Network Modeling Analysis in Health Informatics and Bioinformatics (2021) 10:12
https://doi.org/10.1007/s13721-020-00283-2

ORIGINAL ARTICLE

Recognition of psychological emotion by EEG features

Chunyuan Huang[1]

Received: 18 November 2020 / Revised: 20 December 2020 / Accepted: 29 December 2020

Abstract

With the rapid development of emotion recognition technology, how to realize the naturalization and intellectualization of human–computer interaction, so that the human emotional state can be effectively recognized by the machine, and then get natural and harmonious emotional feedback results, has become the focus of research in the field of emotion recognition. The purpose of this study is to analyze the recognition of psychological emotions by electroencephalogram (EEG). In this study, Weibo, Fudan, and diary data sets were selected as data for psychological emotional research. The experimenter has mounted an electrode cap to test changes in the EEG signals when viewing various types of images, text and video. In this study, we extract and process EEG signals using wavelet transform and effectively identify and classify psychological emotions using support vector machines (SVM) and k-nearest neighbor algorithm. The results show that the average recognition rate of the improved grid PSVM method is 0.5% higher than that of the grid proximal support vector machine (PSVM) method; the average recognition rate of the improved grid RSVM method is 0.7% higher than that of the grid ranking support vector machines (RSVM) method; and the average recognition rate of the improved grid MKSVM method is 0.8% higher than that of the grid multi kernel support vector machine (MKSVM) method. It is concluded that the wavelet transform used in this study is more accurate in the extraction and processing of EEG features, and the method in this study is more accurate through the recognition of psychological emotions. It contributes to the recognition of psychological emotion by artificial intelligence.

Keywords EEG signal · Psycho analysis · Emotion recognition · Wavelet transform

1 Introduction

Emotion plays an important role in people's communication and interaction. Recognizing and expressing emotional states is part of normal communication. There are more than 90 definitions of emotion. Emotion is the expression of personal needs and hopes, as well as the attitude and action response to objective things. Feelings can be divided into three categories: positive feelings, neutral feelings and negative feelings. According to their experience, researchers have made several research results from the initial speculation of people's feelings to the use of high-tech detection methods to determine the changes of people's inner feelings, from the study of emotional cognition based on facial features and voice features to the study of emotional cognition based on physiological electrical signals.

✉ Chunyuan Huang
hcylxz19760108@126.com

[1] Zhaoqing University, Zhaoqing 526061, Guangdong, China

Electroencephalogram (EEG) signals are characterized by the fact that the EEG signals are difficult to hide and have real time differences. Emotion recognition by electroencephalogram signals has become widely used by many researchers to study emotions. Therefore, emotional cognitive analysis is not only important topic in cognitive science, neuroscience, psychology, artificial intelligence, but also closely related to our life conditions and quality. Among them, the study of emotional EEG signals is very important. Feature extraction of EEG signals is the first link of the emotion recognition process.

In the study of emotion recognition and EEG signal, Van Meter A R thinks that studying the difference of people's response to the stimulation and regulation of subsequent emotions may help to clarify the important mechanism of depression or mild mania. He recruited healthy young people with bipolar disorder ($n=23$) or depression ($n=21$) to study their emotions and emotions. The participants were asked to complete the measurement of current symptoms and emotion regulation strategies. His method is not accurate enough (Meter and Youngstrom 2016). A D A can reveal

Published online: 20 February 2021

the relationship between emotional intelligence (EI) and subjective assessment of physical state, depression, anxiety and mental health, and determine whether these factors are reliable predictors of emotional influencing factors. His method used the ei-darl-v1/V2 scale, which included 73 traditional questionnaires; emotional, social and interpersonal situational tasks; and emotion recognition in facial expressions (pictures). He used multi-step factor analysis method to divide the questionnaire into five sub scales. At the same time, he designed a special questionnaire and submitted it to the participants together with the EI questionnaire to evaluate the subjective assessment of physical and mental health, depression, anxiety and mental health. There are many factors influencing his method (Antinienė and Lekavičienė 2017). According to the mechanism and characteristics of motion imaging EEG signal, Shi T designed the EEG acquisition experiment. After removing the abnormal samples, he uses the wavelet reconstruction method to extract the specific frequency band of the motor imaging EEG signal. According to the characteristics of EEG signals of moving images, the feature recognition algorithm of convolution neural network is discussed. After in-depth analysis of the reasons for choosing the algorithm, he designed and trained a variety of different network structures. His method is not practical (Shi et al. 2019). Yilmaz G evaluates the interference in EEG by obtaining a surface representation of a motor unit, and adds the surface representations of several tonally active motor units to estimate the total myogenic contamination in the EEG. Therefore, he uses the method of recombination (RC) to generate EEG like artifacts from the surface representation of a single motion unit (RC). In addition, he also compared the signal characteristics of RC signals at different positions and EEG signals recorded synchronously from two aspects of power spectral density and coherence. First, he found that RC signals represent the power spectrum distribution of EMG signals. Second, the RC signal reflects the discharge rate of SMU, and the surface shows the largest amplitude and the strongest interference, and a resolvable frequency peak appears in the RC power spectrum. His method is not stable (Yilmaz et al. 2018). A H L uses non negative matrix decomposition (KNMF) to extract discriminant spectrum features from the time–frequency representation of EEG signals, which is an important work of EEG signal classification (Lee et al. 2009). Especially when KNMF with linear kernel is used, it is easy to calculate spectral characteristics by matrix multiplication. In standard NMF, multiplication update needs to be repeated, and other factor matrices are fixed, or pseudo inverse of matrix is required. Hu G compared the differences in estimation accuracy, stability (repeatability of results) and time complexity between four NMF algorithms and simulation data, and used hierarchical clustering algorithm to evaluate the stability of NMF algorithm (Hu et al. 2020). Casalino G discusses non-negative matrix factorization (NMF) technology from the perspective of intelligent data analysis (IDA), that is, intelligent application of human professional knowledge and computing model for advanced data analysis (Casalino et al. 2016).

