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Analysis of emotion recognition based on brain-computer interface technology

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Abstract. The lifetime prevalence of social anxiety disorder is pretty high, and Brain-computer Interface (BCI) technology has become the main solution to the above problems. In order to solve this problem, this paper firstly introduced the sentiment classification and the theoretical basis of BCI emotion recognition, and bring up the specific mechanism and detailed process of emotion recognition. Secondly the selection of data sets and the detailed process of EEG signal analysis are mainly discussed, including pre-processing, feature extraction, classification of signal recognition, accuracy analysis and so on. Thirdly, the paper summarized some examples of current representative applications and the existing problems, improvements and breakthroughs in recent years. In the end, the future development trend of affective brain-computer interface is prospected. Although the brain computer interface (BCI) emotion recognition is still an immature technology in the initial stage and has so many challenging problems, but this paper wish and believe it can have a brilliant development prospect.

Keywords: BCI, emotion recognition, sentiment classification, EEG signal analysis.

1. Introduction

Epidemiological studies in the United States, Canada, and Germany show a lifetime prevalence of social anxiety disorder is about 7 to 10 percent. And according to the World Health Organization's estimate, the global burden of depression is about 4.4%, but the people who have experienced depression are about 10%-15% [1]. It can be seen that emotions play an important role in people's daily life and work, but emotional problems have become more and more common in recent years. At the same time in the field of human-computer interaction, has not yet developed a comprehensive related application, and emotion recognition is a key step to apply emotion computing to the field of human-computer interaction, which has gradually attracted wide attention in the past decade.

At the beginning of this paper, the theoretical basis of BCI emotion recognition is expounded, and then the specific mechanism and detailed process of emotion recognition are introduced. The selection of data sets and the detailed process of signal analysis are mainly discussed, including pre-processing, feature extraction, classification of signal recognition, accuracy analysis and so on. Besides, some examples of current representative applications are given, and the existing problems, improvements and breakthroughs in recent years are summarized. Finally, the future development trend of affective brain-computer interface is prospected.

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As a matter of fact, the research on emotion recognition has only received widespread attention in academia and industry recently, while the research on emotion brain-computer interface is relatively new. At the same time, there are relatively few laboratories and teams engaged in the research of emotion brain-computer interface at home and abroad, so the emotion recognition of brain-computer interface has great research significance.

2. Theoretical basis of emotion recognition based on brain-computer interfacee

2.1. Emotion recognition classification

Emotion is a kind of psychological and physiological process, which itself has a very high complexity and abstraction, leading to many researchers do not reach a unified emotion classification standard when doing emotion computing related work. In addition, contemporary human-computer interaction systems lack the ability to interpret emotional information, so they cannot effectively identify people's emotional states, and cannot effectively use such information to decide the appropriate action instructions to be executed. Therefore, a complete set of emotion discriminative indicators is crucial to the research of emotion recognition through brain-computer interface.

Currently, the emotion models that are highly recognized and widely used include the VA and VAD models: VA model is a two-dimensional model of emotion representation, which called Valence-arousal Model, was first proposed by psychologist Russell in 1980 through an experiment summary [2]. In this experiment, all participants were asked to watch 40 videos in order, and asked them to score the videos one by one. V (valence) represented the specific evaluation score of the video by the participants, A (arousal) represented the arousal degree of the video, that is, whether it aroused the viewer's attention. Through the combination of these two scales, the two-dimensional emotion model as shown in the figure can be obtained, corresponding to happiness, distress, frustration and relaxation. The 2-D classification of the emotion was shown in figure 1.

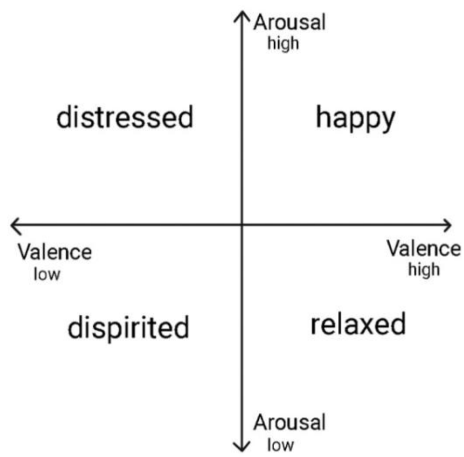

Figure 1. 2-D representation of emotions.

And the three-dimensional model, that's what Mehrabian came up with, he proposed to add a D (dominance), which indicates the dominance of the video in the viewer's mind, to the VA (Valence-arousal) model because the two-dimensional representation of emotions could not effectively discriminate between certain basic emotions, such as fear and anger [3]. As is shown in figure 2, the three-dimensional emotion model, also known as the VAD(Valence-arousal-dominance) model. Anger has a high degree of support, while fear has a low degree of dominance.

