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Affective Brain Computer Interface—Using closed-loop BCI to recognize emotions and solve emotion problems

Zhuoxuan Xiong *
The Teresian School, Dublin, D04 E9X5, Ireland
* Corresponding Author Email: 20zxiong@teresian.ie

Abstract. Affective Brain Computer Interface (BCI) is an interdisciplinary system that integrates neuroscience, psychology, and computer science to detect and interpret human emotional states by analyzing brain and physiological signals. This article illustrates how affective BCI using Electroencephalography (EEG) and other physiological signals to recognize different emotions and diagnose mental diseases. With questionaries and interviews, this closed-loop BCI can personalize a specific treatment option. Affective Brain–Computer Interfaces (aBCIs) combine insights from neuroscience, psychology, and computing to better understand and influence human emotions. These systems can interpret signals such as EEG, ECoG, and fNIRS, offering a more objective way to assess conditions like depression or anxiety, which are often measured through self-reports. Unlike traditional open-loop BCIs, a closed-loop aBCI can track emotional states in real time and provide adaptive feedback through methods such as neurofeedback, non-invasive brain stimulation, or even deep brain stimulation. This paper outlines the foundations of emotion modeling, techniques for collecting and classifying signals, and strategies for system design. It also highlights key applications and ongoing challenges. With advances in machine learning and adaptive algorithms, closed-loop aBCIs present a potential pathway toward more personalized and ethically aware approaches to emotional health and treatment.

Keywords: Affective BCI; Close-Loop; Emotion Recognition; Self-Learning.

1. Introduction

Nowadays, the number of people who have neurological and mental illnesses is increasing year by year. The World Health Organization points out that there are more than 264 million people suffering from depression worldwide [1]. However, the main methods to detect mental diseases such as depression are based on self-assessment scale. It is subjective and has a large individual difference. Also, the treatment of mental diseases is limited. The mainstream treatments are usually psychological counselling and medicine taken.

In order to solve this problem, an objective assessment and treatment system for depression is designed according to the model made. Emotion recognition has a large individual difference; a personalised adaptation mechanism is needed to set up based on different people's demands according to adaptive intervention and reinforcement learning [2]. A closed-loop affective aBCI is utilized to recognise emotions and solve emotion problems. It is a technique combined Neuroscience, Psychology and Computer Science. Through decoding phycological signals related to emotions in the brain, it aims to recognise and regulate human's emotion state. To treat depression and other mental problems more personalised and intelligent, a real-time emotion recognition and intervention feedback system is designed. It helps users recognize and manage emotions and collect data for researchers to improve their BCI application.

As a result, status judgment and trigger mechanism are needed to create. At the beginning, the methods used are based on expert system and data base. With EEG and other physiological signals, considering the self-assessment scales patients did, experts can give a clear diagnose. Based on this diagnosis, a more personal and detailed treatment is made. A small and specific model especially for one patient is created.

This article illustrates aBCI in four parts, theoretical basis, system designed, applications and challenges.

2. Theoretical Basis of Emotion Recognition in BCI

2.1. Emotion Representation Models

There are two different types of models utilized in affective BCI, discrete model and dimensional model. Discrete model identifies emotions as compositions of many different, discrete basic emotions [2]. Paul Ekman classified emotions into six: happiness, sadness, anger, fear, disgust. It makes emotions easy to be understood and classified, but emotions are complex, this model is difficult to combine emotions together [3]. Dimensional model defines emotions in a coordinate system composed of multiple dimensions. James Arthur Russell proposed two-dimensional model of emotions in 1980. It describes all the human emotions with dots in the coordinate system of valence and arousal [4].

2.2. Signal acquisition

Signal acquisition is the first component of BCI. It is responsible for receiving and recording the signals produced by neural activity. These data are then sent to the processing component to amplify and reduce noise. There are two methods categorized to collect brain signals, invasive and non-invasive.

EEG is a non-invasive measurement, using externally inserted electrodes. It can measure neural activity useful for a BCI. It is safe, inexpensive, non-invasive, easy to use, portable, and maintains high temporal resolution. EEG signals are measured by wearable EEG helmets and headsets that position noninvasive electrodes along the scalp [5].

EEG signals are classified into five categories based on the variation in frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (> 30 Hz), as depicted in Fig.1 [6].