To improve the accuracy of emotion recognition by end-to-end automatic learning of emotional features in temporal and spatial dimensions of EEG, Chen J X proposed a learning and classification method based on time feature, frequency feature and deep convolution neural network (CNN) (Chen et al. 2019; Steinwender et al. 2015). Xing B collected EEG data of 39 subjects after watching emotional video clips, and established a fusion data set of EEG and video features (Xing et al. 2019). Then, he using machine learning algorithms, including liblinear, reptree, xgboost, multilayerperceptron, random tree and RBF network, an optimization model of video emotion recognition based on multimodal data set is obtained.

This study first introduces the mechanism of emotion generation, and introduces the composition and specific functions of the four main parts of the brain. Then three common EEG signal processing methods are described, and the frequency domain correlation characteristics and five frequency bands of EEG signal are explained. The algorithm of this study is mainly for feature extraction of EEG signal. In this study, Weibo, Fudan and diary datasets were selected as the research objects, and the changes of electroencephalogram (EEG) signals were tested by different images and videos. Combined with the experimental results, the parameters of EEG signal, data feature extraction and classification analysis, EEG signal algorithm comparison analysis of emotional characteristics, emotion classification of EEG signal and emotion recognition results of EEG signal were analyzed. The conclusion is that this research method has higher accuracy in emotion recognition.

2 EEG signal and mental emotion recognition

2.1 Brain mechanism of emotion

The brain is the regulating organ of human body function. It is the largest and most complex structure in the central nervous system. It is also the material basis of human memory, learning, intellectual and spiritual activities. The brain mainly includes the left and right hemispheres, and there are different gullies and cracks on the surface of each hemisphere. According to the gullies and cracks, it is divided into four main parts: the lateral cephalic lobe, the posterior cephalic lobe, the prefrontal lobe, and the parietal lobe (Doré et al. 2016; Demirtas et al. 2019).

Frontal lobe: it is the most advanced part of brain structure. Its main function is to provide abstract thinking, self-determination, knowledge reasoning, creative suggestions, and planning. It is primarily responsible, closely related to the mental state and emotional needs of people (Sutton and Altarriba 2016).

The parietal lobe: located between the central groove and the fissure of the occipital region, is a high level sensory center of the human body. It is primarily responsible for reactions to pain, tactile, body temperature and pressure. This field is also associated with logical reasoning (Hoyt et al. 2017; Fernandez et al. 2016).

Occipital lobe: mainly responsible for visual function and visual information processing. In addition, this field involves human behavior, language, abstract concepts and memory (Tarbox-Berry et al. 2017).

Temporal lobe area: behind the front lobe, below the parietal lobe and in front of the posterior lobe. Three vertical and horizontal grooves are responsible for comprehensive analysis and judgment of hearing and visual information, and generation of storage related memory primarily.

At the same time, the brain can be divided into limbic system, cerebral cortex and nucleus. The cerebral cortex covers the whole surface of the brain and undertakes the high level of human cognitive. The limbic system is composed of amino starch and optic bed (Muehlenkamp and Brausch 2016; Dill-Shackleford et al. 2016).

2.2 Common EEG signal processing methods

2.2.1 Time domain signal processing

In time domain signal processing, the information of the signal which varies with time is used as characteristic information, and the information such as the average deviation, the standard deviation, and the dispersion of the fixed period are calculated, and the characteristic value is calculated using the time domain signal. This type of internal value is great, and has the advantages of convenient, intuitive, easy to operate. After denoising and artifact free processing, the pure signal is obtained, and the characteristic value of the time domain signal can be directly obtained by using the standard deviation. The use of time domain characteristic signals is to analyze potential changes caused by changes in emotions and emotions. An event related potential refers to a signal change caused by a particular stimulus of the brain or EEG signal generated by stimulating the corresponding portion of the nervous system at a corresponding time (Guelzow et al. 2017; Banks and Bowman 2016).

2.2.2 Frequency domain signal processing

The frequency-domain signal processing method is to process the signal into different spectrum features, and to identify the emotion using the spectrum features.

2.2.3 Time frequency domain signal processing

An unstable signal or frequency domain. To enhance the optimization of processing function, the combination of frequency and time is used to further improve the accuracy of information. Having sex? Based on this, the window function, short-time Fourier transform algorithm, is one of the commonly used processing methods. Wavelet transform is one of the important methods of time–frequency signal feature processing, and special methods are generally used. The law of spectrum rate conversion is obtained by calculating the original signal. Wavelet transform is different from short-time Fourier algorithm, and its window function changes with frequency (Schmid and Amodio 2017; Yan et al. 2019).

2.3 Frequency domain correlation characteristics of EEG signals

The frequency range of EEG is 1–100 Hz, and the low-frequency (1–30 Hz) signal is closely related to people's emotional and cognitive activities. The researchers put cognitive related EEG signals in five frequency bands, namely δ band (1–4 Hz), θ band (4–8 Hz), α band (8–13 Hz), β band (13–30 Hz) and gamma band (> 30 Hz), as well as these five frequency bands of EEG signal frequency domain, which are closely related to human cognitive characteristics and human physiological and psychological activities. The researchers extracted the power spectral density. Power spectrum and energy are used as EEG characteristics for emotion recognition research (Sreeja et al. 2018; SeemaKute 2017).

δ band: it belongs to the slow wave rarely detected by the general person, and is not involved in the information processing process of the emotion recognition in general.

Theta waves: it belongs to a low amplitude to medium amplitude creep wave, which is often generated when relaxation is changed to sleep. It is thought that the central nervous system is suppressed and is related to the load of working memory in general (Lo et al. (2017)).

Alpha bands belong to low amplitude synchronized waves, which are the main waveforms recorded in arousal and stable states, and are generally associated with brain preparation.

