Research on emotion classification based on EEG

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Abstract

Research shows that human emotion production is closely related to the activity correlation of cerebral cortex, so the research of emotion classification by EEG provides a reliable basis. The feature extraction and classification application of EEG have made rapid development, so we combine EEG with emotion to study emotion classification. However, there are differences between EEG signals of different subjects, which have a certain impact on emotion classification. How to ensure the high accuracy and robustness of recognition is a problem. In view of this problem, the spectrum analysis method is used to extract features to study different subjects in different states. The extracted features are classified into emotion by discriminant analysis algorithm, and the classification effect is satisfactory. There are many methods involved in feature extraction and the space is long, different feature extraction methods will be compared later, so as to improve the robustness and efficiency of emotional classification of EEG signals.

Keywords: EEG; Feature extraction; Channel selection; Spectrum analysis; Sentiment classification

1. Introduction

The emotional state of a person has a certain influence on the body's own cognitive and behavioral aspects. At present, the well-known emotion research mainly focuses on the external analysis of speech tones, word language and facial expressions. Human emotions are mainly generated by their own physiological and psychological information. This information alone cannot accurately reflect human emotion changes. The field of brain research has become an important research field. With the development of neuroscience and brain science, emotions are no longer unpredictable. Using EEG information data to classify and identify different emotions, aiming at improving the classification and recognition effect of emotions and exploring the adjustment mechanism of different emotions. For emotional exploration, it not only helps the treatment of mental illnesses such as depression, but also has great significance in the field of brain-computer interaction.

In emotion research, researchers designed different experimental models to detect emotion through different signals and different stimulus materials. Koelstra [1] et al. Used 40 audio and video clips as stimulus materials to induce EEG signals and peripheral physiological signals of subjects. The later research of deap emotion analysis database created by the experiment made great contributions. Lin [2] et al. extracted the differential laterality (DLAT) features of the original EEG signals, so as to link the spectral pattern of EEG space with the hidden emotional state, and explore the feasibility of improving the emotional classification performance by using the multi day EEG data of each person [3].

There are differences between the EEG signals of different subjects, which have a certain impact on the emotional classification. How to ensure high accuracy and robustness of identification, this paper uses spectrum analysis method to extract features and discriminate and analyze EEG data.

2. Principle of emotion recognition

2.1 EEG data emotion recognition principle

The complete EEG emotional recognition system consists of emotional EEG data sets, preprocessing, feature extraction and sentiment discrimination classification, which is shown in Figure 1.

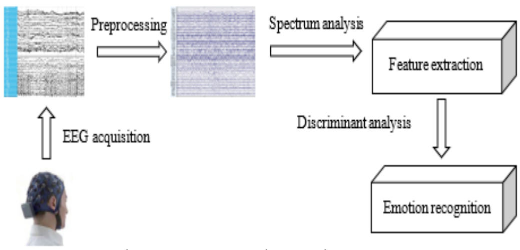

Fig1. System schematic

2.2 Emotional model

The most famous emotional dimension in emotional research is the Valence-Arousal model, but the model does not accurately map all human emotions. Therefore, a three-dimensional model appears. As shown in Figure 2, each dimension represents the degree of unpleasantness and happiness. The degree of excitement and the degree of relaxation to tension provide a strong support for emotional research [4].

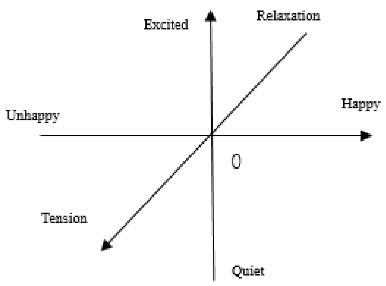

Fig2. Three-dimensional emotion model

3. Experiment

3.1 Experimental data acquisition

The EEG acquisition uses a Neuroscan Synamps 2 brain electrical amplifier with a sampling frequency set to 1000 Hz. The electrode is set according to the international 10-20 system, and the top of the head is selected as the reference electrode. The 32-lead electrode cap is used for recording, and all electrode impedances are lower than 10KΩ as shown in Figure 3.

