Enhancement of Human Feeling via AI-based BCI: A Survey

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Abstract. Technology developments related with brain-computer interface (BCI) promote study and research in emotion recognition. In study recognizes, classifies human emotional states, electroencephalograph (EEG) signal acquired by BCI devices will go through several process include data analysis in computational research. This article performs a survey in recent study use EEG as signal acquisition equipment, compare research targets, and provide summary of both research-grade EEG, consumer-grade EEG devices used in recent research. A comprehensive view of emotion recognition research process is given. The last section focuses on advanced processing method of extracted EEG signals proposed in recent study and compare their performances.

Keywords: Emotion Recognition, Electroencephalograph, Artificial Intelligence, Machine Learning.

1. Introduction

BCI has become a popular research direction as it enables the human brain to communicate directly with the outside world. BCI devices are mainly classified into invasive and non-invasive. Invasive devices are primarily used in the clinical, surgical implantation of electrodes, deep brain stimulation for Parkinson's epilepsy, and other movement-related diseases. For capturing the brain signal, most commonly used non-invasive BCI is electroencephalogram (EEG). The process of determining what type of emotion (feelings) a person is expressing is known as emotion recognition. The emergence and advancement of BCI devices have been a major aid and boost to the field of emotion recognition. The development of efficient algorithms for recognizing human emotions is a huge difficulty in the field of affective computing and could have a dramatic impact on how people interact with operating systems of computing devices.

In general, psychobiological, and cognitive study, emotions, affect, feeling and mood have been classified into four categories specifically. One most convenient classified the four terms as follow shown in Table.1 [1].

In order to set the boundaries, a fundamental proposed model can distinguish 66 emotions as two groups: 10 basic and 56 secondary emtions [1]. In some of recent studies [2] addressing emotion recognition and classification with EEG signal, the limitation exist which clear classification is not identified. The commonly used classification is two-stage (negative and positive).

Table 1. Comparison of emotions, affect, feeling and mood

	Definition	**Duration and intensity**
Emotion	A response of the organism to a particular stimulus (person, situation, or event)	Short duration, intense, well aware
Affect	A result of the effect caused by emotion and includes their dynamic interaction	N/A
Feeling	An experience in relation to particular object	Duration depends on the length of time that the representation of the object remains active in the person's mind
Mood	In the Background affect affective state of a person to positive or negative direction.	Long duration, less intensive, subtler

2. Method

There are two types of methods for evaluating human emotions, including self-reporting techniques based on emotions. questionnaire-based self-assessment and machine assessment using measurements of human body parameters [1]. The typical self-assessment method gathered the feedback at the end of elicitation may make it difficult to ascertain the precise time and activity, However EEG device could collect the data simultaneously and record the data of brain activity when unconscious response occurred. The common input or resources for emotion elicitation could be speech, music, or vision. Comparably, large portion of the research provide emotional stimuli in a more standard and similar way, using single emotional trigger such as music [3, 4]. Fewer portions use more interactive, event-related conditions [5], which may be able to apply results to everyday circumstances.

Table 2. Review of scientific research use different emotional trigger.

Ref.	Aim	Emotional trigger	Innovations
[5]	Investigate emotions in different stages	E-commerce activity	Maybe generalizable to more interactive circumstances
[4]	Recognizing Emotions Evoked by Music	Music	Free database available
[7]	Investigation of familiarity effects in music	Songs	N/A
[6]	Identify basic or complex emotion	BCI-based Game	Active emotion provoking methods

2.1. Hardware product

The demand for EEG devices has increased in recent decades as research into brain activity has increased. Traditional research-grade BCI systems obtain several drawbacks, such as complex setup interface and cleaning ways, relative immobility causes subjects being tethered to the device by wires, and the high cost of understanding the nature of emotionally relevant or task-related neural activity [2]. Since research-grade EEG devices can be costly and shrink funding spend. Numerous researchers are seeking an EEG device that is less expensive and produces equivalent quality data. Several studies have been completed comparing quantitative EEG recordings and reliable self-testing of medical-grade and consumer-grade EEG devices and have shown successful results. Non-invasive BCI hardware products have several benefits. Usually, offer high-quality electrical conductivity with minimal setup. It can be used to assess the reliability of auditory and visual ERPs in research [7]. Emotiv is world-class brand producing consumer-grade EEG devices. Specializing in wireless EEG, they provided solutions for various scenarios, including scientific and consumer research. Their polymer sensor technology enables detecting moisture from the environment and minimal fluid priming, it makes preparation simpler without extensive setup. The products are not intended for medical diagnosis [8]. We summarize these products as following list and Table. 3.

EPOC flex is Emotiv's most dense and adaptable wireless EEG Brainwear system, designed primarily for academic use.

EPOC X is the newest product, improved for EPOC+ with a broader scope. 14 electrodes are located to record the electrical activity from cerebral cortex. It is usually used for scalable and contextual human brain research.

Insight is a consumer-grade device, which records activity from all cortical lobes of the brain.

Insight 2.0 is the latest product released in April 2022. Insight 2.0 provides detailed information which is prevalent among researching communities. And polymer sensor technology from Insight is easy to setup.