Beta band: high frequency low amplitude fast wave that reflects brain alert. Usually, emotion appears to be excited, excited and neurotic, indicating that the cerebral cortex is excited (Min et al. 2018; Park et al. 2016).

Gamma band: it belongs to the high frequency part, and has a high degree of brain information receiving, sending, feedback and other functions. It plays an important role in human brain cognitive activities, and is related to sensory stimulation and high attention activities (Li et al. 2017).

2.4 Feature extraction of EEG signals

2.4.1 Continuous wavelet transform

Given a basic function $\psi(t)$, let

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), \tag{1}$$

where a and B are constants, and $a > 0$. Obviously, $\psi_{a,b}(t)$ is obtained by the basic function $\psi(t)$ after shifting and then scaling. If a and B change continuously, we can get a family of functions $\psi_{a,b}(t)$. Given the square integrable signal x (T), that is $x(t) \in L^2(R)$, then the wavelet transform (WT) of X (0) is defined as

$$WT_x(a, b) = \frac{1}{\sqrt{a}}\int x(t)\psi^*\left(\frac{t-b}{a}\right)dt = \int x(t)\psi^*_{a,b}(t)\,dt =< x(t), \psi_{a,b}(t) > \tag{2}$$

In this formula, a, $b >$ and T are continuous variables, so this formula is also called continuous wavelet transform (CWT). Wavelet transform has a "micro" function, which can describe the details of signals, and is particularly suitable for the analysis of non-stationary random signals (He et al. 2018; Quiroz et al. 2017).

The results of continuous wavelet transform can be used to reconstruct the original signal, but the requirements of basic wavelet become higher (Bhattacharjee et al. 2019). The basic wavelet $\psi(t)$ should satisfy the "admissible condition": let $x(t)$, $\psi(t) \in L^2R$ be set and $\Psi(\Omega)$ be the Fourier transform of $\psi(t)$

$$c_\psi \stackrel{\Delta}{=} \int_0^\infty \frac{|\Psi(\Omega)|^2}{\Omega} < \infty \tag{3}$$

The $x(t)$ in the formula can be recovered by wavelet transform $WT_x(a, b)$. The reconstruction formula of wavelet transform

$$x(t) = \frac{1}{c_\psi}\int_0^\infty a^{-2}\int_{-\infty}^{\infty} WT_x(a,b)\,\psi_{a,b}(t)dadb \tag{4}$$

Because of $\Psi(\Omega)|_{\Omega=0} = 0$, therefore

$$\int \psi(t)dt = 0 \tag{5}$$

2.4.2 Wavelet multiresolution analysis

Let $\{V_j\}_{j\in Z}$ be a multiresolution analysis in L^2R spaces, then there exists a unique function $\varphi(t) \in L^2R$ such that:

$$\varphi_{j,k} = 2^{-j/2}\varphi(2^{-j}t - k),\ k \in Z \tag{6}$$

$\varphi(t)$ is called scaling function.

If $\varphi(t)$ generates a multiresolution analysis, then $\varphi \in V_0$, V_{-1}, and because $\{\varphi_{-1,k} : k \in Z\}$ is a Riesz basis of V-1, there is a unique L2 sequence which describes the two-scale relationship of scale function ϕ

$$\varphi(t) = \sqrt{2}\sum_{k=-\infty}^{\infty} h(k)\varphi(2t-k) \tag{7}$$

$V_{j+1} \in V_j, \forall j \in Z,$ so

$$V_j = V_{j+1} \oplus W_{j+1} \tag{8}$$

$$L^2(R) = \bigoplus_{j\in Z} W_j \tag{9}$$

Just as $\varphi(t)$ generates $V0$, there is a function $\psi(t)$ that generates closed subspace $W0$. And there are similar two-scale equations

$$\psi(t) = \sqrt{2}\sum_{k=-\infty}^{\infty} g(k)\varphi(2t-k) \tag{10}$$

The construction of scale function and wavelet function is attributed to the design of coefficients

$$H(\omega) = \sum_{k=-\infty}^{\infty}\frac{h(k)}{\sqrt{2}}e^{-j\omega k}, G(\omega) = \sum_{k=-\infty}^{\infty}\frac{g(k)}{\sqrt{2}}e^{-j\omega k} \tag{11}$$

The design of scale function and wavelet function can be attributed to the design of filter $H(\omega)$, $G(\omega)$. When constructing orthogonal wavelet, filter $H(\omega)$, $G(\omega)$ must satisfy the following three conditions

$$|H(\omega)|^2 + |H(\omega+\pi)|^2 = 1 \tag{12}$$

$$|G(\omega)|^2 + |G(\omega+\pi)|^2 = 1 \tag{13}$$

$$H(\omega)G^*(\omega) + H(\omega)G^*(\omega+\pi) = 0 \tag{14}$$

It can be obtained by joint solution

$$G(\omega) = e^{-jw} H^{*}(\omega + \pi) \tag{15}$$

You can get it immediately from the formula

$$g(k) = (-1)^{1-k} h^{*}(1-k), k \in Z \tag{16}$$

To design orthogonal wavelet, we only need to design filter $H(\omega)$.

3 Emotion recognition experiment of EEG signals

3.1 Experimental acquisition equipment

To collect the brainwave signal of the subject in various feelings, it is necessary to prepare the appropriate collection equipment. In this paper, we obtain a system using neuroscan EEG. Mainly composed of electrode covers, nuamps amp, 40 reading scan 4.3 software, demonstration software. In the experiment, the EEG frequency is 128 Hz, and the ability to filter 50 Hz noise by scanning software is enabled.

In the experiment, 10/20 lead electrode configuration was used. However, in this way, functional segmentation of the cerebral cortex is well suited to the electrode configuration. The reading system has 21 electrodes. The lead electrodes are generally symmetrically distributed, of which the even number of electrodes is distributed on the right side of the brain, and the three electrodes FZ, CZ and PZ are distributed in the longitudinal fissure of the brain.

