Information Fusion 59 (2020) 127–138

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

Feature-level fusion approaches based on multimodal EEG data for depression recognition

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A R T I C L E I N F O

Keyword:
Depression recognition
EEG
Multimodal
Audio stimulus
Fusion

A B S T R A C T

This study aimed to construct a novel multimodal model by fusing different electroencephalogram (EEG) data sources, which were under neutral, negative and positive audio stimulation, to discriminate between depressed patients and normal controls. The EEG data of different modalities were fused using a feature-level fusion technique to construct a depression recognition model. The EEG signals of 86 depressed patients and 92 normal controls were recorded simultaneously while receiving different audio stimuli. Then, from the EEG signals of each modality, linear and nonlinear features were extracted and selected to obtain features of each modality. In addition, a linear combination technique was used to fuse the EEG features of different modalities to build a global feature vector and find several powerful features. Furthermore, genetic algorithms were used to perform feature weighting to improve the overall performance of the recognition framework. The classification accuracy of each classifier, namely the k-nearest neighbor (KNN), decision tree (DT), and support vector machine (SVM), was compared, and the results were encouraging. The highest classification accuracy of 86.98% was obtained by the KNN classifier in the fusion of positive and negative audio stimuli, demonstrating that the fusion modality could achieve higher depression recognition accuracy rate compared with the individual modality schemes. This study may provide an additional tool for identifying depression patients.

1. Introduction

Depressive disorder is a common affective disorder, also known as depression. According to incomplete statistics from the World Health Organization (WHO), about 340 million people suffer from different degrees of depression worldwide. However, Chinese statistics has shown that more than 30 million Chinese citizens suffer from depression [1]. Depression ranks fourth among the top 10 diseases in the world. It is estimated that by 2020, depression will be the second biggest killer in the world after heart disease [2]. Patients with depression have severe psychological disorders and bad emotions, usually characterized by grief, fatigue, despair, and so on. Patients with severe depression may even have suicidal behavior [3].

The clinical research on depression has been gradually carried out since as early as the mid-19th century. However, due to the unclear underlying neurological mechanism and pathological principle, the clinical diagnosis of depression has become difficult. Currently, the most commonly used international diagnostic criteria are the *International Statistical Classification of Diseases and Related Health Problems, 10th revision* developed by WHO [4] and the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition* developed by the United States [5]. Moreover, patients with mental illness are no different from normal people physically, and clinicians can only make a subjective diagnosis based on relevant information of patients; therefore, the results are dependent on the doctor's experience. Mitchell et al. conducted a meta-analysis of 50,371 patients in 118 studies and found that the correct recognition rate for depression was only 47.3% [6]. More importantly, the traditional diagnosis method based on interview and questionnaire requires a lot of time and energy [7]. In recent years, the sensor networks were widely used in areas such as healthcare and biology community [8,9]. The EEG technology has been gradually used in the auxiliary diagnosis of diseases such as schizophrenia [10], mild cognitive impairment [11], epilepsy [12], and Alzheimer's [13]. Especially, A close relationship has been found between the brain and depression. The cognitive ability of patients with depression changes with mood, and these changes affect the EEG [14]. Therefore, more studies are engaged in electroencephalogram (EEG)-

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https://doi.org/10.1016/j.inffus.2020.01.008
Received 15 March 2019; Received in revised form 15 November 2019; Accepted 30 January 2020
Available online 3 February 2020
1566-2535/

based research to explore objective and pervasive diagnostic techniques and methods for depression.

Although EEG technology is used in the auxiliary diagnosis of depression, the most commonly EEG acquisition systems for research purposes are 128-electrode and 256-electrode brain caps [15,16]. The EEG collection device needs to soak the brain cap or apply the conductive paste at the corresponding electrode position before wearing. The operation process of the experiment is relatively complicated and the pollution is relatively large. And the comfort of the subject wearing this equipment is very poor, so it is easy exits during the EEG monitoring and it is difficult to obtain a large sample size. This paper mainly studies the subject of depression recognition. Considering the actual situation and the patient's cooperation degree, this experiment does not use this equipment. In addition, Carmen CY et al. pointed out the battery operating time and sensor size are two important factors in determining the usability of BSN sensors [17–19]. Therefore, a pervasive and low-power consumption EEG acquisition sensor is great important for more researches. Moreover, most of the previous studies extracted the features of depressive EEG in the individual modality, usually in the resting state. Recently, the multiple modalities has gained popularity in several areas by fusing two or more modalities to achieve better results, and the advantage of multiple modalities helps in increasing the usability where the weaknesses of one modality were offset by the strengths of another [20,21].

Therefore, this study aimed to fuse different modalities of three-electrode EEG data to construct a novel multimodal framework to determine the effective features of depressive EEG under normalization conditions and to create a depression classification model of universal EEG.

2. Related work

The EEG signals are spontaneous, rhythmic discharge activity of neurons from the scalp surface. It was first discovered by German psychiatrist Hansberg in 1926. He described the waveforms of the EEG signals, including alpha and beta waves, in an attempt to discover the physiological basis of psychological phenomena. With the development of science and technology, the research on EEG technology has made some progress. EEG is safe, low cost, easy to operate and non-invasive, so EEG technology has been applied to the diagnosis of brain diseases. First of all, EEG can represent most psychological activities and cognitive behaviors, which have been widely proved in neuroscience, psychology and cognitive science research [22,23]. Secondly, the EEG signals are closely related to human brain activity and emotional state, and can reflect emotional changes in real time [24,25]. The study by Harmon-jones et al. found that reduced activity in the left frontal of the EEG was associated with reduced positive and increased negative emotions. Klinesch et al. found that the oscillations of alpha wave and theta wave of EEG can reflect the performance of cognitive and memory functions [26]. Moretti et al. proved that the power ratio of EEG was related to the memory performance of mild cognitive impairment [27]. Theta wave and low alpha wave in the prefrontal of human brain studied by Aftanas et al. reflect the positive emotional state and attention level [28]. Adeli et al. found that EEG of epileptic patients and healthy people had correlation latitude differences in Beta wave and Gamma wave subband at higher frequencies [29]. Arns et al.'s analysis proved that the ratio of theta wave and beta wave in EEG was different between ADHD patients and healthy people [30]. Smit et al. have shown that EEG asymmetry in the frontal of the human brain is associated with anxiety disorders [31]. Siddiqui et al. believe that EEG is an important tool for diagnosing sleep disorders [32].