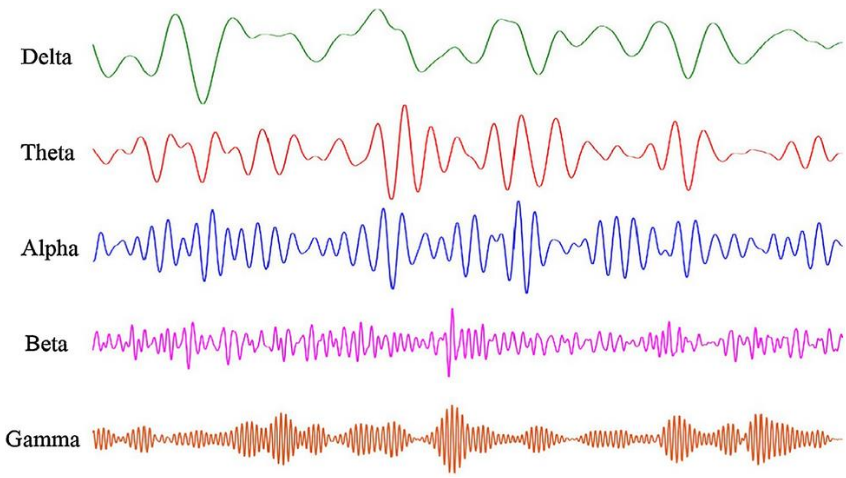

Figure 1. The waveforms of five EEG bands [6]

Delta waves (20–200 μV) appear in the frontal cortex during unconscious states like deep sleep or anesthesia. Theta waves (100–150 μV) occur in the parietal/temporal lobes during relaxation and working memory tasks, increasing with positive emotions. Alpha waves (20–100 μV) dominate the occipital/parietal lobes when eyes are closed but fade with mental activity or external stimuli. Beta waves (5–20 μV) emerge in the frontal lobe during focused or stressed states, replacing alpha waves under tension. Gamma waves (<2 μV) are linked to high-level cognition, sensory integration, and intense concentration. Each wave reflects distinct brain states, from deep rest to active processing.

Electrocorticography (ECoG) is an invasive detection technique placing electrodes on the surface of the cerebral cortex. ECoG signals collected are clearer with stronger noise immunity than EEG signals, but clinically researchers don't use ECoG as it needs craniotomy [7, 8].

These physiological signals can effectively illustrate the mental state of patients. Unlike facial expressions and voices that can be forged, EEG with eye movement can't be controlled by users, so it is more precise.

2.3. Feature Extraction

Feature selection is an effective technique to remove a great number of unnecessary or redundant features based on particular usefulness criteria. It aims to obtain the best results with the least amount of data processing. The chance of overfitting is lower by feature selection approaches if the database includes many features but there are not enough observations. Ideally, the reduced representations of data should contain the fewest number of parameters necessary to account for the data's observed properties. By extracting crucial information from a database, main features of different types of emotions are identified. Feature reduction seeks to transform high-dimensional data into a comprehensible representation of lower dimensions. It is lower the calculation and energy consumption and make emotions easier to recognise [9].

2.4. Classification & Algorithms

Traditional machine learning algorithms, such as k-nearest neighbours, decision tree, and support vector machine (SVM), can be used for emotion recognition. The choice of algorithm depends on factors such as the type of neural data, noise levels, and the complexity of the targeted emotional model, difference between discrete model and dimensional model. Hybrid approaches that combine multiple classifiers have also shown promise in improving robustness and reliability [10].

2.5. Self-learning, Deep learning and Self-supervised learning

Self-learning techniques in affective BCI allow the system to adapt dynamically to individual users without requiring extensive manual calibration. By continuously updating its models based on new emotional data, the system can gradually improve accuracy in recognizing subtle affective states. This adaptability is crucial, as emotional responses are highly subjective and may vary across contexts, cultures, and even within the same individual over time [11].

Feature extraction and classification can be integrated into a single end-to-end neural network, when deep learning is utilized. So manual feature extraction may not be necessary. Deep learning architectures—such as convolutional or recurrent neural networks—can automatically learn relevant patterns linked to emotional processing. This not only improves classification accuracy but also enhances the generalizability of the system across diverse emotional stimulate [12].

Self-supervised learning is a machine learning method between unsupervised and supervised learning. It generates training labels from raw data, eliminating the need for manual annotation. Self-supervised learning begins with a pre-training task, allowing the model to learn useful features from the data. After completing this pre-training task, the learned features can be transferred to actual downstream tasks, such as emotion classification and depression detection. The advantage of self-supervised learning is that it reduces reliance on manual labelling. There is no need to manually label, to figure out the emotions of EEG signals by person. Useful features are automatically learned from raw EEG, fNIRS, ECoG, and other signals. This improves model performance in small sample sizes [13].