3.2 Experimental data set

Three data sets, Weibo, Fudan and diary, were used to test the model.

(1) Weibo: the dataset was acquired from the labo data training group which is manual capture and annotation of sinaweibo data. The total number of samples is 3 million. This experiment randomly selected 40000 datasets with positive emotions, 50000 data with negative emotions, and 10000 data sets with neutral emotions.
(2) Fudan University: a collection of classified articles of Fudan University, including 20 categories of art, education, energy, and about 11000 data, which are classified collections of Chinese articles.
(3) Journal: this dataset is used to manually retrieve journals from Baidu, Weibo, mental health and other network platforms and manually mark each text. Store more than 2000 journal text annotation data. As shown in Table 1, data set information. Train/Dev/Test represents the row and column of data, the number of development and the number of tests. Len is the length of the data.

3.3 EEG signal acquisition

The research process can be divided into the following steps: before collecting the EEG signal, the received EEG signal must be carefully selected for the music clip, test object and experimental environment required by the experiment, and try not to be affected by external interference. As shown in Fig. 1, EEG signal acquisition process.

As shown in Fig. 1, EPQ scale test was conducted first to collect data to prepare for the experiment. Then, the EEG signal is obtained and processed. The conclusion is drawn after analyzing the characteristics.

3.4 Experimental process

3.4.1 Preliminary preparation stage

First, to remove the dry skin and oil from the scalp surface of the subjects, prepare to wash their hair with bath gel. According to the international 10–20 system, normal saline was used to wipe the brain area where the electrode was placed to make the electrode in good contact with the cerebral cortex. Then, the electrode cover was installed on the head of the test object. Then, the conductive paste is injected into the corresponding electrode of the electrode cover with a cylinder, so that the electrode and the scalp surface are in good contact. Then, nt9200 series program is started in the EEG signal acquisition system to reduce the impedance of each electrode as much as possible by using its impedance function. Below 10 K Ω. To create a quiet and comfortable experimental environment for the test object, the influence of the experimenter on the test object must be controlled to a minimum, and the test object should not be disturbed in the experiment. At the

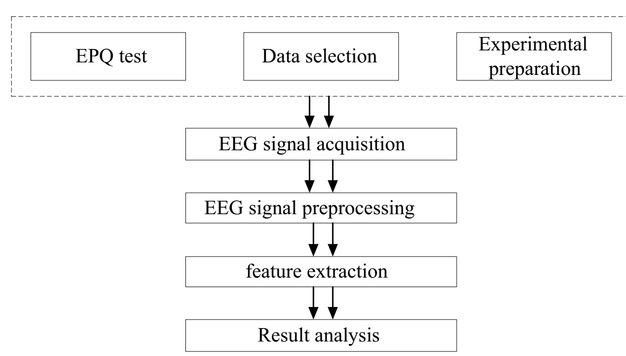

Fig. 1 EEG signal acquisition process

end of the preparation, the subjects were seated about 1 m in front of the computer that prompted the image stimulus.

3.4.2 The beginning of the experiment

First, the white screen is displayed in the center of the computer screen for 8 s, and the "+ 1" second is displayed in the center of the screen. In this experiment, considering the fact that the display time of the image is only 2 s, the subject's emotional experience may be relatively weak to reach the subject. To generate a stronger emotional EEG signal, the emotion is triggered using three consecutive emotional images of the same type. 8 s ago, the effect is clear. At this stage, the subjects can settle down, because they can move their hands and feet slightly, blinking, and closing the eyes. When "+" is displayed again, they enter the next stage of the emotional induction process. At this point, the subject must focus on the preparation of the following series of emotional imaging stimuli. In this experiment, the subjects collected the abdominal electrical signals for 9 min and conducted two groups of experiments.

3.4.3 The experiment is over

After testing, the test results of each test object will be tested, tested, and then tested. Put it back in place. After the subjects cleaned the hair electrode paste, they communicated with the subjects, asked questions in the experiment, recorded relevant opinions and adopted them, and the experimental process was gradually improved.

4 Emotion recognition effect of EEG signals

4.1 Parameter setting of EEG

4.1.1 Amplitude of EEG

Signal histogram (analysis is to divide the specific characteristics of the signal according to different levels, the relative frequency of each level is represented by bar chart or rectangular bar, and the distribution of signal characteristics is analyzed visually. The width of the rectangular bar is the interval of the specific characteristics of the signal. The height of the rectangle bar represents the specific interval of the characteristic distribution of the signal.

According to the geometric characteristics of EEG signal, the histogram analysis methods of EEG signal usually include zero crossing interval histogram, interval to peak histogram, amplitude histogram analysis, frequency histogram analysis, etc. Extract more general features. The

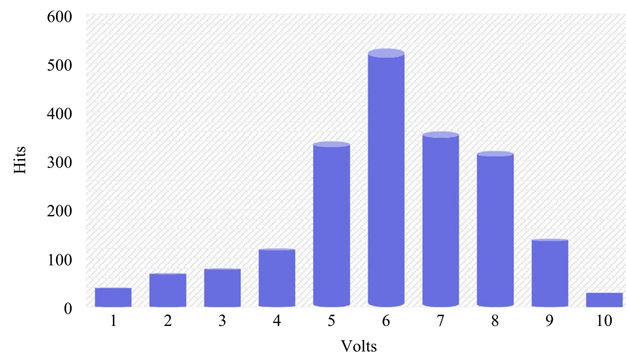

Fig. 2 Amplitude histogram of EEG signal

amplitude histogram of EEG signal in front lobe can clearly observe the distribution of EEG signal with amplitude. As shown in Fig. 2, the amplitude histogram of EEG signals.