In recent years, many researchers have used EEG to study depression. More and more studies have found that the EEG data of depressed patients and healthy controls have different variation rules in the parameters such as wave band, power and amplitude. Debener et al. studied resting EEG data of 15 clinically depressed patients and 22 healthy people based on the theory that asymmetric forebrain activity and emotion, and found that the asymmetry of alpha wave in the prefrontal is one of the characteristics of depression. Hughes et al. found that about 20–40% of patients with depression had an EEG that was different from that of normal individuals [33]. Kühn et al meta-analyzed the resting EEG data of 470 participants in 11 studies and found hyperactivation of the prefrontal cortex in patients with major depression [34]. Leuchter et al analyzed resting EEG data from 121 moderately depressed patients and 37 healthy controls and found that depressed patients in the delta, theta, alpha, and beta bands showed a higher overall than normal controls. However, at the same time, the power and synchrony of the alpha band of the prefrontal lobe were significantly different from those of the normal controls [35].

Moreover, based on the features proposed by previous studies, the researchers used machine learning to classify the EEG data of depressed and healthy people. Erguzel et al. used Back propagation Neural Network (BPNN) to classify 147 subjects with the highest classification accuracy of 89.12% [36]. Spyrou et al. classified the EEG data of 34 healthy controls and 32 depressed patients, and the accuracy rate of the random forest classifier reached 95.5% [37]. However, The EEG data used by these researchers were obtained in individual modality.

Recently, fusion of the data from multimodal sources is becoming a fundamental task. It seems obvious that a multimodal system that fuses different channels and cues is expected to provide more accurate recognition than unimodal approache [38]. Ghasemzadeh H et al. introduced data fusion in the domains of emotion recognition and general-health [39] and provided a unique method of human balance based on EMG signals for novel interpretation of the neuromuscular system [40]. Xiaomao F et al. proposed a multi-scale fusion of deep convolutional neural networks (MS-CNN) for screening atrial fibrillation records from single-lead short electrocardiogram (ECG) records [41]. Arun et.al discuss fusion at the feature level for fusion of face and hand modalities to determine or verify the identity of an individual [42]. D'Mello and Kory solved the problem of the impact of multimodal on classifiers by conducting a meta-analysis on 30 published studies [43]. The results showed that regardless of the naturalness of the training data, the multimodal accuracy is higher than the second-best individual modality.

While there is a large amount of research in the general area of individual modality EEG and depression recognition, there exists little work dealing specifically with depression recognition using multimodal EEG data. In this work, we aimed to fuse different modalities of three-electrode EEG data to construct a novel multimodal framework to determine the effective EEG features of depression and to create a depression classification model of universal EEG.

3. Proposed method

In this paper, we propose multimodal depression recognition model based on the fusion of the EEG data collected under the neutral, negative and positive audio stimulus. As shown in Fig. 1, the fusion is based on the following considerations:(I) Depressed patients have less subjective experience of positive emotional stimuli (positive emotions are weakened), (II) Depressed patients are more sensitive to negative emotional stimuli, manifested by increased attention to negative emotions and increased emotional response (negative emotions are enhanced), (III) In the case of individual differences, the features extracted in individual modality (positive audio stimulation or negative audio stimulation) are inaccurate. In view of the disadvantages, fusing multiple modalities features can compensate effectively for the lack of individual modality features.

The fusion of EEG data in this paper is performed at the feature level. A block diagram of our fusion method is shown in Fig. 2. It mainly consists of six components: depression recognition under neutral audio stimulation, depression recognition under negative audio stimulation, depression recognition under positive audio stimulation, feature-level fusion, the selection of features of fusion and the weighting of features of fusion.

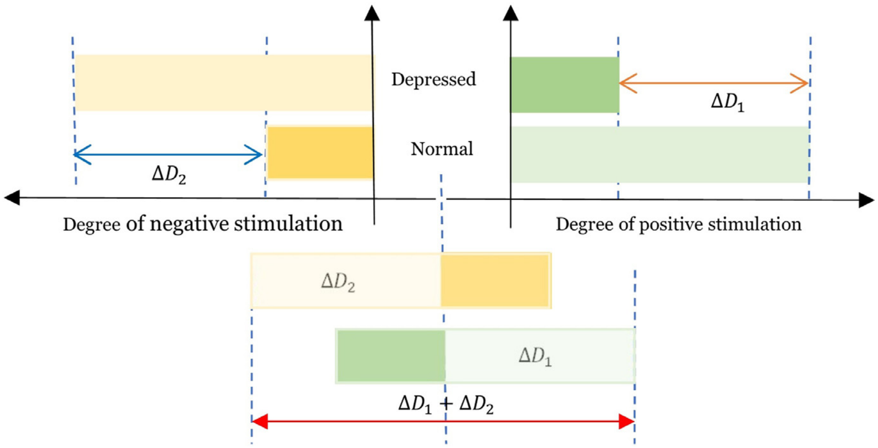


Fig. 1. the mechanism of multimodal fusion.

(I) The EEG acquisition device is used to simultaneously collect the subject's EEG data while they are receiving neutral, negative and positive audio stimuli, and then EEG data are preprocessed. (II) The features extracted under neutral audio stimulation are taken as neuEF; the features extracted under negative audio stimulation are taken as negEF; the features extracted under positive audio stimulation are taken as posEF. (III) The three features that were combined linearly in the third step are recorded as neg_neuEF, pos_neuEF and pos_negEF. (IV) neg_neuEF, pos_neuEF and pos_negEF are selected and weighed to obtain new features which are neg_neuSF, pos_neuSF and pos_negSF. (V) neg_neuSF, pos_neuSF and pos_negSF are sent to the classifier to be trained to construct a depression recognition model.

3.1. Participants and experiment

3.1.1. Experimental equipment

Previous studies have shown the involvement of the amygdala and orbitofrontal cortex in positive and negative emotions [44]. Harmon-Jones et al. have revealed that anger and cognitive dissonance, emotions with negative valence, and approach motivational tendencies are greater associated with relative left-frontal activity [45]. In addition, the EEG signal collected in the forehead position without hair over has low impedance, low distortion, and high usability. Therefore, FP1, Fpz, and Fp2 were the ideal choices of scalp position in the present study. As shown in Fig. 3(B), the three-electrode EEG data of frontal FP1, Fpz, and Fp2 were collected synchronously in this study, and the earlobe was used as the reference electrode. The data were stored in the computer using Bluetooth connectivity. A pervasive three-electrode EEG acquisition sensor is shown in Fig. 3(A), which is independently developed by the Ubiquitous Awareness and Intelligent Solutions Lab of Lanzhou University. The sensor had high flexibility and could be easily placed in different positions according to the need. The sampling frequency was 250 Hz per channel; the sampling precision was 24 bits; the impedance of all electrodes was <50 kΩ; and the common model rejection ratio was −110dB.