3. System Design and Application Analysis

3.1. System Design of a Close-loop BCI

Before, during and after interventions, EEG and other data are collected to compare whether the interventions are affected or not. Useful samples are then labelled and fed back into our model to improve accuracy over time.

A personalized fine-tuning strategy is implemented on top of a pre-trained model. By feeding individual EEG responses back into the system and updating model weights, more accurate and adaptive emotional state recognition—essential for effective, closed-loop interventions, is achieved.

To make the model more suitable for every patient, distil is utilized to make model more specific to individuals. This model will be small and low energy consumption.

After decoding human emotions, emotion regulation brain-computer interfaces can achieve effective emotion regulation. In the diagnosis and treatment of emotional disorders, people hope to use multimodal emotional brain-computer interfaces to assess patients' depressive states and perform neural modulation at the appropriate time. In invasive neural modulation systems, deep brain stimulation (DBS) technology can be used to stimulate specific brain regions, thereby regulating emotions [14].

Closed-loop brain-computer interfaces primarily focus on determining the optimal timing and method for intervention. Optimal intervention strategies may vary among individuals. Through reinforcement learning, intervention methods can be adaptively adjusted based on feedback from the affective brain-computer interface. For example, by adjusting the stimulation parameters of deep brain stimulation, optimal regulatory effects can be achieved. Fig.2 illustrates a reinforcement learning-based closed-loop neural modulation framework for the treatment of treatment-resistant depression [2].

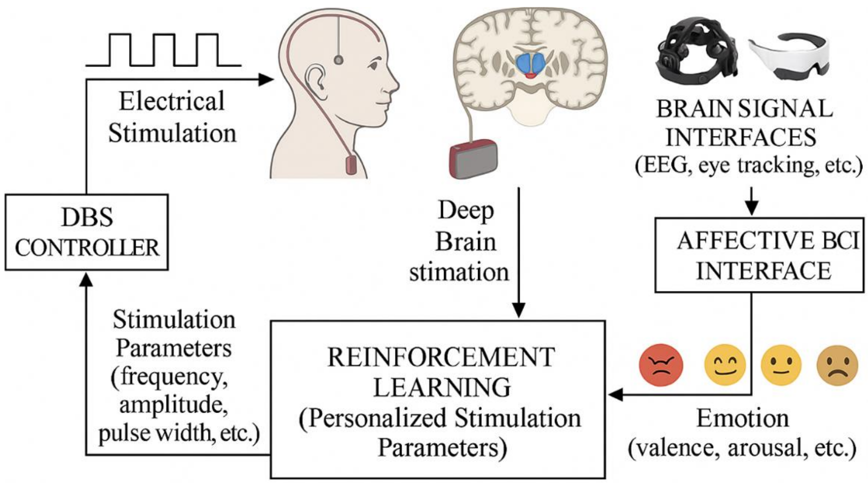

Figure 2. Reinforcement learning-based closed-loop neural modulation framework [2]

3.2. Application Analysis

3.2.1. Non-invasive interventions.

Transcranial direct current stimulation, or tDCS can treat depression. This method is very gentle. It only requires placing two small electrodes on the scalp, and passing a tiny electrical current through the brain. For depression treatment, the most common target is an area on the upper left part of the forehead, called the "left dorsolateral prefrontal cortex," or Left DLPFC. This part of the brain is involved in emotional control, logical thinking, and decision-making. When it's not working well, a person may be more vulnerable to negative emotions. Scientists have found that using a current of 1.5 to 2 milliamps, for around 20 to 30 minutes, can make this region more active. It's like giving the brain a little boost — helping it reconnects the networks that depression might have disrupted. That's why tDCS is being explored as a safe, simple, and promising tool for treating depression.

There is also another similar to tDCS but the region of neurons stimulated are different. This method uses a small device placed on the neck to gently stimulate the vagus nerve — a key part of our body's relaxation system. By doing this, it can reduce heart rate, calm stress responses, and activate emotional brain regions like the amygdala and prefrontal cortex [15]. Neurofeedback is also a useful method. Real-time feedback of EEG activity allows users to train and adjust their own brain state. Commonly used for anxiety and ADHD.

3.2.2. Invasive interventions.

Deep brain stimulation (DBS) can stimulate different sites of brain to interfere with dysfunctional network function in major depression. It can interrupt abnormal nerve signals to reduce limb tremor in Essential Tremor or Parkinson's disease. What's more, DBS can also be utilized to stimulate nucleus accumbens. Nucleus accumbens is a key structure of reward system in our brain. When it can't work as normal, people can't have the feeling of happiness. It is the main feature of depression, anhedonia. Patients lose interest in things they used to love. It is highly related to the dysfunction of reward system. Anhedonia in refractory major depression can be reduced by deep brain stimulation to reward circuitry [15].

