Advances in Computer, Signals and Systems (2021) 5: 60-66
Clausius Scientific Press, Canada

DOI: 10.23977/acss.2021.050109
ISSN 2371-8838

Testing the feasibility of EEG signals for emotion recognition

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Keywords: EEG, emotion recognition, accuracy

Abstract: We use the DEAP data set, perform data preprocessing on it, select only the channels corresponding to Fp1, Fp2, F3 and F4, and extract and merge the relevant EEG information to verify the feasibility of EEG signals for emotion recognition. The number of parameters in each group is reduced to between 1 and 25 utilizing principal component analysis. The linear discriminant model and the Naive Bayes model are also used.

1. Overview

Emotions, as an important component of human psychological activities, play a critical role in organizing and guiding people's behaviors, communication, and predicting others' thoughts. Physiological changes, changes in facial expression, changes in voice, and other factors cause people to produce corresponding signals when expressing their emotions, contributing others to assume that this is the process of emotion recognition. Many scholars regard emotion recognition research as an important field of psychology and cognition science. According to "Human Emotions" written by Zhaolan Meng, "Understanding Emotion" written by Keith Oatly, Dacher Keltner, Jennifer M Jenkins and other literature, people discussed the definition and classification of emotions, the definition of emotion recognition, current research situation and the existence of current research. They have high aspirations of emotion recognition research and its practical application, which will provide a certain reference value to the field of emotional psychology research.

As an important part of human-computer interaction, emotion analysis has made great progress in recent years with the popularity of artificial intelligence. Many physical characteristics can be used to calculate and evaluate human emotions, such as respiratory signal (RSP), electrocardiographic signal (ECG), electromyographic signal (EMG), electrical skin signal (SC), etc. EEG is the sum of neuronal firing phenomena in cerebral cortex. How to recognize the subject's emotions from EEG signals has attracted wide attention in various research fields. Professor Picard of the MIT Media Lab put forward the concept of “affective computing” in his 1995 technical report and then published the first monograph "Affective Computing" in 1997, which aroused a wide range of researchers’ concern; Hu Baogang from the Institute of Automation of the Chinese Academy of Science also proposed the definition of emotional computing: “The purpose of emotional computing is to establish a harmonious human-computer environment by giving computers the ability to recognize, understand, express, and adapt to human emotions, and make the computer have a higher and comprehensive intelligence". As an important part of human-computer interaction, emotional computing has played a vital role in the development of artificial intelligence.

EEG signals, as the carrier of emotion analysis, are potential changes recorded on the scalp of humans or animals, which mainly reflect the characteristics of the electrical activity of the brain. EEG uses the potential of brain cell clusters as the vertical axis and time as the horizontal axis. It is displayed in the form of a curve. It is also called the emotional state of a person recognized by brain waves from EEG. It can not only be used for human-computer interaction, but also can be used for the detection of human psychological and physiological diseases. EEG has broad application prospects. In this article, I will use the DEAP data set to test the feasibility of EEG signals for emotion recognition.

2. Experimental Data

The DEAP (Database for Emotion Analysis using Physiological Signals) database is collected by Koelstra and other people from Queen Mary University of London [1], the University of Twente in the Netherlands, the University of Geneva in Switzerland, and the Swiss Federal Institute of Technology. It is used to study Multi-channel data of human emotional states. The database is based on the physiological signals generated by the stimuli induced by music video materials. It recorded the physiological signals generated by 32 subjects who watched 40 minutes of music videos (1 minute for each music video) and the subjects' scores of Valence, Arousal, Dominance, and Liking. It also includes facial expression videos of the first 22 participants. This database can study physiological signals under multi-modality, and is of great significance to the research of emotional EEG.

Physiological signals are sampled at 512Hz, multi-sampled at 128Hz (pre-processed multi-sampled data is provided by the official). The physiological signal matrix of each subject is 40*40*8064 (40 pieces of experimental music, 40 physiological signal channels, 8064 Sampling points) of which 40 pieces of music are different types of music videos with a duration of 1 minute. The 40 physiological signals include 32 EEG signals under 10-20 system and 2 eye electrical signals (1 horizontal eye electrical signals, 1 vertical eye electrical signal) [EOG], 2 electromyography signal (EMG), 1 GSR signal, 1 Breathing signal, 1 plethysmograph, 1 temperature recording signal. 8064 is the data sampled at 128Hz in 60s. Each segment of signal has 3s quiet time before recording.

Among the 40 physiological signal channels collected, the first 32 channels collect EEG signals. The EEG channels select the positions of 32 channels according to the international 10-20 system, which are Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Oz, Pz, Fp2, AF4, Fz, F4, F8, FC6, FC, Cz, C4, T8, Cp6, Cp2, P4, P8, PO4 , O2. The 10-20 system is shown in the figure below.