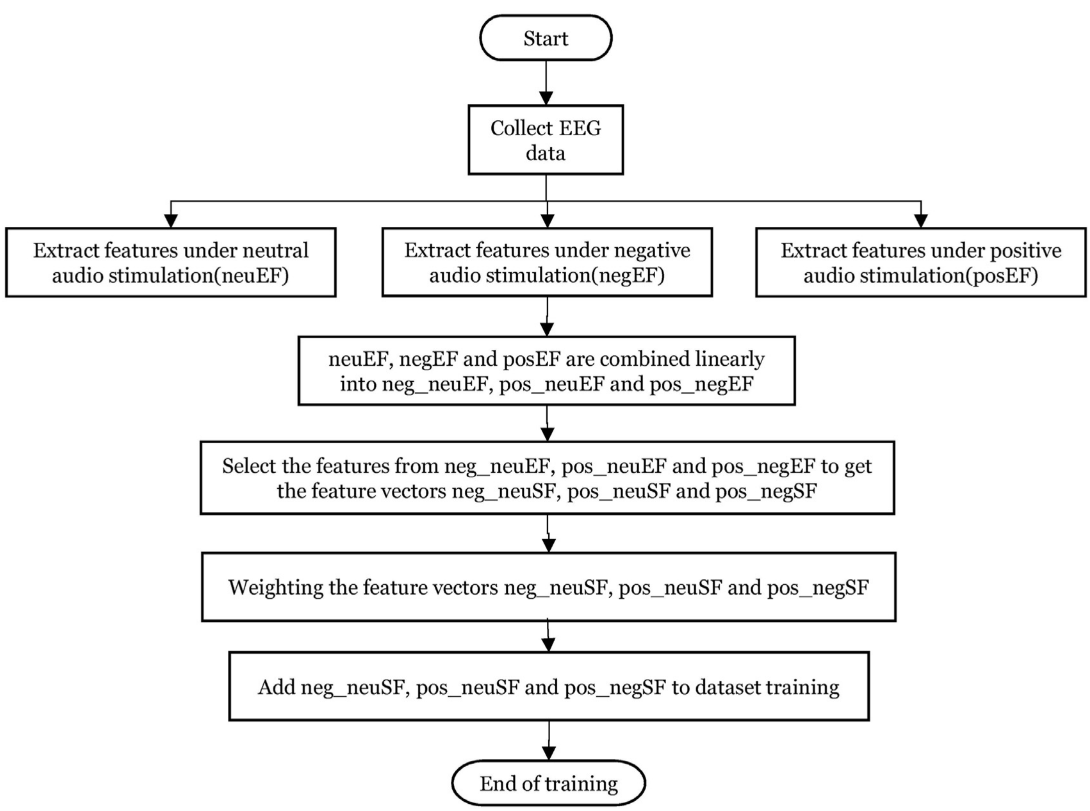


Fig. 2. Method flow diagram.

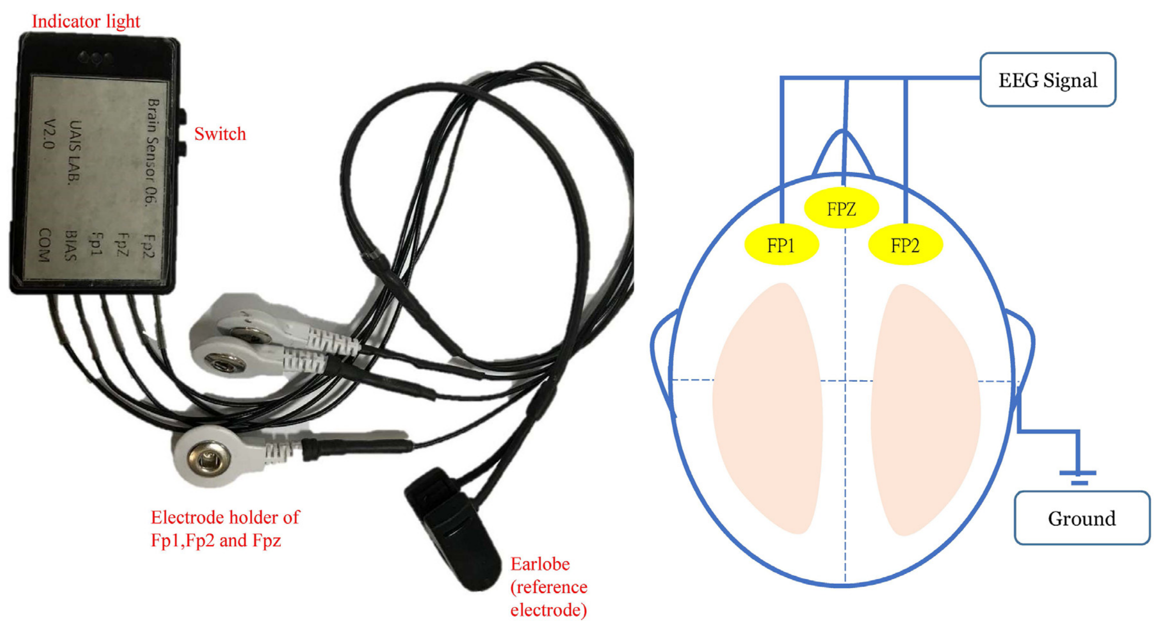


Fig. 3. Diagram of EEG-sensing device. (A) Pervasive three-electrode EEG acquisition sensor. (B) Electrode position of Fp1, Fpz, and Fp2.

Table 1
The inclusion criteria of pervasive EEG experiments for depression recognition.

	Patients with depression	Healthy control group
Inclusion criteria	1. Between the ages of 18-55 years old, male or female 2. Primary school or higher education level 3. PHQ-9 score was greater than or equal to 5. 4. No psychotropic medications taken within two weeks prior to the trial 5. Patients or other legal guardian to sign an informed consent form	1. Between the ages of 18-55 years old, male or female 2. Primary school or higher education level 3. Past or current undetermined diagnosis of mental disorders 4. Normal intellectual activity 5. Sign the informed consent form

Table 2
Audio stimulation profile.

Number	Name	Property
(1)	Cattle	Neutral
(2)	Painting	Neutral
(3)	Babies cry	Negative
(4)	Dentist drill	Negative
(5)	Babies laughter	Positive

3.1.2. Inclusion criteria

In order to ensure the authenticity and reliability of the experimental data, this paper tries to achieve full coverage of the sample in terms of quantity and type when selecting experimental samples. The experimental process was strictly in accordance with the experimental design. The evaluation tools for the experimental subjects included M.I.N.I. (Mini International Neuropsychiatric Interview), PHQ-9(The Patient Health Questionnaire), PSQI (The Pittsburgh Sleep Quality Index), CTQ (Childhood Trauma Questionnaire), EPQ (Eysenck Personality Questionnaire), LES (Life Event Scale) etc.

Depressed participants were selected by professional psychiatrists using evaluation tools. The inclusion criteria as follows:

Patients with depression: The patients with depression met the diagnostic criteria of The Mini-International Neuropsychiatric (MINI), and their Patient Health Questionnaire (PHQ-9) score was greater than or equal to 5.

Healthy control group: No mental disorder was diagnosed by MINI, and all other scales results were normal.