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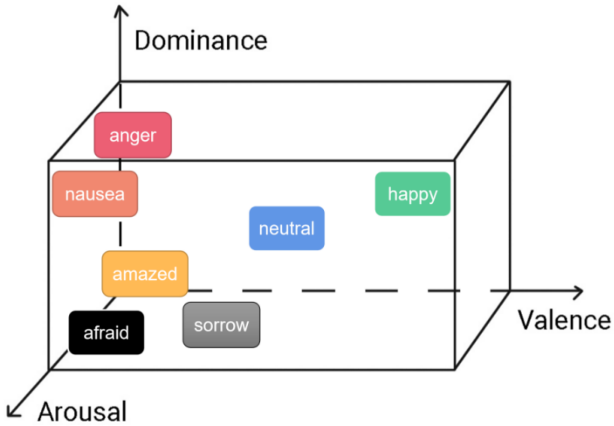

Figure 2. 3-D representation of emotions.

2.2. Theoretical basis of brain-computer interface

The structure of BCI system is divided into signal acquisition and signal analysis, and signal analysis includes three modules: pre-processing, feature extraction, clustering and classification. The typical BCI device module is shown in the figure 3.

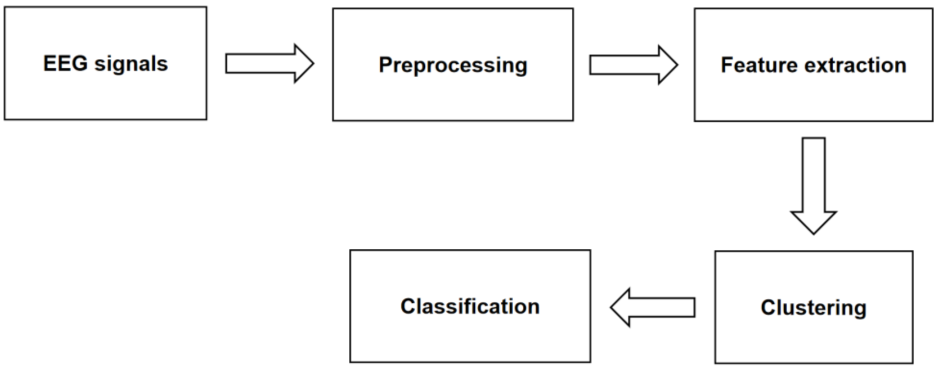

Figure 3. Brain computer interface device module.

Signal acquisition module's main function is to use electrodes to record brain electrical signal, filtering and modulus conversion operation. Among them, the electrode can be divided into two kinds: invasive & non-invasive. Invasive electrode is through the electrodes implanted within the frequency signal acquisition, have high spatial resolution and signal-to-noise ratio is very high. And non-invasive electrode is through collecting the participants on the surface of the scalp electrical signals, because of the no wound and safety characteristics, it is more widely applied in the study of the general.

As for signal analysis, its main function is to pre-process the collected EEG signals, extract features and classify features, and finally install them into feedback signals transmitted to external devices. This is the most important part of the BCI system. And we'll go into more detail in the following sections.

3. Emotion recognition mechanisms and processes

3.1. Emotion recognition classification

DEAP, which is "a Dataset for Emotion Analysis using Physiological Signals", is a multimodal emotional data sets collected by Twente University. The data set adopted the Russell's emotional loop pattern, and is mainly composed of EEG signals and the outer weekly intra-articular. These signals are collected from 32 volunteers (50/50 men and women, age range 19-37), volunteers were asked to watch 40 videos each length for 1 minute, and rating on each segment of the video index, these indicators

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including arousal, valence, like/dislike, dominance [4]. All the electrical data used Biosemi Active Two System for recording, and the initial signal sampling frequency is 512 Hz, downloaded from the website data sets have been used by the sampling to 128 Hz, in which the effects of EOG has been removed by bandpass filter. It is worth emphasizing that each EEG label in the DEAP data set is determined by the self-evaluation completed by participants themselves [5].

3.2. Emotion recognition classification

As the DEAP data set has mentioned above, actually, itself has already carried on some simple pre-treatment, but there are still many problems: the sampling rate is too high, lead to increase the amount of calculation and deep learning network training speed slowly; noise removal work for not doing enough; low signal-to-noise ratio; different degree of noise interference of subjects will seriously affect the results.