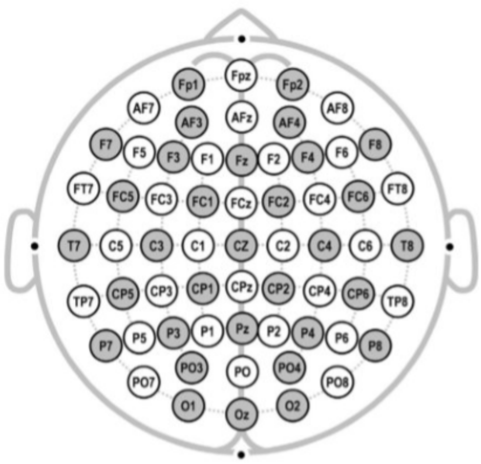

Figure 1: The position of 32 electrodes in the international 10-20 system (marked as a gray circle)

Participants need to conduct self-assessment in time after watching a video, using a Self-assessment Manikins (SAM) questionnaire. This process will last approximately 15 seconds. Participants need to conduct self-assessment based on the real emotional experience after watching the music video each time. Each participant needs to conduct 40 experiments, and a timely self-assessment after each experiment. Each participant needs to conduct 40 self-assessments on the SAM questionnaire.

3. Experimental Procedure and Result Analysis

3.1 Data Preprocessing

The EEG signal is very weak, and it is easily affected by changes in the internal or external environment during the measurement process [2]. This will make the measured signal mixed with many non-EEG components and unreliable. Common interferences consist of: EOG signal, ECG signal, EMG signal, high frequency noise, etc. These interferences are usually called artifacts in medical field. For the external environment, it can be controlled artificially to a certain extent, but for some activities of the human body, it is difficult for us to control the existence of artifacts which seriously hinders the accuracy of EEG signal analysis, so we have to remove the noise in the EEG signal in the preprocessing part, so as to analyze the EEG signal characteristics and extract the essential characteristics of the signal more precisely [3]. The EEG signals has been preprocessed in the source. Since the EMG signal is mainly composed of high-frequency signals, and the electrooculogram signal is mainly composed of low-frequency signals, we can use a band-pass filter to remove these two artifacts. This article uses a band-pass filter with the bandwidth of 41Hz (4.0-45.0Hz), removes electrooculogram (EOG) artifacts and electromyography (EMG) artifacts, and downsamples them from 512Hz to 128Hz.

3.2 Emotional rating

Participants rated five factors: valence, arousal, dominance, liking, and familiarity. After each experiment, a 9-point (Non-integer allowed) scale was used to directly assess valence, arousal, dominance, and preference, and after the experiment, a 5-point scale (integer only) was used to assess familiarity.

Visualized character models are used to represent the emotions in different states. Valence and Arousal are used to measure the emotional state. Valence indicates the degree of pleasure of a person, and the range of change transitions gradually from a negative state to a positive state, which corresponds to a scoring scale from 1 to 9. Arousal indicates the degree of excitement of a person's state, and the range of change gradually transitions from a calm state to an excited state, corresponding to a scoring scale from 1 to 9. Each participant needs to choose a score that represents emotions after each experiment. The different emotions of the participants after a displayed video can be visually expressed through the score.

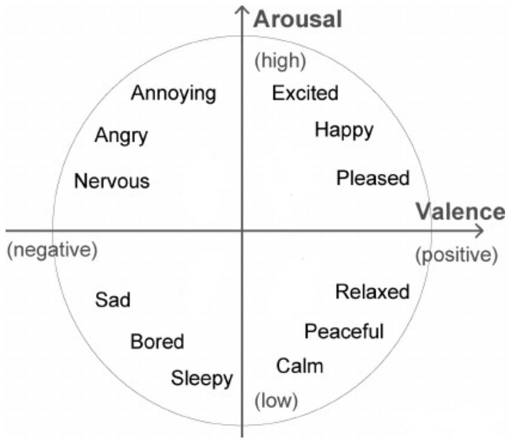

Figure 2: The circumplex model of affect

This thesis uses a two-dimensional valence-arousal model to classify emotions, and it only extracts the scores of valence and arousal. According to the valence-arousal model, the scores of valence and arousal are further simplified into binary levels "high" and "low". A score between 0 and 4.5 is marked as "low", and any score above 4.5 is marked as "high". This simplifies the classification process and will greatly improve the accuracy of the model.