All subjects must also meet the following criteria: no other mental disorders; no other major or chronic physical illness; no psychotropic medications taken within two weeks prior to the trial. Detailed items for the inclusion criteria are shown in the Table 1.

The participants of this study were identified using the screening criteria of the 973 National Key Research and Development Program. Data sets were created with 86 depressed patients and 92 normal controls.

3.1.3. Experimental process and materials

The emotional response of depressed patients to outside stimulus has been found to be different from that of normal controls [46]. Depressive patients are relatively numb to positive emotional stimuli, and relatively sensitive to negative emotional stimuli. Therefore, this study design used three types of audio stimuli with different emotions as three different modalities. Recording and analysis of the EEG signals of the participants were done in five segments of audio stimuli, including two neutral stimuli, two negative stimuli, and one positive stimulation. Table 2 describes each audio stimulation. The source of stimulus was derived from the International Affective Digitized Sounds, 2nd edition [47], which is a standardized database of 167 naturally occurring sounds, widely used in the study of emotions, each 6 s long.

The entire experiment was carried out in a dedicated laboratory that was quiet, soundproof, glare-free and well ventilated. No strong electromagnetic interference throughout the experimental environment; and No other noise effects during the experiment. The specific experimental scheme included the following (Fig. 4):

The detailed experiment process is shown below:

(I) Ensure that the participant is awake and meet the inclusion criteria;
(II) Explain the experimental content, process and related precautions for the participant;
(III) Wear the three-electrode EEG sensor for participant;
(IV) Make sure the electrodes were in the accurate position and in good contact;

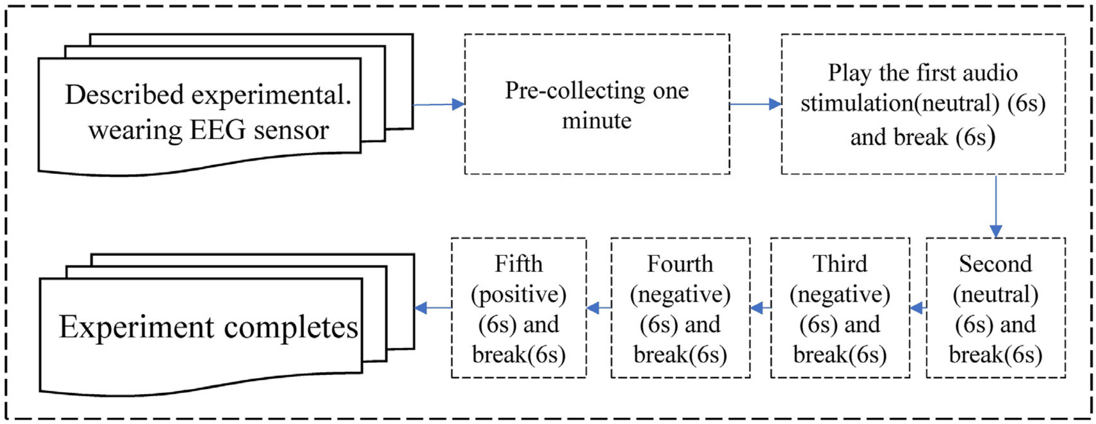


Fig. 4. Process of EEG signal acquisition.

(V) Pre-collection was done for one minute to ensure that the correct EEG signals were collected and device should be adjusted currently if abnormal signals were found;
(VI) After the pre-experiment is normal, the experiment is officially started;
(VII) Play each segment of audio stimulation in sequence and simultaneously acquire the EEG signals of the participant. After each audio stimulation, the participant rests for 6 s. The order of playback was as follows: first neutral audio stimulus, second neutral audio stimulus, first negative audio stimulus, second negative audio stimulus, and finally positive audio stimulus;
(VIII) Inform participant that the experiment is over and check the quality of the data. If the quality is poor, the data need to be collected again.

3.2. Data processing

In the process of EEG signal acquisition, many noises were inevitably introduced. Noise usually includes power frequency noise caused by environment and equipment and other noises, such as electrocardiogram (ECG), electrooculography (EOG), and electromyogram (EMG), caused by the body's own physiological signals. To obtain relatively pure EEG data, the original EEG signals were preprocessed. First, the power frequency noise was mainly caused by the power supply of the device itself, and its frequency was 50 Hz. During the process, a 50-Hz notch filter was used to remove the signal with a frequency of 50 Hz. Second, ECG was generated by the rhythmic operation of the heart, with a large amplitude. As the heart is located farther from the head, the ECG signal greatly diminished when it was transmitted to the scalp. Therefore, when preprocessing the EEG signals, the ECG was usually ignored. Third, EMG was produced by muscle contraction, and the frequency of EMG was mainly concentrated in the high-frequency band >100 Hz. In the present study, the frequency of EEG was 0.5–50 Hz. Thus, a finite impulse response filter based on the Blackman time window was used to remove the high-band noise caused by the EMG. Fourth, EOG was recorded inevitably while using the prefrontal-lobe EEG sites; however, the frequency of EOG was 0.1–100 Hz, which overlapped the EEG. The present study used the Kalman filtering method combined with the discrete wavelet transformation and an adaptive predictor filter to estimate the pure EOG artifact [48]. Subsequently, the ocular artifact was removed from the original EEG signal to obtain a relatively pure EEG signal. The comparison between EEG signals before and after removing EEG noise is shown in Fig. 5.

The red waveform represents the EEG signal waveform before the EOG is removed; The blue waveform represents the EEG signal waveform after the EOG is removed.

3.3. Feature extraction

Traditional EEG signal analysis is generally conducted by doctors according to their own clinical experience, which relies on the subjective judgment of doctors. Therefore, it is easy to ignore a large amount of information during the diagnostic process. The general EEG analysis is mainly linear analysis to extract certain linear features such as frequency, power spectrum, and peak. However, many studies have proved that EEG signals are nonstationary and random [49], and a simple linear analysis is unable to extract all the information contained in these signals. Therefore, this study extracted the linear and nonlinear features of the preprocessed EEG data to comprehensively analyze the EEG signals. Finally, 60 linear features and 36 nonlinear features of EEG signals were selected in the whole band (0.5–50 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz).

(1) EEG linear features:

The EEG linear features include relative center frequency, absolute center frequency, and relative power and absolute power of theta, alpha, beta, and gamma waves, as well as absolute power, center frequency, skewness, kurtosis and peak of the whole band.

(2) EEG nonlinear features:

The EEG nonlinear features include variance, Hjorth's activity, power spectral entropy, Kolmogorov entropy, Shannon entropy, correlation dimension, and c0-complexity of the whole band.

(A) Power spectral entropy: The power spectral entropy evaluates the strength of brain activity; the large the entropy, the more active the brain. In this study, the information entropy of the power spectrum of EEG signals was used as the power spectral entropy.

$$H_w = -\sum_{i=0}^{N-1} p_x(w_i)\log_2 p_x(w_i)$$

$$p_x(w_i) = p'_x(w_i) / \sum_{i=0}^{N-1} p'_x(w_i)$$

where $p'_x(w_i)$ is the power spectrum of signal.