The brain electrical signals that system collected initially contains a lot of noise, including noise caused by environmental and equipment (such as electromagnetic interference, etc.), other noise produced by organs (such as electrical, electrical, etc.) and many useless brain electrical components, combined with disturbance of consciousness patients whose brain electrical signal response amplitude and strength had great difference to normal people. In order to improve the signal-to-noise ratio, the initial signal pre-processing operations, which will be introduced in this paper, as figure 4 has shown, mainly including eliminate bad channel and experimental data, subsection interception, smooth filtering, baseline removing, filter filtering and so on [6].

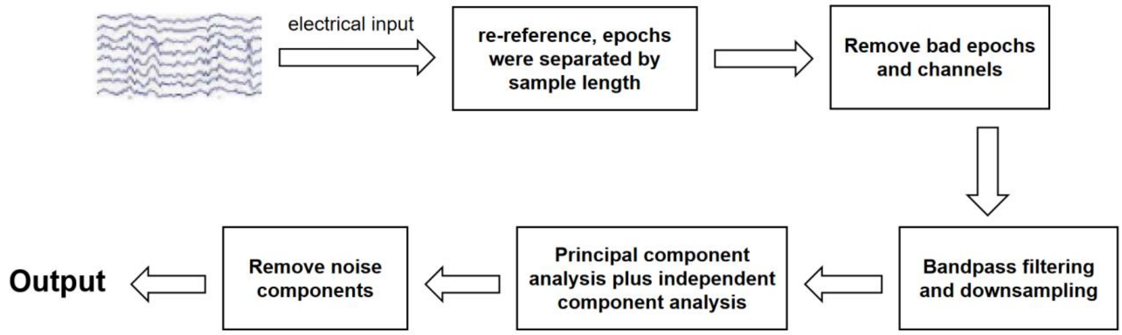

Figure 4. Preprocessing flow chart.

3.2.1. Eliminate bad channel and experimental data. In the process of data collection, interference problems, incorrect collecting equipment, improper operation during the test or the subjects' movement interference could all effect the data collecting, therefore eliminating them is essential. And for patients with different conditions, the corresponding channel data should be eliminated.

3.2.2. Subsection interception. Signal analysis is for all data in EEG integral data, so it is necessary to intercept the required data in sections and analyze them one by one.

3.2.3. Smooth filtering. In fact, the EMG signal generated by the human body's own muscle movement has a large noise range. In addition, the environmental noise will also cause interference to the collected EEG signal, and the use of smooth filtering is to remove these noises.

3.2.4. Remove the baseline. After the smooth filtering filters out part of the noise, there is still the problem of zero drift caused by components due to the influence of environmental factors, and these drift phenomena can be well removed by removing the baseline.

3.2.5. Filter filtering. The frequency response curve can be smoothed and the signal to noise ratio can be improved.

3.3. EEG feature extraction

Filter Bank Common Spatial Patterns (FBCSP) is a novel Filter Bank Common Spatial Pattern which is widely used in the field of brain electricity research [7]. It is used to decode a variety of EEG signal information, and the classification effect has high accuracy.

The first step is frequency division, and the collected EEG signals are divided according to the frequency; the second step is to use the CSP algorithm to filter each frequency segment; the third step is to integrate the EEG signals obtained in the second step and select their features; the fourth step is to classify them according to the result of feature selection.

The algorithm principle of CSP can be briefly described as the simultaneous diagonalization of the covariance matrix of the two types of tasks to find an optimal spatial projection direction to make the variance difference of the two types of signals as large as possible, so as to obtain the feature vector that is easy to classify.

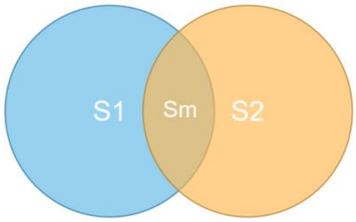

Figure 5. Separate common and unique source signals.

As shown in the figure 5, S represents brain electrical signal source, Sm represents the common EEG source signals of two types, S1 and S2 are the specific source signals of two types of tasks. Assuming that the S1 and S2 respectively by the m1, m2, a source, C1 and C2 is uniquely and two components related to my, m2 consisting of a common space mode, The CM and corresponding spatial patterns of SM [8]. Assume X1 and X2 the matrices of multi-channel EEG data of the two types of tasks respectively, and they are represented by the following formula (1):

$$X_1 = [C_1 C_M]\begin{bmatrix} S_1 \\ S_M \end{bmatrix},\ X_2 = [C_2 C_M]\begin{bmatrix} S_2 \\ S_M \end{bmatrix} \tag{1}$$