B-Alert is from Advance Brain monitoring, it shows the best behavior similarity among three 'non-traditional' systems.

g.Hlamp is the traditional research-grade EEG device, used as a comparison with low-cost consumer-grade devices in event-related neural response experiments. g. Hlamp has a wide input sensitivity range and great signal resolution, enabling it to record EEG, ECG, ECoG, EOG, and EMG data without saturation.

Table 3. Comparison of both research-grade EEG device and consumer-grade EEG device

Product name	Release year	Electrodes sensor	Set up time	Sensor technology	Sampling rate (Hz)
EPOC FLEX	2018	Up to 32 sensors	15-30 min	Saline/Gel	128
EPOC X	2020	14	3-2 min	Saline soaked felt	128/256
EPOC+	2013	14	3-5 min	Saline soaked felt	128/256
INSIGHT 2.0	2022	5	1-2 min	Semi-dry polymer	128
B-Alert	N/A	21	16-23	N/A	N/A
g.HIamp	N/A	256	5-24 min	N/A	N/A

2.2. BCI-based emotion recognition

Numerous studies indicate that the central nervous system's electrical activity and emotional states are related. In [9], authors indicated that brain functional connectivity using EEG signals is effective to investigate relationship between brain activity and emotions. Exploring the association between specific brain regions and emotional status is the fundamental theory of Emotion recognition using BCI. The whole workflow of recognition system is comprised of several components: data collection, signal processing containing preprocessing, feature extraction and selection, model built, and performance evaluation [1]. researcher could also obtain EEG data from public databases like DEAP, SEED, DREAMER, etc. Different databases collect different emotion data from different elicitation. After raw data is obtained, the processing part include signal cleaning and enhancement to avoid noise contamination. After signal has less interference, researchers need to extract specific feature from EEG signal. Frequency domain features is a critical and popular feature that reflect emotion states. Gamma rhythm is associate with positive spiritual feelings. Visually self-introduced emotions from positive and negative aspects are related to Beta frequency. Alpha is linked to conscious feelings, such as relaxing or wakeful status. Theta waves appear in relaxation states and also correlate with anxious feelings. Delta frequency present in deep NREM 3 sleep stage [1]. All different stimuli will cause different frequency. Beta frequency band appears when receiving stimulation of motor activity or imagery. The aim of these type of research is to develop novel methods to distinguish emotion from EEG signals. In this section, we investigate 4 models from different aspects.

In [4] develop an advanced feature extraction technique. Researchers compared the approaches used in 33 research to extract features, and they then introduced a new method that combined CNN and LSTM networks to choose features on a self-recorded data set. The LSTM-CNN network improves the proposed algorithm's accuracy and stability. Additionally, they achieved 2-stage and 3-stage emotion accuracy of 97.42% and 95.23% for the 12 active channels.

In [9], researchers described a novel signal processing approach intended for EEG signals achieving emotion recognition purpose utilizing deep neural network (DNN) and obtained good performance on SEED and DEAP data sets. Using the k-means cluster technique, a set of vocabularies made up of 10 cluster centers from each class are calculated. Finally, the histogram of the vocabulary set compiled from the unprocessed features of a single channel is used to depict the emotion of each subject. The BoDF model outperforms other cutting-edge approaches to human emotion recognition, with 93.8% and 77.4% accuracy on SEED and DEAP dataset respectively.

SincNet-R, an extension of SincNet, consists of three DNN layers, it was refined and proposed by researchers in [10]. The accuracy and robustness of the classification made possible by emotional EEG signals are then tested using SincNet-R. They suggested SincNet-R model has improved classification performance and better robustness, as demonstrated by comparison results with the original SincNet model and other conventional classifiers including CNN, LSTM, and SVM. The greatest accuracy achieved by SincNet-R, which outperforms the other four classifiers, is 95.22%.

In [11], In order to build EEG-based emotion identification models, this research introduces deep belief networks (DBNs) to learn key frequency bands and channels. Differential entropy characteristics from multichannel EEG data are used to train DBNs. They explored the crucial frequency bands and channels and look at the weights of the trained DBNs. There are four different profiles available, with 4, 6, 9, and 12 channels. The best recognition accuracy of these four profiles is 86.65%, which is significantly greater than that of the original 62 channels and is relatively consistent. DBN, SVM, LR, and KNN had average accuracies of 86.08%, 83.99%, 82.70%, and 72.60%, respectively.

Table 4. Recent studies about deep learning-based emotion recognition.

Emotion types	Measurement methods	Data analysis methods	Performance	Year	Ref.
Positive, negative	EEG, self-report questionnaire	DNN	Achieved 97.42% and 95.23% accuracy for 2-stage and 3-stage of emotion for 12 active channels	2021	[4]
Negative, positive, neutral, alert, calm, happy, sad	SEED, DEPA data	Neural Network	Achieves 93.8% accuracy in the SEED data set and 77.4% accuracy in the DEAP data set	2019	[12]
Positive, negative, and natural	SEED data	CNN, DNN	Highest accuracy reaches 95.22%	2019	[13]
Positive, negative, natural	EEG	DNN	Stable with the best accuracy of 86.65%	2018	[14]

3. Conclusion

Emotion recognition is a popular researching field using non-invasive BCI as main data recording technique. A major portion of recent study is focusing on developing advanced computational method. The combination of various modalities has unlimited possibility. Machine learning algorithms could enhance model's reliability. The invention of less costly and more mobile devices has made experiments conducted in real-life environments more accessible.

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