(B) Kolmogorov entropy: The Kolmogorov entropy is used to describe the loss of information per unit time; it is useful for the measurement of chaos in dynamic systems [50,51]. In this study, the Kolmogorov entropy was used to evaluate the state of EEG signals per unit time. The Kolmogorov entropy is defined as follows:

$$KE = \lim_{T\to 0}\lim_{\in\to 0^+}\lim_{N\to\infty}\frac{1}{NT}\sum_{n=0}^{N-1}(K_{n+1}-K_n)$$

where $K_{n+1} - K_n$ measures the information loss of the system from time n to n+1.

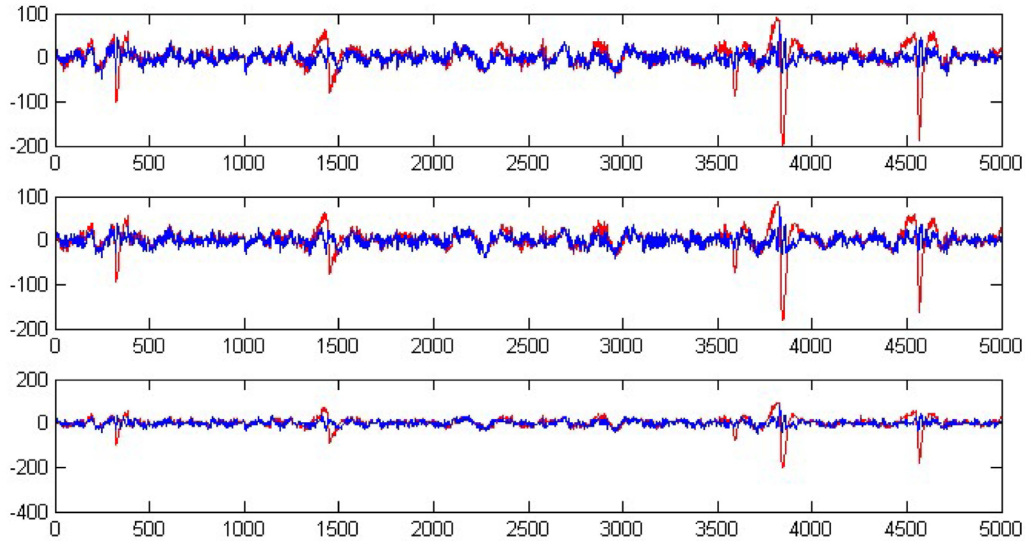


Fig. 5. Comparison of EEG signals before and after removal of EOG.

(C) Shannon entropy: The Shannon entropy was described by Shannon in 1948 in a study entitled “A Mathematical Theory of Communication” [52]. It is a measure of the uncertainty of random variables and random signals. The size of the information is directly related to its uncertainty. The amount of information is equal to the amount of uncertainty. The greater the entropy, the greater the uncertainty and randomness. In this study, the Shannon entropy was used to measure the order status of EEG signals [53]. The Shannon entropy is defined as follows:

$$K = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i)$$

(D) Correlation dimension: The correlation dimension was introduced by Grassberger and Procacia in 1983 [54]. It is the most common method for the nonlinear analysis of chaotic time series. The correlation dimension mainly uses the associated integral to calculate the correlation before and after the variable, so as to describe the deterministic law of the signal. The correlation dimension can reflect the degree of association between points in the state space, which can measure the complexity of the system. The larger the dimension, the lower the degree of association, which proves that the complexity of the system is higher. It can be defined by

$$D_2 = \lim_{r\to 0} \mathrm{In}C(r)/\log r$$

where $C(r)$ is the correlation integral and r is the radial distance around each reference point.

(E) C0-complexity: The c0-complexity was proposed by Shen et al [55]. Its main idea is to decompose the EEG signal into regular and irregular components, which is used to reflect the proportion of irregular components in the EEG timing signal to the original EEG signal. The higher the value of c0-complexity, the stronger the randomness of the EEG sequence. The c0-complexity calculation formula is as follows:

$$\mathrm{C0} = \sum_{t=1}^{N} |s(t) - s'(t)| / \sum_{t=1}^{N} |s(t)|$$

where $s(t)$ is the original sequence, $s'(t) = FT^{-1}(FT(s(t)))$, and FT is the Fourier transform.

3.4. Feature fusion

Most of the previous studies used individual modality EEG data as the research content and usually extracted features at rest. If the feature is extracted in only unimodal, the acquired features are relatively simple, which inevitably leads to insufficient EEG information, thus affecting the overall classification performance. Feature fusion provides a solution to the aforementioned problem because the features of multiple modalities can fully describe the EEG information compared with the individual modality feature, so as to achieve mutual complementarity between features. Early information fusion was the source of feature fusion methods, and the data obtained from several different sensors were fused for research. In recent years, data fusion has been widely used in the fields of target tracking and recognition [56,57], pattern analysis, and classification [58].

In general, data fusion is performed at three different processing levels depending on the stage of convergence: pixel level, feature level, and decision level. Pixel-level fusion refers to the fusion of the original data layer, that is, comprehensive analysis of the information before the original information is preprocessed [59,60]. Decision-level fusion makes individual decisions according to different feature sets and then coordinates or combines them into a global decision [61,62]. Feature-level fusion is a combination of different features in a linear or nonlinear manner after feature extraction to obtain new fusion features. This method combines the advantages of the other two fusion methods, and the original information is not easy to be lost after fusion and has good real-time performance, which is helpful for the final classification of results [60,61].

In this study, the feature-level fusion was used. First, according to the experimental paradigm, the EEG data of the participants were successively collected in three modalities (neutral, negative, and positive audio stimuli). Next, the EEG features under each individual modality were extracted. The feature matrices are as follows:

$$x_{pos} = \{x_1, x_2 \ldots x_m\}$$

$$x_{neu} = \{x'_1, x'_2 \ldots x'_m\}$$

$$x_{neg} = \{x''_1, x''_2 \ldots x''_m\}$$

where x_{pos}represents the feature matrix under the positive audio stimulation modality; x_{neu}represents the feature matrix under the neutral audio stimulation modality; and x_{neg}represents the feature matrix under the negative audio stimulation modality.

Second, the feature-level fusion method was used to linearly combine the feature matrices of the three modalities. A new feature matrix was used as U, where $U_1 = \{u_1, u_2 \ldots u_m\}$, $U_2 = \{v_1, v_2 \ldots v_m\}$, $U_3 = \{w_1, w_2 \ldots w_m\}$.

Table 3
Features selected from the fusion matrix of positive and negative audio stimuli.