4.1.2 Spectrum asymmetry index of EEG signal

To reduce the complexity of output processing, we classify and recognize the related functions according to the brain domain. The distribution of 16 sensing electrodes was divided into 8 brain regions: left anterior field, right anterior field, left head area, right head area, frontal, central, overhead and posterior brain regions. Because there are two electrodes, in a specific brain region, there are positive Sasi index characteristics of $20 \times 2 \times 36 = 1440$, neutral Sasi index characteristics and negative Sasi index characteristics. The feature set of spectrum asymmetry index extracted from different brain regions is shown in Table 2.

As can be seen from Table 2, the purpose of processing spectral asymmetry index characteristics of EEG signals in brain domain is clear. According to the investigation of spectral asymmetry index of EEG signals, we found that the left head area, the right head area and the posterior lobe are as follows. The spectral asymmetry index of EEG signal is the most obvious. In these asymmetric brain regions, there is a positive signal, which is an asymmetric signal. The sensitivity of brain domain and SIG domain are compared.

4.2 Data feature extraction and classification

4.2.1 Classification of different eigenvectors

According to the five feature extraction algorithms of wavelet energy, approximate entropy, sample entropy, fuzzy entropy and multi-scale fuzzy entropy, the improved grid MKSVM classification method is used to classify three kinds of emotional EEG signals. As shown in Table 3, the classification of different eigenvectors.

As can be seen from Table 3, the average recognition rate of wavelet energy features is 75.8%, which is lower than the average recognition rate of all entropy features. Compared with the wavelet energy of linear features, the entropy of nonlinear features reflects the difference, I know. Different emotional states. The average recognition rate of sample entropy is 80.3%, which is 1.2% higher than that of rough entropy feature. This is because the sampling entropy is the reciprocal of the natural logarithm of the conditional probability of the sequence compared with the deviation of the individual data comparison imported by the sample entropy in the approximate entropy calculation, and the accuracy will be improved if no independent data comparison is included in the calculation. The average recognition rate of fuzzy entropy is 81.3%, which is 1.0% higher than that of sample entropy feature. The average recognition rate of multi-scale fuzzy entropy feature is 85.8 and 4.5% higher than that of fuzzy entropy feature.

4.2.2 Normalization of emotional features

For positive, neutral and negative emotions, take multi-scale fuzzy entropy as an example, and the normalized value is shown in Fig. 3.

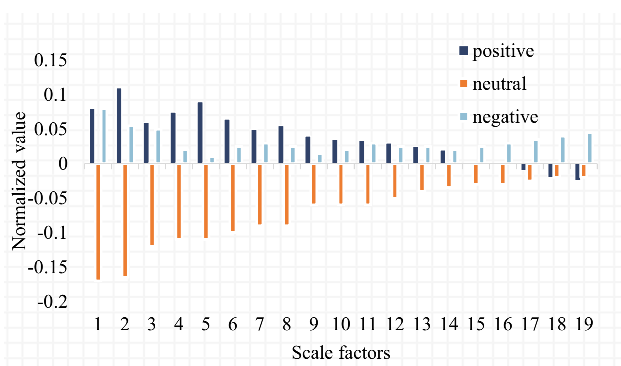

Fig. 3 The normalized value map of multiscale fuzzy entropy under three kinds of emotions

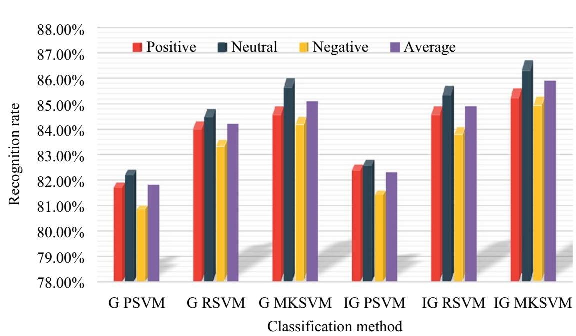

Fig. 4 The results of three kinds of emotional EEG signals under different methods

As can be seen from Fig. 3, the normalization values of positive and negative categories are basically the same on the first scale. When the scaling ratio is changed, the normalized value will also change. On the fifth scale, the recognition of positive, neutral and negative normalized values is very high, which is far better than the first scale. This is because fuzzy entropy is a measure of the complexity of sequence entropy in single scale. In addition, multi-scale fuzzy entropy introduces scale factor based on fuzzy entropy. This is the scale of time series complexity under multi-scale factors. Due to the randomness and instability of emotional EEG signals, the time series will reflect more information under multi-scale factors.

4.3 Comparison of EEG signal algorithms based on emotional features

In this paper, we use the method of mesh search and the method of mesh search. When the improved grid search method is used for fine search, the addition and subtraction of the best parameters of the traditional grid search method are taken as the range, and then the local parameters are optimized by multiplying 20.1. The range of polynomial kernel parameter values is the integer in (Antinienė and Lekavičienė (2017); Hu et al. 2020). The value range of weighting coefficient *m* is (0,1), and the step size is 0.02. The improved methods are VM grid and VM grid. As shown in Table 4, the results of three kinds of emotional EEG signals under different combination classification methods.

As shown in Fig. 4, the situation of different emotion EEG signals in different combination classification methods.

As can be seen from Table 4 and Fig. 4, the average recognition rate of the improved grid PSVM mode is increased by 0.5% compared with the grid PSVM mode, and the average recognition rate of the improved grid RSVM mode is increased by 0.7% compared with the grid RSVM mode. Compared with the improved grid MKSVM, the average recognition rate increases by 0.8%.

The average recognition rate of grid MKSVM is 0.9 and 3.3% higher than that of grid ppsvm and grid SRSVM, respectively. The recognition rate was improved by 1.0 and 3.6%, respectively. The classification results show that compared with RBF kernel and poly kernel, the characteristics of emotional EEG signal are input into the hybrid kernel function of RBF kernel and poly kernel, so it can represent data more appropriately in the new feature space.