3.3 Feature Extraction

Since the most primitive state of the EEG signal is the digital waveform signal, the expression ability of this characteristic information is usually very limited. It usually cannot be directly used in the process of emotion recognition analysis based on EEG. So effective feature extraction is required. EEG signals are processed to extract key features that can distinguish the differences in EEG patterns in different emotional states [4]. This is a very critical step in the process of EEG emotion recognition. This can not only reduce the dimension of the feature, and make subsequent classifier designs easier to implement in calculation. It can also eliminate the correlation between original features, reduce the redundancy of data information, and be more conducive in classification. In addition, because the EEG signal is very abrupt, the extracted EEG features usually include some features that are not related to emotion recognition. Therefore, it is necessary to further smooth the EEG features on the basis of feature extraction.

In this article, we use principal component analysis (PCA) to reduce each group of 8064 digital features to between 1 and 25. The basic idea of principal component analysis is to calculate a set of new features arranged in descending order of importance from a set of features. They are a linear combination of the original features, and the new features are irrelevant. We calculated that the mapping value of the original feature on the new feature is the new sample after dimension reduction. And our goal is to use a set of orthogonal vectors to transform the original feature to obtain a new feature, which is a linear combination of the original features. After extracting features, we use this range of features to train linear discriminant models and Naive Bayes models.

In addition, since among the available 32 EEG channels, Fp1, Fp2, F3, and F4 channels can best reflect the characteristics of EEG signals, I only select these four channels for subsequent research.

3.4 Data Filtering

For each channel, I apply a bandpass Butterworth filter to smooth the data to get the alpha (8-12Hz) and beta (12-30Hz) frequency bands of each channel.

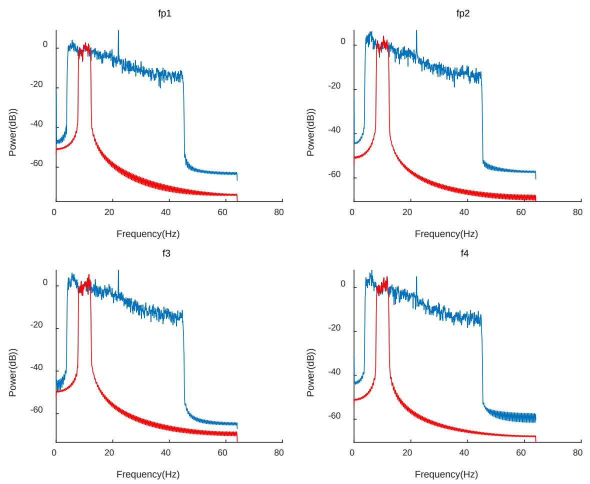

Figure 3: The power spectral density of each channel before (blue) and after(red) filtering in the Alpha band

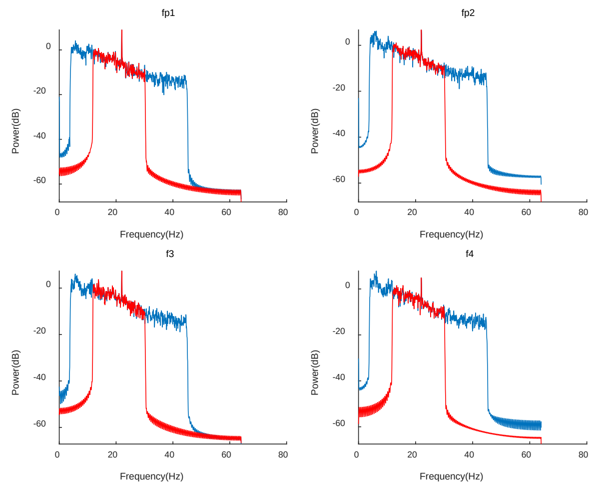

Figure 4: The power spectral density of each channel before(blue)and after(red) filtering in the Beta band

3.5 Classification

In this article, I choose to train linear discriminant model and naive Bayes model to classify.

For linear discriminant model, is one of the most widely used and extremely effective methods in the application of dimension reduction and pattern classification.During training, the training samples are projected onto a certain straight line[5]. This straight line can make the projection points of the same type of samples as close as possible, and make the projection points of samples of different types as far as possible. When predicting, project the data to be predicted onto the straight line above, and determine the category it belongs to according to the position of the projection point. It can directly obtain the analytical solution based on the generalized eigenvalue problem, thus avoiding the local minimum problem that we often encounter in general nonlinear algorithms. It's not necessary to artificially encode the output category of the mode, therefore its processing shows obvious advantages. Compared with the neural network method, the linear discriminant model does not need to adjust the parameters, so there are no problems such as learning parameters, optimizing weights, and selecting neuron activation functions.