Feature matrix	Name
U_1	Δrelative power of theta wave (Fp2), Δrelative power of theta wave (Fpz), Δrelative power of theta wave (Fp1), Δpower spectral entropy of alpha wave (Fp2), Δpower spectral entropy of alpha wave (Fpz), Δabsolute power of beta wave (Fp1), Δabsolute center frequency of beta wave (Fp1), Δpower spectral entropy of beta wave (Fp1), Δabsolute center frequency of gamma wave (Fp2), Δabsolute center frequency of gamma wave (Fpz), Δabsolute center frequency of gamma wave (Fp1), Δrelative center frequency of gamma wave (Fp1), Δcenter frequency of full-band EEG (Fp2), ΔShannon entropy of full-band EEG (Fp2), Δcorrelation dimension of full-band EEG (Fpz), and ΔKolmogorov entropy of full-band EEG (Fpz)

Table 4
Features selected from the fusion matrix of positive and neutral audio stimuli.

Feature matrix	Name
U_2	Δrelative power of alpha wave (Fp2), Δrelative power of alpha wave (Fpz), Δrelative center frequency of beta wave (Fpz), Δabsolute center frequency of beta wave (Fp1), Δpower spectral entropy of gamma wave (Fp2), Δabsolute center frequency of gamma wave (Fpz), Δskew of full-band EEG (Fp2), Δskew of full-band EEG (Fpz)

Table 5
Features selected from the fusion matrix of negative and neutral audio stimuli.

Feature matrix	Name
U_3	Δabsolute center frequency of theta wave (Fp2), Δrelative power of gamma wave (Fpz), Δskew of full-band EEG (Fp2), Δc0-complexity of full-band EEG (Fp1)

Finally, the fused feature matrix was calculated as follows:

$$U_1 = \beta x_{pos} + \gamma x_{neg},\ U_2 = \beta x_{pos} + \gamma x_{neu},\ U_3 = \beta x_{neg} + \gamma x_{neu}$$

$$u_i = \beta x_i + \gamma x_i'', v_i = \beta x_i + \gamma x_i', w_i = \beta x_i'' + \gamma x_i'.$$

In this study, β was taken as 1 and γ as −1.

U_1 represented the feature matrix of fusing positive audio stimulation and negative audio stimulation, U_2 represented the feature matrix of fusing positive audio stimulation and neutral audio stimulation, and U_3 represented the feature matrix of fusing negative audio stimulation and neutral audio stimulation.

3.5. Feature selection

In statistics, testing whether a variable has significant difference between two types of samples is a classic hypothesis test problem. The usual methods are *t* test, rank-sum test, and so on. These methods give a statistic to reflect the difference between the two types of samples and a *P* value that reflects the statistical difference between them. From the classification perspective, the features used for classification are significantly different between the two categories. Therefore, these statistics can be used to measure the ability of the features when selecting them. In this study, the *t* test was adopted as the method of feature selection. The differences in the fused new features were compared between the depressed patients and the normal controls, and each available u_i, v_i, w_i with the value of $p < 0.05$ in U_1, U_2 and U_3 was selected. The available features are shown in Tables 3–5.

3.6. Feature weighting

In the traditional machine learning classification model, it is generally considered that all features in the feature set are equally important. However, in the actual situation, the feature set may contain features with low correlation so that redundant or secondary features and other features have the same importance, and this affects the generalization ability of the classification model. An increasing number of recent studies focus on the feature weighting methods to improve the generalization ability of the model.

According to the different combinations of feature evaluation function and classification model, the feature weight setting methods can be divided into three categories: filter, wrapper, and embedding. In this study, the wrapped feature weighting method was mainly used, which combined the feature weighting process and the classification model and used the performance of the model as a criterion for evaluating feature weights. Its goal was to provide the feature weights that best contributed to its performance for a given classification model. A detailed comparative analysis of these methods has been conducted by Kohavi and John [63].

The classical wrapper feature weighting method mainly includes feature adaptive weighting method based on genetic algorithm and feature weighting method based on particle swarm optimization. This study adopted the feature weighting method based on genetic algorithm.

3.6.1. Genetic algorithms

Note that the Genetic Algorithms (GA) is a global optimization tool, proposed by Holland [64] and used in many applications in the literature. Genetic Algorithms is inspired from the biological evolution process. Including reproduction, crossover, mutation, etc., the core of the algorithm is: starting from a population, through a series of genetic operations such as selection, cross-recombination, and gene mutation under certain conditions, to produce a high-quality group suitable for survival. As the number of breeding algebra increases, when a better region in the search space produces a good population, it will tend to adapt to the best individual in the corresponding environment. This is the optimal solution to solve the problem. There are considerably many Genetic Algorithm applications in various areas. For the sake of the limited space

Table 6
The parameters of the classification algorithm.

Classifier	Core parameters
KNN	n_neighbor=3, algorithm= 'ball_tree', metric=' euclideanDis'
DT	Criterion='gini', max_depth=None
SVM	C=1.0, kernel='rbf', gamma='auto'

we will only consider their applications in feature weighting problems. The references [65,66], are among the examples of genetic algorithm-based feature weighting methods in the literature.

3.6.2. Parameter control of genetic algorithm

The algorithm often needs to adjust four parameters, namely Pop, T, Pc, Pm. The setting of each parameter requires several adjustments to get a reasonable value that ultimately applies to the problem to be solved.

Pop: The number of populations. The larger the value, the greater the diversity, but the computational efficiency will decrease. Therefore, it is necessary to set a reasonable population quantity during the adjustment.

T: A number of generations to accomplish;

Pc: A probability of mating each individual at each generation;

Pm: A probability of mutating each individual at each generation;

Genetic algorithms usually have two ways of terminating. One is that the set evolutionary algebra is exhausted and the algorithm is terminated. In another case, when the optimal solution is not found in a certain algebra, the algorithm needs to be terminated.

Through multiple adjustment, we finally choose Pop = 30, $T = 500$, Pc = 0.9, Pm = 0.5.

4. Experimental results

In this section, we design a depression recognition model based on feature-level fusion of multimodal EEG data, including three issues: (I)Verifying the validity of the linear combinations of features; (II)Comparing the performance of models between individual modalities and fusion modalities; (III)Determining a universal depression recognition model. During the construction of model, the classifiers including KNN, SVM and DT were used to evaluated the performance of individual modality and fusion modality, furthermore, the tenfold cross-validation was to evaluate the generalization ability of each classification model.

4.1. Classification techniques

4.1.1. KNN

KNN is a commonly used multivariate classification algorithm. Its basic idea is to calculate the distance between the unknown sample and the selected sample set, and then select the nearest k samples. If the k samples mostly belong to one category, the unknown samples also belong to this category [67].

4.1.2. DT

Decision Trees (DTs) are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features [68].

4.1.3. SVM

The SVM was introduced by Vapnik et al. [69] in 1995. Its basic idea is to classify samples by finding the hyperplane with the largest distance between samples. It has good nonlinear characteristics.

4.1.4. The parameters of the classification algorithm

The detailed parameters of the classifier are shown in Table 6.