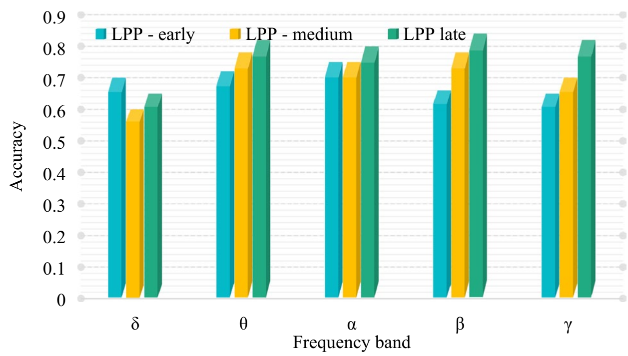

Fig. 5 Recognition accuracy of early, middle and late positive potentials of posterior segment

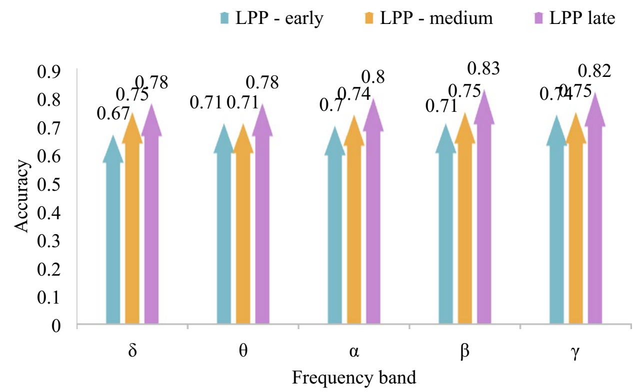

Fig. 6 Recognition accuracy based on positive potential characteristics of posterior segment

4.4 Emotion classification of EEG signals

4.4.1 Characteristics of posterior segment positive potential

As shown in Fig. 5, the recognition accuracy of the early, middle and late features of the posterior segment positive potential is shown.

From Fig. 5, it can be seen that blue represents the emotion recognition accuracy of the initial characteristics of EEG signal positive potential, green represents the emotion recognition accuracy of the middle positive potential feature of EEG signal, and red represents positive EEG signal. The positive rate of emotion recognition of potential late features. In delta band, the recognition accuracy of EEG signal emotion classification of the initial characteristics of post-positive potential is higher than that of the middle and later features of post-positive potential and the post-positive potential of delta band. The recognition accuracy of emotion classification of EEG signal in the initial, medium and later stages and the positive solution rate of the positive potential of EEG signal in the initial, middle and later stages of EEG signals are relatively low. In the five frequency bands (δ, theta, α, β, and signal), the accuracy of EEG signal after positive potential is higher than that of signal. Besides delta band, the emotion classification and recognition accuracy of EEG signal in the later period of positive potential is higher than that of brain in the early and middle period of positive potential. The positive resolution rate of emotion recognition of EEG signal is almost 60%.

4.4.2 K nearest neighbor algorithm

The classification step of the nearest k neighbor classification algorithm is to normalize the attribute values of each sample of EEG signal collected to interval [0, 1], then classify the samples, and then divide the next test sample. Please note that the samples to be tested and the training samples in the samples and training samples should not overlap. Finally, for the data of the samples to be tested, the Euclidean distance between the tested samples and the training samples is calculated, and the EEG signal of the samples to be tested is calculated. The correctness of three emotions: accumulation, neutral and negative. As shown in Fig. 6, the recognition accuracy of the early, middle and late positive potential features in the rear section is obtained.

It can be seen from Fig. 6 that the mid and late (1000–1500 ms) characteristics of positive EEG signals in five frequency bands (δ, θ, α, β, γ waves) are more accurately identified than positive EEG signals. The features of the possibility of emotion recognition in the early stage (300–600 MS) and the medium-term (600–1000 MS) of the possibility of emotion recognition; the features of the middle stage (300–600 MS) of the positive possibility after the EEG signal are that the positive resolution rate of the five bands is not high in the middle positive phase (600–100 ms) and the later stage (1000–1500 ms) of the EEG signal; the correctness of the emotion feature recognition.

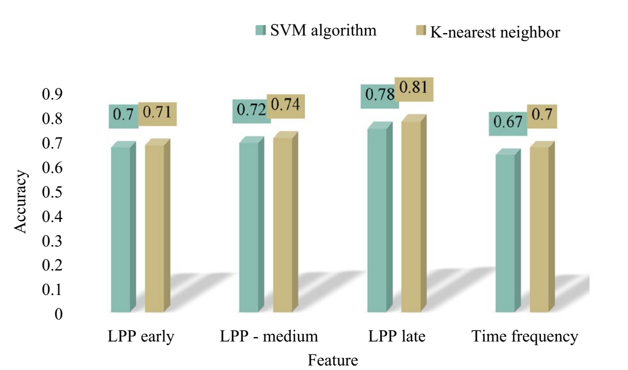

Fig. 7 Comparison of recognition accuracy of positive potential and time–frequency features

4.5 Emotion recognition results of EEG signals

4.5.1 Emotion recognition results of positive posterior segment potentials

After extracting the positive potential feature set of the back segment of EEG, the support vector machine algorithm and k-nearest neighbor algorithm are used to classify and recognize the EEG signals. The classification and recognition results are as follows. As shown in Table 5, the feature recognition accuracy of different algorithms.

As shown in Fig. 7, the accuracy rate of feature recognition of different algorithms.

The results of Fig. 7 show that the emotion recognition accuracy of initial LPP, intermediate LPP and late LPP functions is higher than that of time frequency function whether it is based on SVM algorithm or k-nearest neighbor algorithm. In addition, the LPP late function (1000–1500 ms) has the highest recognition accuracy. One of the obvious features of EEG is that it can recognize emotion with high accuracy.