For instance, there is a case for three patients suffering from extremely resistant forms of depression. They didn't respond to any medicine therapy, psychotherapy and electroconvulsive therapy. So, they were implanted with bilateral DBS electrodes in the nucleus accumbens. This experiment used double-blind manner so that both doctors and patients don't know whether the stimulation is opened or not to avoid subjective influence. After each adjustment of stimulation parameters like current intensity, frequency, the improvement of patients' depressive symptoms was assessed. The result turned out to be that in all three patients when the stimulator was on, and worsened in all three patients when the stimulator was turned off. These preliminary findings suggest that DBS to the nucleus accumbens might be a hypothesis-guided approach for refractory major depression [16].

3.2.3. Digital and behavioural intervention.

Digital and behavioural interventions are commonly used alongside affective BCIs to help regulate emotions. For example, meditation exercises train users to focus their attention and increase awareness, which can reduce emotional fluctuations and cortical excitability. Virtual reality (VR) interactions provide immersive experiences that can guide users through calming environments or simulate situations for emotional training. Mandala colouring exercises, which involve concentrating on intricate patterns, have also been shown to promote relaxation and mindfulness. When combined with real-time monitoring of EEG and other physiological signals, these interventions can form part of a closed-loop system, allowing the BCI to adjust activities according to the user's emotional state and enhance the effectiveness of emotional regulation. Through training to focus attention and awareness, it can reduce cortical excitability and emotional fluctuations. It is often combined with BCI to form a closed-loop system. Also, through EEG and other physiological signals, emotion states are known. Different kinds of light music, breath guide and ideal scenes can be chosen to help patients to relax.

4. Challenges and Optimization Analysis

4.1. Challenges

Problems about emotion recognition. Emotions are related to a variety of phycological signals, but they are difficult to collect at the same time. Emotion recognition has a large individual differences, personalized adaptation mechanism is needed to set up based on different people's demand according to adaptive intervention and reinforcement learning. Emotions are not discrete labels, but continuous, multi-dimensional states. The database is small, lack of data. Some of the data are labeled incorrectly. Physiological signal labels are few, as they are objective.

Difficulty in accurately determining the location of stimulation. It is difficult to determine the location of stimulate accurately. Stimulation of one region may affect multiple functional networks simultaneously. Non-invasive stimulation (such as tDCS) has low spatial resolution and a large current diffusion range, making it difficult to accurately stimulate specific brain areas.

Emotion is a very important part in human's life. Using Human intervention to change one's emotions may be considered to violate human rights. It may undermine individuals' autonomy in interpreting their emotions. How to use interventions properly need to be thought more [17].

4.2. Optimization Analysis

The general model should be distilled to be suitable for individuals so that it can achieve personification design.

Multimodal approach is utilized to get clear and correct labelled signals with emotions categorized. brain signals, physiological signals, behavioural signals and environmental information are integrated to understand and regulate emotions more accurately and comprehensively, such as EEG with eye movement combined. More patients' data should be collected and analysed correctly. It can avoid relying on a single signal and reduce misjudgement. After identification, multiple signals can be used to verify the feedback effect in real time.

For accurate stimulation, the target area stimulated needs to be precise, and the electrodes need to be small enough, the current is more focused.

5. Conclusion

Affective Brain Computer Interface is a very effective and promising project to utilize in recognise emotions. It can help doctors to diagnose mental diseases and give more scientific treatments. EEG helmets and headsets are utilized to collect signals. Data are collected and processed to be clear and corrected labelled. Its main feature is extracted for emotion recognition. Data is then feed in the pre-training model. Through self-learning, deep learning and self-supervised learning, a more personal model is created for individuals.

Traditional open-loop frameworks have been successful in detecting affective states through EEG, fNIRS, or ECoG signals, but their impact on emotional regulation remains limited. Closed-loop aBCIs, by contrast, provide a dynamic cycle in which brain signals are continuously monitored, processed, and fed back to the user through personalized interventions such as neurofeedback, music, virtual reality, or brain stimulation. This feedback not only validates the accuracy of emotion recognition but also enables real-time modulation of emotional states, offering potential solutions to emotion-related problems such as stress, anxiety, and depression. Despite challenges including signal variability, individual differences, and ethical concerns, closed-loop aBCIs open a pathway toward more precise, user-centered, and clinically relevant emotion regulation technologies. Future research should focus on improving multimodal signal integration, adaptive machine learning algorithms, and long-term validation in naturalistic environments to ensure both reliability and ethical application of this technology.

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