Table 7
Classification results of $\boldsymbol{m}_{pos\_neg}$ and $\boldsymbol{f}_{pos\_neg}$(%).

Classifier	m_{pos_neg}	f_{pos_neg}
KNN	79.15	86.98
DT	66.32	69.80
SVM	56.86	71.36
Average	67.44	76.05

Table 8
Classification results of $\boldsymbol{m}_{pos\_neu}$ and $\boldsymbol{f}_{pos\_neu}$(%).

Classifier	m_{pos_neu}	f_{pos_neu}
KNN	74.14	70.22
DT	63.40	62.74
SVM	55.05	62.69
Average	64.20	65.22

Table 9
Classification results of $\boldsymbol{m}_{neg\_neu}$ and $\boldsymbol{f}_{neg\_neu}$(%).

Classifier	m_{neg_neu}	f_{neg_neu}
KNN	63.11	64.88
DT	54.58	61.69
SVM	52.16	62.27
Average	56.62	62.95

4.2. Experiment on method of feature fusion

The simplest form of fusion is concatenate the feature matrices of the different modalities to form a new single feature vector. However, as more modalities are joined, this increases the dimension of the feature vectors.

To overcome this issue, in the framework of the multimodal fusion depression recognition system, this paper carries out a comparison experiment using two strategies: (I)merge the feature matrices extracted in different modes into a new feature matrix; (II)create a fusion feature matrix using the linear combination formula described in Section 3.4, for example,

$$\boldsymbol{m}_{pos\_neg} = \left\{ \boldsymbol{x}_{pos1}, \boldsymbol{x}_{pos2} \cdots \boldsymbol{x}_{posm}, \boldsymbol{x}''_{neg1}, \boldsymbol{x}''_{neg2} \cdots \boldsymbol{x}''_{negm} \right\}$$

$$\boldsymbol{f}_{pos\_neg} = \left\{ \boldsymbol{x}_{pos1} - \boldsymbol{x}''_{neg1}, \boldsymbol{x}_{pos2} - \boldsymbol{x}''_{neg2} \cdots \boldsymbol{x}_{posm} - \boldsymbol{x}''_{negm} \right\}$$

Then different classifiers, namely, KNN, SVM and DT are tested to determine if the linear combination is best suited for feature-level fusion. In the process of comparison, we used the same feature selection and feature weighting for these two feature matrices.

Tables 7–9 shows the classification results of feature matrices generated by two strategies.

Fig. 6 presents the performance comparison of two types of strategies on three classifiers. The results of linear combination of features are higher than the results of using all features of two modalities. The fusion method of features linearly combination in performance increases compared with the performance of the method of merging. The use of individual modality features does not solve our problem well for our particular data sets. Therefore, we believed that the linear combination of features in the fusion modality can enhance the expression ability of features of individual modality.

Table 10
Performance of each recognition model in various modalities (%).

(a)Individual modal	Feature	KNN	SVM	DT	Average
Pos	$\{\boldsymbol{x}_{posi}\}$	75.85	69.36	68.06	71.08
Neg	$\{\boldsymbol{x}_{negi}\}$	73.13	63.56	70.22	68.97
Neu	$\{\boldsymbol{x}_{neui}\}$	67.78	68.93	68.80	68.50
(b)Fusion modal	Feature combined	KNN	SVM	DT	Average
F1: Pos-Neg	$\{\boldsymbol{x}_{posi-}\boldsymbol{x}''_{negi}\}$	86.98	71.36	69.80	76.04
F2: Pos-Neu	$\{\boldsymbol{x}_{posi-}\boldsymbol{x}''_{neui}\}$	70.22	62.69	62.74	65.22
F3: Neg-Neu	$\{\boldsymbol{x}_{negi-}\boldsymbol{x}''_{neui}\}$	64.88	62.27	61.69	62.95

(a) The classification accuracies of individual modality features.
(b) Combinate features between individual modalities separately and compare classification accuracies of fusion modality features. Best individual modality combination is presented here.

Table 11
Average performance of each classifier in individual and fusion modalities. (%)

Classifier	Individual	Fusion	Average
KNN	**72.25**	**74.03**	**73.14**
SVM	67.28	65.44	66.36
DT	69.03	64.74	66.89

Bold values signify the best performance afforded by the classifier.

Table 12
The best classifier for best individual modal and fusion modal (%)

Model	Positive modality	Fusion modality of positive and negative
KNN	75.85	86.98

4.3. Experiment on the performance of recognition models

In order to determine the great depression recognition model based on three-electrode EEG data, this paper conducted two comparison experiments: (I)Finding the best classification modality among individual modalities and fusion modalities. (II) Creating the best classification model for the classification of depression EEG based on the classification modality.

4.3.1. Experiment on fusion modality

Table 10 lists the classification results for the features of individual modality and fusion modality.

For a clear comparison, Fig. 7 shows the classification performance of individual modalities and fusion modalities, as shown, for the individual modalities, the best classification accuracy was obtained from the features of positive audio stimulation modality; for the fusion modalities, the fusion of positive and negative audio stimuli performed the best.

Furthermore, this paper also compared the effect of different combinations of individual modalities. Fig. 8 shows the performance of the different fused modalities and the individual modalities that compose of them. As shown, the fusion modality of positive and negative audio stimuli performs better than the two individual modalities that make up it. However, the results show the accuracy has no significant increased for the fusion modality of positive and neutral audio stimulus and the fusion modality of negative and neutral audio stimulus than two individual modalities that make up them. Therefore, according to the results of Figs. 7 and 8, this paper thinks the best fusion modality is the fusion of the positive and negative audio stimuli.

4.3.2. Experiment on classifiers

For classifiers, three traditional classifiers including KNN, SVM and DT were used in this paper, the parameters of the classifiers are shown in Table 5(in Section 4.1.4). Table 11 describes the average classification results of individual modality and fusion modality, according to the results, among all the three classifiers of KNN, SVM and DT, the KNN classifier has been achieve the best performance both in the individual modality and in the fusion modality.

Therefore, this paper thinks the KNN classifier is more suitable for classification of depression EEG.

In order to determine the best classification modality, as shown in Fig. 9, for all classifiers, the best depression recognition modality in individual modalities is the positive audio stimulation modality, the average accuracy is 71.08%, and the best recognition modality in fusion modalities is the fusion of positive and negative audio stimuli, the average accuracy is 76.04%. The average accuracy of the fusion modality is 5% higher than the individual modality.

What's more, in order to find the best depression recognition model and modality, Table 12 list the best classifier for best the individual and the fusion modality, the classifier is KNN, and the depression recognition accuracy in the best fusion modality is approximately 12% higher than that in the best individual modality.