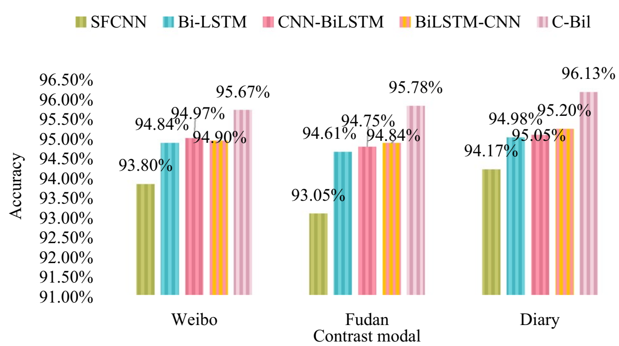

Fig. 8 Algorithm accuracy comparison

Table 1 Data set information

Data set	C	Train/Dev/Test	Len
Weibo	3	80,000/10,000/10,000	569
Fudan	20	8824/982/9833	2982
Diary	5	1900/200/200	540

Table 2 Spectrum asymmetry index feature set of EEG signal

	Positive index	Neutral index	Negative index
Left frontal	1440	1440	1440
Right frontal	1440	1440	1440
Left temporal	1440	1440	1440
Right temporal	1440	1440	1440
Forehead	1440	1440	1440
Center	1440	1440	1440
Parietal region	1440	1440	1440
Occipital lobe	1440	1440	1440

Table 3 Classification of different eigenvectors

Features	Positive (%)	Neutral (%)	Negative (%)	Average rate (%)
Wavelet energy	75.8	76.4	75.7	75.9
Approximate entropy	79.0	79.8	78.7	79.2
Sample entropy	79.7	81.9	79.6	80.4
Fuzzy entropy	81.0	82.5	80.8	81.4
Multiscale entropy	85.6	86.8	85.3	85.9

4.5.2 Emotion recognition results under dichotomy

When the final recognition result is two categories (Weibo data set abandons neutral emotion; Fudan data set selects two of them; diary data set merges two categories of "pleasure and relaxation" and "calm and calm", and merges three categories of "anxiety and confusion", "sadness and self blame" and "pain and despair"), the experimental accuracy results are shown in Table 6.

As shown in Fig. 8, the algorithm accuracy is compared.

As shown in Fig. 8, in the diary data set, the accuracy of the C-BIL model was 0.93% higher than that of BiLSTIM-CNN. In microblog data sets, the accuracy of C-BIL model is 0.77% higher than BILSTM-CNN, 0.7% higher than CNN-BiLSTM, 0.63% higher than Bi-LSTM, 1.67% higher than SFCNN model, and 0.94% higher than BiLSTM-CNN. In the Fudan data set, the accuracy of the C-BIL model was 1.03% higher than that of the CNN-BILSTM, 0.77% higher than that of the BiLSTM, and 2.33% higher than that of the SFCNN model.

5 Conclusion

The idea of this study is to use positive, neutral and negative photos to induce the feelings of the subjects in the three categories of positive, neutral and negative. The EEG signals collected are preprocessed to eliminate noise and artifacts. The module uses wavelet transform to divide the EEG signal into five frequency bands (δ, θ, α, β, B) to remove high-frequency noise and extract the positive potential characteristics of EEG signal for comparison. The accuracy of emotion recognition and classification and the time–frequency characteristics of EEG signal are tested using the image spectrum algorithm. The emotional recognition accuracy of EEG positive potential features in the early, middle and late stages is higher than that of time frequency features.

Table 4 Results of three types of emotional EEG signals

Pattern Classification	Positive (%)	Neutral (%)	Negative (%)	Average rate (%)
Grid PSVM	81.9	82.4	81.0	81.8
Grid RSVM	84.3	84.8	83.6	84.2
Grid MKSVM	84.9	86.0	84.5	85.1
Improved grid PSVM	82.6	82.8	81.6	82.3
Improved grid RSVM	84.9	85.7	84.1	84.9
Improved grid MKSVM	85.6	86.7	85.3	85.9

Table 5 Feature recognition accuracy of different algorithms

	LPP early	LPP—medium	LPP late	Time frequency
SVM algorithm	0.7	0.72	0.78	0.67
K-nearest neighbor	0.71	0.74	0.81	0.7

Table 6 Accuracy under two categories

Contrast model	Weibo (%)	Fudan (%)	Diary (%)
SFCNN	93.80	93.05	94.17
Bi-LSTM	94.84	94.61	94.98
CNN-BiLSTM	94.97	94.75	95.05
BiLSTM-CNN	94.90	94.84	95.20
C-Bil	95.67	95.78	96.13

The Sasi index function of EEG signal is extracted from brain domain, and 1440 Sasi index function is extracted from each brain domain in a single emotional state. The nearest neighbor algorithm is used to test the accuracy of emotion recognition. The results show that the accuracy of emotion recognition of left and right emotion states is more than 80%, and the accuracy of emotion recognition in the area of posterior lobe of three emotional states is more than 75%. The recognition accuracy of left prefrontal lobe under positive emotion is higher than that of right prefrontal lobe, and the recognition accuracy of left prefrontal lobe under positive emotion is also higher than that of right prefrontal lobe. In addition, the spectral asymmetry index of EEG signal can be used as an obvious function of emotion recognition.

Based on this study, a library of materials based on photos, music clips, movie clips, and other emotional stimuli was established. A set of effective experimental procedures for emotion induction was designed. Most EEG data of subjects in various emotional states were collected, and the emotion recognition processing program based on EEG was effectively tested and analyzed. Finally, the experimental results show that the emotion recognition method proposed in this paper can accurately identify the emotional state of the subjects to a certain extent. Due to the limited time and knowledge, there are some deficiencies in this paper. More types of data samples should be included to enhance the representativeness of research conclusions. Therefore, in the future research, the data sample size needs to be expanded.