The covariance matrices of the two types of data: R1, R2 and the covariance matrix of the mixed space R, were calculated using the following formulas (2 & 3):

$$R_1 = \frac{X_1 X_1^T}{\mathrm{trace}(X_1 X_1^T)}, R_2 = \frac{X_2 X_2^T}{\mathrm{trace}(X_2 X_2^T)} \tag{2}$$

$$R = \overline{R_1} + \overline{R_2} \tag{3}$$

After eigenvalue decomposition of the mixed space covariance matrix R, formula (4) is obtained, where U is the eigenvector matrix of λ, and λ is the diagonal matrix formed by the corresponding eigenvalues:

$$R = U\lambda U^T \tag{4}$$

The source signals S1 and S2 can be obtained by transforming the two covariance matrices after sorting the eigenvalues in descending order:

$$S_1 = PR_1P^T, S_2 = PR_2P^T \tag{5}$$

In order to further separate the two types of samples, the projection matrix W can be obtained through the transformation of the feature matrix as shown below:

$$W = B^T P \tag{5}$$

For CSP feature extraction, the EEG signal matrix X is multiplied with the projection matrix W to obtain the feature Z:

$$Z = W \times X \tag{6}$$

Finally, the feature vector f can be found as the sign of classification:

$$f = \log(1 + VAR(Z)) \tag{7}$$

In addition, FBCSP adds multiple frequency domain features on the basis of CSP algorithm, so it is more accurate than CSP in electric field imagination movement. Moreover, FBCSP has high accuracy in signal classification, energy signal extraction and spatial feature extraction, because it is difficult to lose the frequency domain features and has strong anti-interference ability, which is complementary to the deficiency of CSP. However, it is undeniable that the computational difficulty of FBCSP is much higher than that of other algorithms [8].

3.4. Recognition of EEG signals

Shallow convolutional neural network is a model of forced processing of two-dimensional EEG signal array based on the improved FBCSP algorithm. It can be clearly seen that different convolutional layers adopt the original clipping strategy to extract the time-domain and spatial features of EEG data, and it also has a high accuracy in the recognition and classification of EEG signals.

It will integrate and further classify the time-domain features and spatial features extracted from the convolutional layer. By clustering, it can cluster objects having several features into different classes without actually knowing the labels, such that the objects belonging to the same class are similar, and otherwise not similar. The cluster centers are obtained in multi-dimensional space, with each data having multiple attributes. Not all attributes of the data are needed and only need a subset of it that can ensure the accuracy of the classifier. There are many classification approaches such as Nearest Neighbor (KNN), artificial neural network (ANN), support vector machine (SVM) and so on, which FBSCP algorithm doesn't have, so it is also more accurate than FBCSP algorithm [9].

3.5. Identification accuracy analysis

Single Subject Research means a single training sample set and test set used in the experiment are from the same subjects, the same experiment. EEG signals, as a kind of physiological signal, has a great difference between different individual, and even with the same individual, if the date of data acquisition vary widely, the characteristics of brain electrical will also vary. Therefore, the single subject research is carried out under the condition that ensure the EEG data difference in test and training sets are as small as possible.

Table 1. Classification accuracy of each method in different frequency bands [10].

EEG+SCN	66.67	68.09	68.48	69.46	69.89	73.75
EEG+DCN	60.57	60.84	62.24	62.71	63.41	66.00

Can be seen from the table 1, the SCN method in multiple frequency bands are made of very high accuracy, at high frequencies (β, γ), and all frequencies, the SCN and feature extraction method of the best DE characteristics compared to the same accuracy. But in low frequency band (δ, θ, α) two convolution neural network performance is much better than the feature extraction method, the SCN can achieve more than 66.5% accuracy at almost any frequency, compared with the accuracy of the traditional feature extraction method, which is about a quarter lower [10]. This phenomenon shows the SCN and DCN method can extract the data in the low frequency characteristics of deep for EEG identification, and these characteristics are difficult to found through the traditional artificial extraction method, so the traditional characteristic in low frequency band is almost no classification ability. Compared SCN with DCN, it can be found that the effect is much better than the DCN, DCN is just a general convolution neural network, and didn't improve itself according to other algorithms, and the SCN is based on FBCSP algorithm design, more suitable for the recognition of emotional EEG. And because the layer number is less, the SCN is also better than DCN network on the training time.