The process of training Naive Bayes model is divided into three stages. The first is the preparation stage. The task of this stage is to make necessary preparations for Naive Bayes classification. The main work is to determine the feature attributes according to the specific situation, and appropriately divide each feature attribute to remove highly correlated attributes. The input of this stage is all the data to be classified, and the output is the feature attributes and training samples. Then comes the classifier training stage. The task of this stage is to generate a classifier. It is necessary to calculate the frequency of occurrence of each category in the training sample and the conditional probability estimation of each feature attribute division for each category, and record the results. The input is feature attributes and training samples, and the output is the classifier. Finally, in the application stage, we use the classifier to classify the items. The input is the classifier and the items to be classified, and the output is the mapping relationship between the items to be classified and the category.

The Naive Bayes model has stable classification efficiency and is not sensitive to the missing data. It performs well on small-scale data with its relatively simple algorithm, high classification accuracy and fast calculation speed. It can also handle multi-classification tasks, but its dependence on training data is very strong. If the error of training data is large, the predicted results will be poor.

The linear discriminant model and the Naive Bayes model are trained using different predictor variables and the principle components. For each combination, the experiment was repeated 10 times, and the analyzed data was randomly divided into training subsets and test subsets at a ratio of 80:20.

Since the accuracy of the model depends on the training data, randomization of the data and the average of the results of multiple runs will be a fairer measure of model performance.

3.6 Results

By training two different models, we get the accuracy of different feature sets under different model training.

Arousal		
Feature Set	Linear Discriminant Classifier (Accuracy %)	Naive Bayes' Classifier (Accuracy %)
F3/F4 Beta Power	69.5	67.0
Fp1, Fp2 Beta Freq	70.3	71.1

Valence		
Feature Set	Linear Discriminant Classifier (Accuracy %)	Naive Bayes' Classifier (Accuracy %)
Fp1, Fp2 Alpha, Beta Power	69.5	67.0
Fp1, Fp2 Alpha Freq	68.9	69.9
Fp1, Fp2 Beta Freq	67.6	69.5
F3/F4 Alpha, Beta Power	68.4	68.4
F3/F4 Beta Power	66.4	66.4
F3/F4 Alpha Freq	68.4	63.6

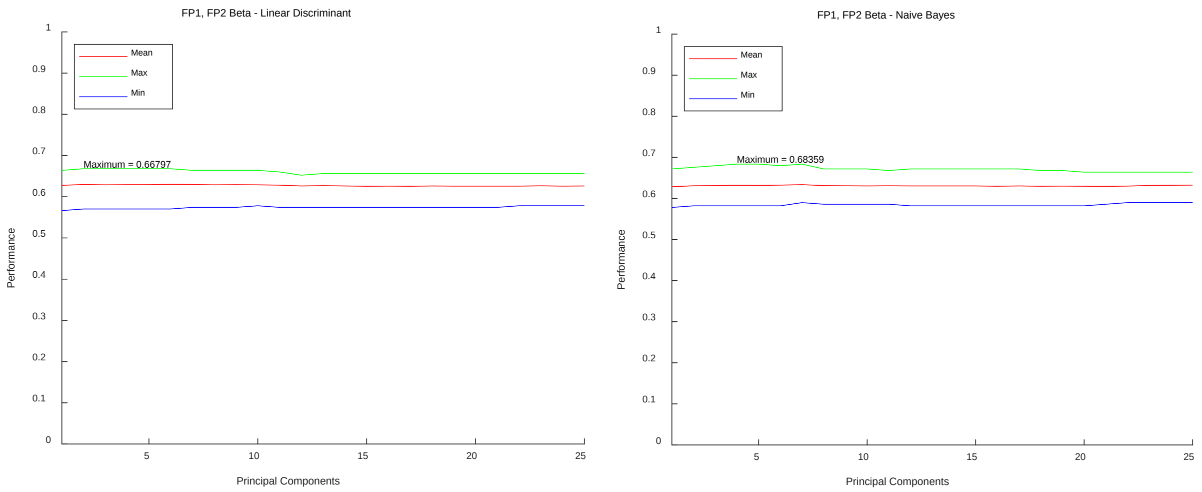

Figure 5: Result presentation

4. Conclusion

The research results were necessary to demonstrate that electroencephalography is a viable method of detecting human emotion. Several factors influence the efficacy of EEG readings for emotion recognition, the most important of which are the positions on the scalp from which the readings are taken and the precise features of the readings that are taken. Since this field is still in its early stages, the full extent of this technology's capabilities is unknown. However, determining its viability is the first step in any future development and serves as critical progress in many other fields. More research can be conducted in the areas of signal processing and data analysis. The performance of the models is highly dependent on both the data and the statistical model used. More research can be conducted to determine the best methods for processing and filtering EEG data, as well as the best statistical model to use for emotion analysis.

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