] gives a system of selection with near 90% accuracy, more data is needed to further establish a better system for distinct emotions. Besides, noise collected in this process adds up as obstacles in later extraction process. A more clear and direct way of gathering brain signals, probably with specifically designed and less redundant channel selection to abate noise influence should be the focus of future studies.

After signal gathering, there is issues related to the process of feature extraction. There is still space of improvement in the accuracy of different feature extraction approaches, particularly to results with an average of 60-70%. A hybrid approach in feature extraction could be anticipated to yield better results. Other physiological features such as facial expression and thermal face images can also be included as reference.

Finally, classification protocol includes problem as well. Nowadays data set such as DEAP and SEED are commonly used for research and classifying reference. However, with only 32 and 15 subjects' brain signals in different emotions, these data sets only provide obscure material. Therefore, classification process is not yet fully developed. A more reliable, massive, and accessible sharing data set is vital in this field. Researchers could also contemplate the difference in brain patterns among regions, genders, cultures, ages, etc, and utilize these findings to further prompt the development of classification models [3].

Future research could also focus on more efficient way of emotion regulation after recognition, using the classification results to mediate depression, angry, violence, and other negative moods in close loop.

5. Conclusion

In the field of emotion recognition, BCI technology basically helps by automatically collecting brain signals and preparing for feature extraction and classification. Many novel theories of ER have been discussed and established to help resolve practical problems. Researchers have focused on various extraction methods and classification processes in an attempt to reach a lower cost and electrode implant and an accuracy as high as possible.

This paper set out to review recent advances and emerging novel aspects of BCI, EEG, and machine learning's usage in emotion recognition and classification. The paper discusses those from

the order of normal ER, giving out models of emotions as basis and then going through approaches, principles, and development in extraction, brain network, and eventually classification process. 30 articles have been analyzed to present the essence of current research and explore future research direction.

Both discrete and dimensional model can be used to categorize emotions. Based on dimensional model, BCI facilitates the process of finding the valence and arousal level. According to time, frequency, and time-frequency domain analysis, researchers are equipped with more accurate feature extraction means through EEG signals. A more effective channel selection system and application of brain network can also be considered.

The development of machine learning bolsters accuracy and simplicity of emotion recognition. CNN, DNN etc. are utilized in many instances and considerably increase the efficacy of ER.

However, there is still distances for BCI-based emotion recognition to mature and stabilize. On the basis of current researches, scientists could improve on the aspects of portability, precision and frugality. Later appliance on timely emotion regulation will be potential topic, as it encourages better communication and mitigates negative impacts of moods and violence to susceptible subjects.

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