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Research Article

Emotion recognition classification by EEG based on spectrum analysis

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ABSTRACT

Research shows that human emotion is closely related to the activity correlation of cerebral cortex, so the research of emotion classification by EEG (Electroencephalogram) provides a reliable basis. The feature extraction and classification application for EEG has been greatly improved in recent years, so we use EEG 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. For this problem, when studying different subjects in different states, spectrum analysis can be used for their feature extraction. When the extracted features are classified, discriminant analysis algorithm is used and achieved better classification results. There are many methods involved in feature extraction, and different feature extraction methods will be compared later, so as to improve the robustness and efficiency of emotional classification by EEG signals.

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. It is impossible to rely on this information alone to accurately reflect changes in human emotions.

The field of brain research has become important. With the development of neuroscience and brain science, emotions are no longer unpredictable. Using EEG information data to classify and identify different emotions can improve the classification and recognition effect of emotions and explore the adjustment mechanism of different emotions. For emotional exploration, it helps in the treatment of mental illnesses such as depression. In Addition, it 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. In this paper, we use spectrum analysis to extract features for recognition and analysis of

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EEG data. The high accuracy and robustness of recognition are ensured.

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.

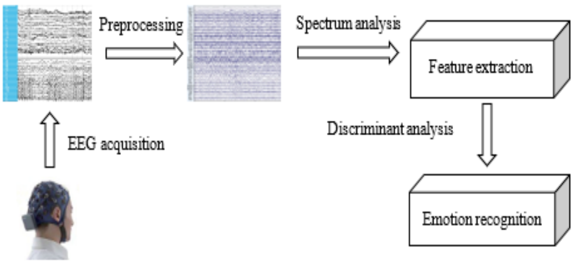

Fig1. System schematic

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 of these dimensions represents the degree of unhappiness and happiness. The degree of excitement and the degree of relaxation to tension provide a strong support for emotional research [4].

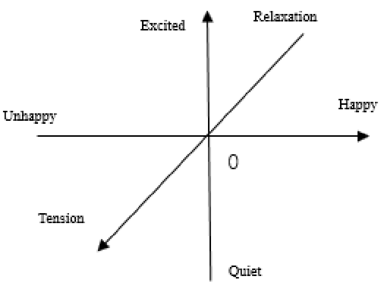

Fig2. Three-dimensional emotion model

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.

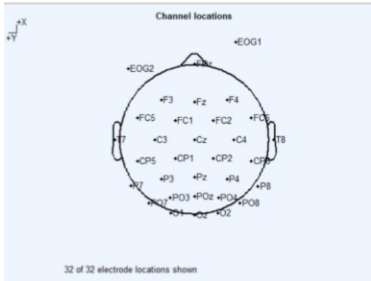

Fig3. Schematic diagram of the 10-20 system recording electrodes distribution of 32 channels

3.2 Data source and preprocessing Clustering results

Five subjects were recorded in the five audio and video states according to the five emotions of pleasure, relaxation, excitement, nervousness and calmness. The five audio and video states are funny, relaxed music, games, horror and learning. The subject is affected by each audio and video state for 1 minute, and then observe and record the data.

The EEG data preprocessing process is as follows: using a 1-50 Hz bandpass filter to remove the 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 2 seconds, 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-frequency domain analysis, spatial domain analysis and nonlinear dynamic analysis. In this paper, the spectrum analysis is used.

The EEG data is a time series signal. Generally speaking, the time domain representation is more pictorial, the frequency domain analysis is more compact, and the analysis problem is more encyclopedic. 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 applied to the theoretical analysis of signals which are continuous in time. 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 during the interval, and the sampling interval is Δt=T/N, then

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

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

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

Where Δw=(w_2-w_1)/k is the frequency domain sampling interval.

Spectrum analysis chart of EEG in different states can be obtained after multiple screening, filtering and channel selection of the signal. Figure 4 is the filtered EEG data image, and Figure 5 is the analyzed spectrum result.