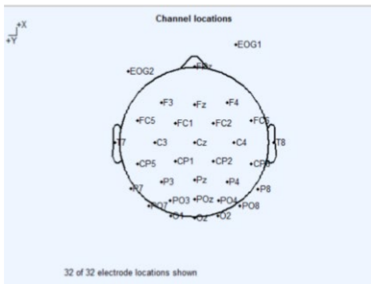

Fig3. Schematic diagram of the 10-20 system recording electrodes distribution of 32 channels

3.2 Data source and preprocessing Clustering results

Five subjects were recorded according to the five emotions of pleasure, relaxation, excitement, nervousness and calmness in the five audio and video states of funny, relaxed music, games, horror and learning. Each audio and video lasted for 1 minute. Make a record. The EEG data preprocessing process is as follows: using a 1-50 Hz bandpass filter to remove low frequency drift, ICA analysis, eliminating A1, A2 useless electrodes, and remaining 30 channels of EEG data. Divide each piece of data into labels every 2S, so each subject's EEG data is 30 segments.

4. Feature extraction

The feature extraction of EEG is mainly for de-evolving, dimensionality reduction and decorrelation. The commonly used feature extraction methods are divided into three categories: time domain frequency domain analysis, spatial domain analysis and nonlinear dynamic analysis. In this paper, spectrum analysis is used. In the future research, the other two types will be used, and will not be described here.

The EEG data is a time series signal. Generally speaking, the time domain representation is more vivid, the frequency domain analysis is more concise, and the analysis problem is more profound. Taking the frequency domain as the coordinate of various physical quantity lines and curves, various amplitude spectrum, phase spectrum, power and various spectral densities can be obtained, and the EEG signals and different waves of different rhythms can be more intuitively distinguished [5]. Continuous-time Fourier transform is suitable for the theoretical analysis of time-continuous signals. Since the function $f(t)$, $F(\omega)$on both sides of the transformation is a continuous function, engineering applications often need to perform Fourier analysis on the sampled data. The numerical calculation method of the Fourier transform [6].

If the main value interval of $f(t)$is $[t_1, t_2]$, define $T = t_2 - t_1$ as the interval length. Sampling N points in this interval, the sampling interval is Δt=T/N, then there are:

$$F(\omega)=\sum_{n=0}^{N-1} f(t_1+n\Delta t)e^{-jw(t_1+n\Delta t)}\Delta t=\Delta t\cdot\sum_{n=0}^{N-1} f(t_1+n\Delta t)\,e^{-jw(t_1+n\Delta t)} \quad (1)$$

The above equation can calculate the Fourier transform value of any frequency point. If the main value interval of $F(\omega)$ is $[w_1, w_2]$, to calculate the k values of uniform sampling between them, there are:

$$F(w_1+k\Delta w)=\Delta t\cdot\sum_{n=0}^{N-1} f(t_1+n\Delta t)e^{-j(w_1+k\Delta w)(t_1+n\Delta t)} \quad (2)$$

Where $\Delta w=(w_2-w_1)/k$ is the frequency domain sampling interval.

After multiple screening, filtering and channel selection, the following spectrum analysis charts in different states are obtained. Figure 4 is the filtered EEG data image, and figure 5 is the analyzed spectrum result. It can be seen from Fig. 4 that the time domain diagram under different states can simply see different points, but the amplitude of each state is not obvious. Thus, the frequency-domain results in Figure 5 show that the amplitude is different in different states. In the pleasant state, the amplitude points are more fluctuating, the amplitude is larger under the excitement, the amplitude is second in the tension state, and the amplitude is smaller in the relaxed and quiet state.