From the above data, it can be seen that SCN can cover the most information in the overall frequency band. With the increase of frequency, the recognition accuracy will gradually improve, reflecting a better classification effect. In addition, related studies have also shown that the multi-dimensional spectrum EEG is dominant in the study of emotional EEG signals [11]. The study also shows that the classification errors of samples show clustering phenomenon. When the classification errors occur, it is likely to have a large area of persistent errors or a very low accuracy rate in a whole data sample.

4. Application and development trend

4.1. Representative Applications

The incidence of neurological and mental diseases in China and the world is increasing year by year, bringing major challenges to human health. This section presents three representative applications of emotion recognition BCI.

4.1.1. Work load detection. With the rapid development of economy, people's working pressure can be seen to rise visually, and there are more and more cases of overload work. Where job conformity is usually defined as the proportional relationship between the demands of the task and the ability of the individual. According to the flow theory, not only will low mental load lead to decreased attention, but also when people are in a state of tension for a long time, the resulting high mental load will have a serious negative impact on work efficiency [12]. As an enterprise, a party or a leader, knowing people's workloads helps to distribute work reasonably. As employees and the public, knowing their own workloads also helps to improve their efficiency and accuracy. Therefore, workload detection is particularly important. At present, the application of workload detection mainly collects and analyzes physiological signals, such as electroencephalogram, eye movement, electromyography, electrocardiogram and respiratory rate in real time, so as to summarize more objective indicators of mental stress assessment.

4.1.2. Adjunctive diagnosis of affective disorders. In 1993, Wheeler R E et al. found that by measuring the power of alpha frequency EEG in the resting state, it was shown that part of the emotion-related responses and emotional stimuli were associated with hemispheric asymmetry in prefrontal activation to a certain extent [13]. At the same time, many related studies have shown that the asymmetric activity of the frontal cortex in the resting state is highly correlated with the behavioral activation system (BAS) and the behavioral inhibition system (BIS) [14]. And research has shown that relatively large left frontal cortex activity is a stable marker of depression. To solve this problem, Thibodeau et al. collated and summarized different experimental conditions, systematically compared and explored the relationship between alpha band asymmetry and affective disorders [15]. Later, Damborska A et al. conducted a controlled experiment on 19 patients with depression, and analyzed and confirmed that the resting-state EEG state could reflect the changes of EEG data related to depressive symptoms to a certain extent [16].

4.1.3. An objective assessment system of depression. LEAF integrates EEG signals and other physiological signals, such as respiration, electromyography, electrocardiogram, eye movement, etc., and finally obtains multimodal data [17]. The synchronous collection of different data can well balance the emotional information of patients and form complementarity, not only modeling from multiple perspectives, but also reducing the interference caused by the single source of signals, so as to improve the accuracy and credibility of emotion recognition and realize some basic functions of objective assessment of depression.

4.2. Existing problems

In recent years, both at home and abroad gradually pay attention to emotion recognition of EEG signals, and considerable progress has been made in this aspect. However, emotion recognition of EEG signals still faces many challenges, such as environmental interference in the process of signal acquisition, objective factors of acquisition equipment, bad data generated by other physiological signals of the human body, and so on. Moreover, traditional recognition methods, which are relatively mature at the present stage, can only manually analyze EEG signals and judge the emotional fluctuations of the subjects, but cannot accurately judge the specific types of emotions of the subjects, thus failing to judge small emotional fluctuations, which leads to the bottleneck of improving the recognition accuracy. In contrast, the newly developed algorithm -- Deep learning algorithm in recent years is more suitable for emotion recognition. Feature extraction through convolution layer and convolution kernel can improve the accuracy to a certain extent, but it still has some limitations such as the single source of neural network. Therefore, it can be seen that although the development of EEG emotion recognition has achieved some progress, it is still challenging.

4.3. Improvements and breakthroughs in recent years

From the perspective of the summary above, although the emotional recognition is facing various difficulties, the researchers have made progress. Deep learning algorithm has become a popular method for emotion recognition in recent years, which has been recognized by researchers and has a good research prospect. It take the cognitive system of human brain as the structure to build a multi-level model, and combine low-level features to form high-level features with more obvious features, so as to make the feature representation of data more effective.

5. Conclusion

This paper mainly reviews the related research on emotion recognition by brain-computer interface. Firstly, the classification of emotion recognition and the related theories of brain-computer interface are introduced from the theoretical basis. Secondly, from the mechanism and process of emotion recognition, the selection of data sets and the relevant steps of signal analysis are introduced in detail. Finally, from the representative applications, the challenges and some breakthroughs in the current research are put forward. Brain computer interface (BCI) emotion recognition is an immature technology in the initial stage. There are still many challenging problems, but there is no doubt that it also has a good development prospect.

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