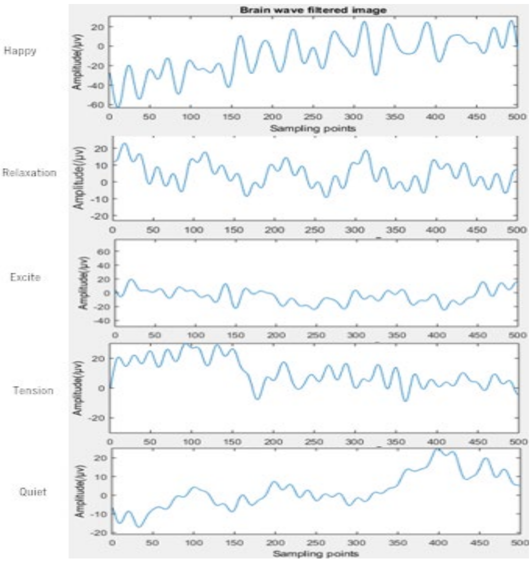

Fig4. Filtered EEG image

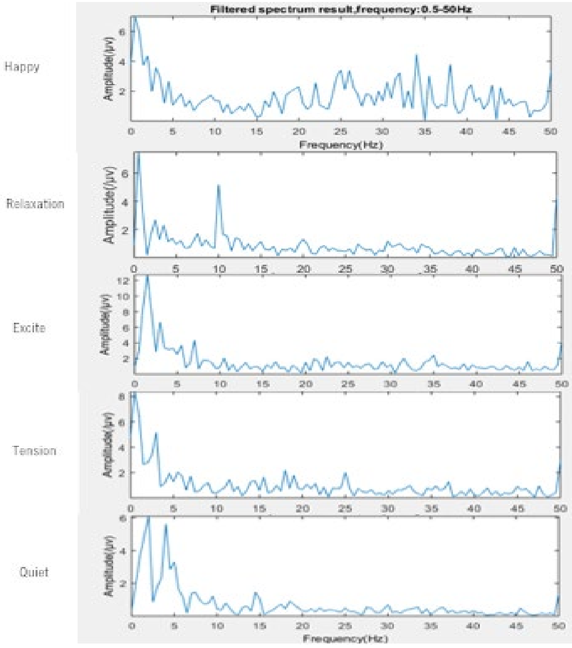

Fig5. Results of spectrum analysis

It can be seen from Figure 4 that the time domain diagram under different states can simply show different points, but the amplitude of each state is not obvious. Therefore, the change in amplitude can be observed more clearly in the frequency domain results of Figure 5.

The amplitudes in different states are as follows: (1) In the pleasant state, the amplitude points are more fluctuating. (2) the amplitude is larger when excitement. (3) the amplitude in the tension state is the second. (4) the amplitude is smaller in the relaxed and quiet state. What can be seen is that the amplitude is different in different states.

5. Classification

LDA (Linear discriminant analysis) can transform high-dimensional EEG data into the 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 and to achieve dimensionality reduction and classification [7].

The important work is to obtain $G_1, G_2, \cdots, G_k$ from the known sample X, which contains K populations. It is now required to determine the X.

The basic idea of discriminant analysis is to first master the known knowledge of K populations and the observed values of indicators with discriminant significance of discriminant samples. 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].

The five emotions can be divided into three levels: active, intermediate and passive, which is denoted by 1, 2 and 3 respectively. According to the scatter plot made by the discriminant score in Figure 6, it can be seen from the figure that the distinction between the three groups is still obvious.

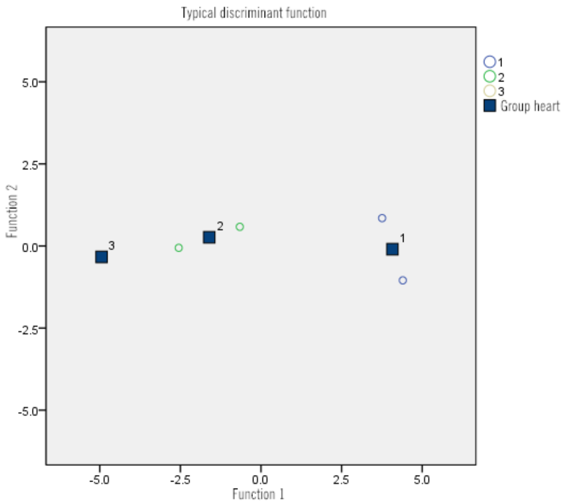

Fig6. Classification scatter plot

6. Conclusion

Through the data collection of 5 subjects in 5 different states, by the spectrum analysis and LDA classifier, a satisfactory classification effect was obtained.

On the whole, spectrum analysis is applicable to the single-channel data. But researchers are always faced with multiple channel selections, which increases complex calculations and data processing. LDA classifiers are only used for linear classification. In later studies, the multi-channel feature extraction and classification screening with multiple classifiers will be proposed to improve the robustness and potency of EEG emotion classification.

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