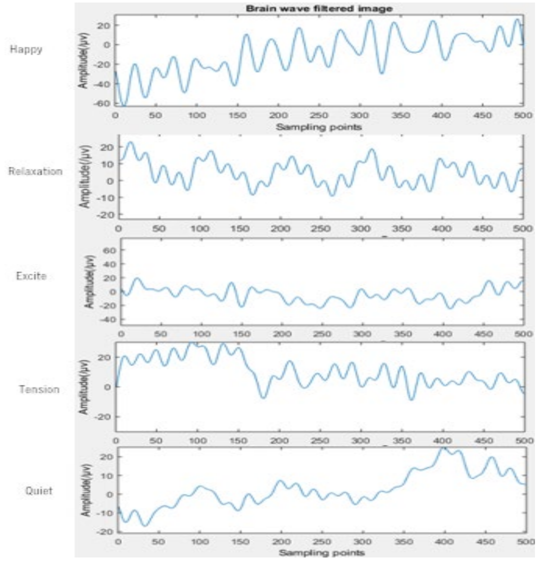

Fig4. Filtered EEG image

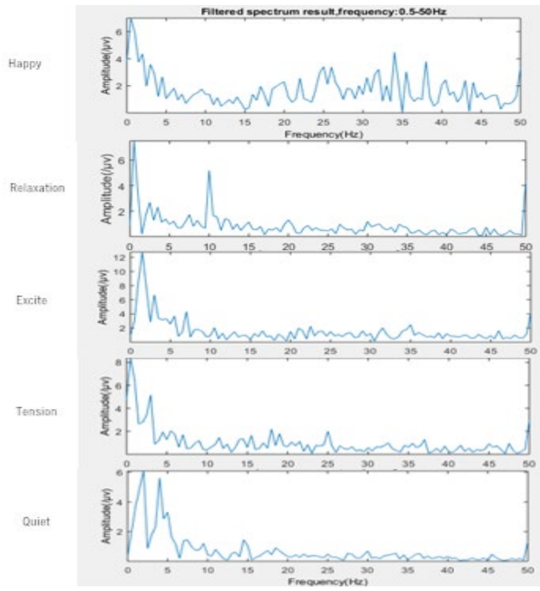

Fig5. Results of spectrum analysis

5. Classification

LDA can transform high-dimensional EEG data into low-dimensional space by means of mapping. In this low-dimensional space, the separability of data is the best, so that the distance between two types of data is maximized. The distance is minimized as much as possible to achieve dimensionality reduction and classification [7].

The general formulation of the problem is to have k totals $G_1, G_2, \cdots, G_k$ and the known sample X is taken from the K populations, and is one of them. It is now required to determine which total X belongs to. The basic idea of discriminant analysis to solve this problem is to first master the known knowledge of K populations and the observed values of indicators with discriminant significance of discriminant samples, and then find out the statistical path between the observed values of some indicators of sample x to be discriminated and the known knowledge according to the comparative analysis of the observed values and the known knowledge of populations, so as to determine the belonging population of sample X [8].

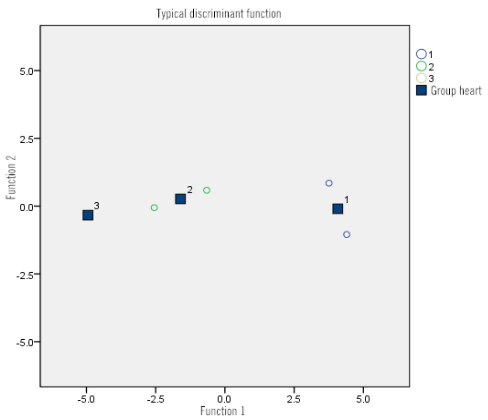

Fig6. Classification scatter plot

The five different emotions are divided into positive, intermediate, and negative levels, which are represented by 1, 2, and 3 respectively. According to the scatter plot made by the discriminant score in Fig. 6, it can be seen from the figure that the distinction between the three groups is still obvious.

6. Conclusion

Through the data collection of 5 subjects in 5 different states, through the spectrum analysis and LDA classifier classification verification, a satisfactory classification effect was obtained. On the whole, spectrum analysis is only applicable to single-channel data. Researchers are faced with multiple channel selections, which increases complex calculations and data processing; LDA classifiers are only for linear classification. In the later research, the multi-channel feature extraction, as well as the classification and screening comparison of multiple classifiers, improve the robustness and efficiency of EEG emotional classification.

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