References

Antinienė D, Lekavičienė R (2017) Psychological and physical well-being of Lithuanian youth: relation to emotional intelligence. Medicina 53(4):277–284

Banks J, Bowman ND (2016) Emotion, anthropomorphism, realism, control: validation of a merged metric for player–avatar interaction (PAX). Comput Hum Behav 54(1):215–223

Bhattacharjee A, Saha S, Fattah SA et al (2019) Sleep apnea detection based on rician modeling of feature variation in multiband EEG signal. IEEE J Biomed Health Inf 23(3):1066–1074

Casalino G, Buono ND, Mencar C (2016) Non negative matrix factorizations for intelligent data analysis. Springer Berlin Heidelberg. 1(2):49–74

Chen JX, Zhang PW, Mao Z J et al (2019) Accurate EEG-based emotion recognition on combined features using deep convolutional neural networks. IEEE Acces 7:44317–44328. https://doi.org/10.1109/ACCESS.2019.2908285

Demirtas O, Arslan A, Karaca M (2019) Why perceived organizational and supervisory family support is important for organizations? Evidence from the field. Rev Manag Sci 13(4):871–873

Dill-Shackleford KE, Vinney C, Hopper-Losenicky K (2016) Connecting the dots between fantasy and reality: the social psychology of our engagement with fictional narrative and its functional value. Soc Pers Psychol Compass 10(11):634–646

Doré BP, Silvers JA, Ochsner KN (2016) Toward a personalized science of emotion regulation. Soc Personal Psychol Compass 10(4):171–187

Fernandez KC, Jazaieri H, Gross JJ (2016) Emotion regulation: a transdiagnostic perspective on a new RDoC domain. Cognit Ther Res 40(3):426–440

Guelzow BT, Loya F, Hinshaw SP (2017) How persistent is ADHD into adulthood? Informant report and diagnostic thresholds in a female sample. J Abnorm Child Psychol 45(2):301–312

He Q, Du S, Zhang Y et al (2018) Classification of motor imagery based on single-channel frame and multi-channel frame. Chin J Sci Instrum 39(9):20–29

Hoyt MA, Nelson CJ, Darabos K et al (2017) Mechanisms of navigating goals after testicular cancer: meaning and emotion regulation. Psycho-Oncology 26(6):747–754

Hu G , Zhou T , Luo S et al (2020) Assessment of nonnegative matrix factorization algorithms for electroencephalography spectral analysis. BioMedical Engineering OnLine 19(1):2–18

Kute S, Kulkarni S (2017) Analysis of mindfulness meditation effect on brain through electroencephalography. Int J Electron Eng Res 9(6):899–911

Lee H, Cichocki A, Choi S (2009) Kernel nonnegative matrix factorization for spectral EEG feature extraction. Neurocomputing 72(13–15):3182–3190

Li X, Sun X, Wang X et al (2017) Research on electroencephalogram emotion recognition based on the feature fusion algorithm of auto regressive model and wavelet packet entropy. J Biomed Eng 34(6):831–836

Lo PC, Tian WJM, Liu FL (2017) Macrostate and microstate of EEG spatio-temporal nonlinear dynamics in zen meditation. J Behav Brain Sci 07(13):705–721

Min W, Sherif A, Nour M et al (2018) Deep gaussian mixture-hidden markov model for classification of EEG signals. IEEE Trans Emerg Top Comput Intell 2(4):278–287

Muehlenkamp JJ, Brausch AM (2016) Reconsidering criterion A for the diagnosis of non-suicidal self-injury disorder. J Psychopathol Behav Assess 38(4):1–12

Park SM, Lee TJ, Sim KB (2016) Heuristic feature extraction method for BCI with harmony search and discrete wavelet transform. Int J Control Autom Syst 14(6):1–6

Quiroz G, Espinoza-Valdez A et al (2017) Coherence analysis of EEG in locomotion using graphs. Revista mexicana de ingeniería biomédica 38(1):235–246

Schmid PC, Amodio DM (2017) Power effects on implicit prejudice and stereotyping: the role of intergroup face processing. Soc Neuro 12(2):218–231

Shi T, Ren L, Cui W (2019) Feature recognition of motor imaging EEG signals based on deep learning. Pers Ubiquit Comput 23(3–4):499–510

Sreeja SR, Sahay RR, Samanta D et al (2018) Removal of eye blink artifacts from EEG signals using sparsity. IEEE Biomed Health Inform 22(5):1362–1372

Steinwender B, Thrimawithana AH, Crowhurst RN et al (2015) pheromone receptor evolution in the cryptic leafroller species, *Ctenopseustis obliquana* and *C. herana*. J Mol Evol 80(1):42–56

Sutton TM, Altarriba J (2016) Color associations to emotion and emotion-laden words: a collection of norms for stimulus construction and selection. Behav Res Methods 48(2):686–728

Tarbox-Berry SI, Perkins DO, Woods SW et al (2017) Premorbid social adjustment and association with attenuated psychotic symptoms in clinical high-risk and help-seeking youth. Psychol Med 48(6):1–15

Van Meter AR, Youngstrom EA (2016) Distinct roles of emotion reactivity and regulation in depressive and manic symptoms among euthymic patients. Cognit Ther Res 40(3):262–274

Xing B, Zhang H, Zhang K et al (2019) Exploiting EEG signals and audiovisual feature fusion for video emotion recognition. IEEE Access. https://doi.org/10.1109/ACCESS.2019.2914872

Yan J, Kuai H, Chen J et al (2019) Analyzing emotional oscillatory brain network for valence and arousal-based emotion recognition using EEG data. Int J Inf Technol Dec Mak 18(04):1359–1378

Yilmaz G, Ungan P, Türker KS (2018) EEG-like signals can be synthesized from surface representations of single motor units of facial muscles. Exp Brain Res 236(4):1–11