As discussed earlier in this paper, depression recognition analysis has been primarily limited to multiple electrodes EEG and single modality information. The use of individual modality features does not solve the problem of depression recognition well for our particular data sets. Not only do three-electrodes EEG data reduce the complexity of depression recognition model, but also the feature-level modal fusion enhances the expression ability of features of individual modalities. Compared to other modalities, for all classifiers, the accuracy of the fusion modality of the positive and negative audio stimulus is higher than that of individual modality and other two fusion modalities. Especially, we found that the classification accuracy rate of KNN was highest among the three classifiers, whether in individual modality and in fusion modality. The classifier KNN obtained the best depression recognition in the fusion modality of positive and negative audio stimuli, and the accuracy is 86.98%. Therefore, this paper believes that the classifier KNN in the fusion of positive and negative audio stimulus more suitable to distinguish depressed and normal group.

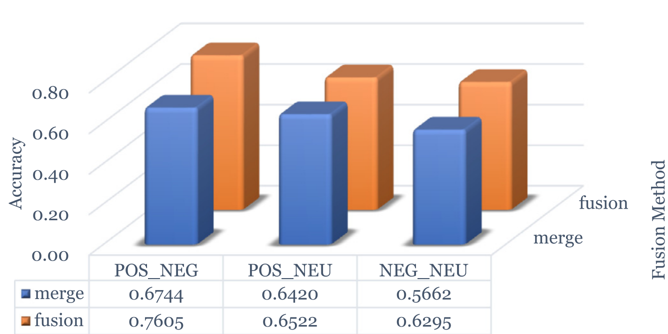


Fig. 6. the performance comparison of two types of strategies on three classifiers.

5. Discussion

As one of the world's major health concerns, diagnosing depression in the early curable stages is very important and may even save the life of a patient. The current recognition of depression depends on the doctor's experience. Some recent studies have started using the EEG technology for depression recognition. However, most of these studies used EEG data from the individual modality (resting state) and used a large number of electrodes. Knott et al. [70] introduced an accuracy of 91.3% by classifying 70 depressed patients and 23 normal controls using 21 electrodes in the resting state. Lei et al. used the 128-channel EEG data to analyze the highest accuracy of the classifier, which was estimated to

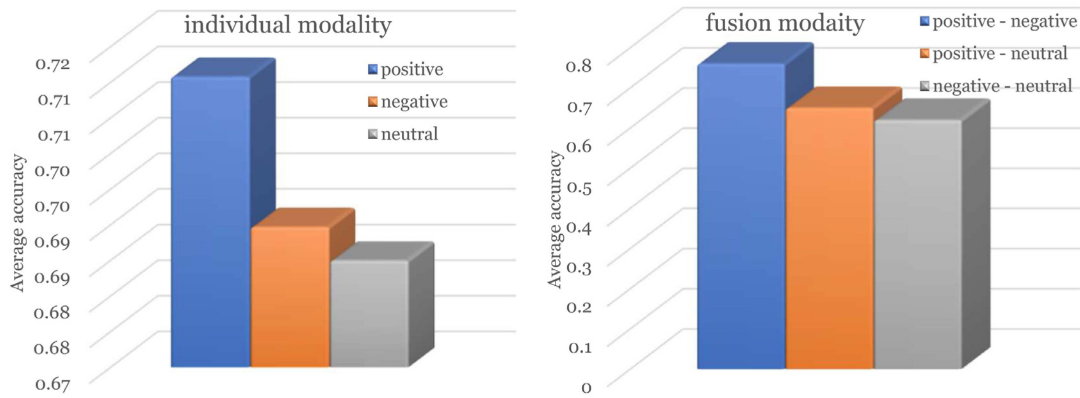


Fig. 7. the classification performance of individual modalities and fusion modalities.

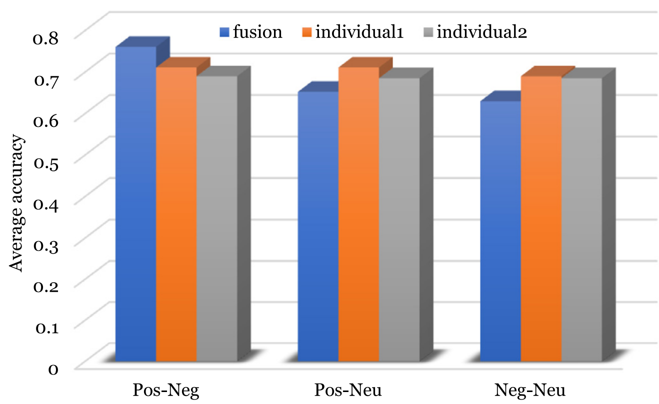
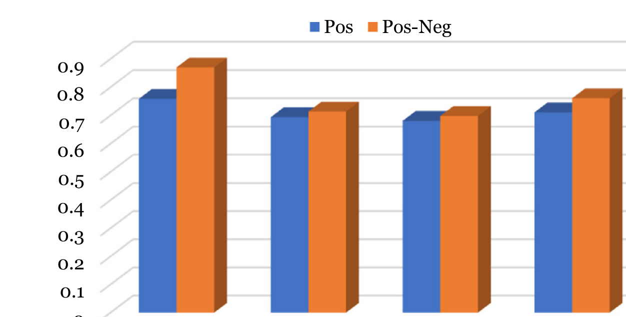


Fig. 8. the performance of the fusion modalities and the individual modalities that compose of them.



	KNN	SVM	DT	Average
Pos	0.7585	0.6936	0.6806	0.7108
Pos-Neg	0.8698	0.7136	0.698	0.7604

Fig. 9. the accuracy of the best individual modality and the best fusion modality.

be 97.67% [71]. Furthermore, Hosseinifard et al. obtained the highest accuracy of 83.3% using 19-electrode data [72]. Compared with these studies, the present study analyzed the classification accuracy of different individual modalities and different fusion modalities for depression recognition using the three-electrode EEG data. Especially, in current study, we used a pervasive three-electrode sensors, which is small, easy to wear, operate and highly flexible.

Therefore, in the present study, positive audio stimulation, negative audio stimulation, and neutral audio stimulation were used as the three modalities of feature extraction. The classification accuracy rate of three-electrode EEG features was compared between depressed patients and normal healthy controls in the individual and fusion modalities. The highest accuracy rate was achieved using the KNN classifier in the positive audio stimulation modality, with an accuracy rate of 75.85%. For further improvement, the EEG data of different modalities were fused, and several powerful features were selected by the *t* test. These were then used as one new feature vector to discriminate between depressed patients and normal controls. The results show that the fusion of the positive and neutral audio stimuli and the fusion of the negative and neutral audio stimuli had no considerable increases in the accuracy rate of all classifiers, but the fusion of the positive and negative audio stimuli improved the accuracy of classification significantly. Accuracy increased by approximately 12%, and the highest accuracy was 86.98%. In addition, in this study, three classifiers (KNN, DT, and SVM) were used. Among these classifiers, the KNN classifier performed the best whether in the individual or the fusion modalities.

6. Conclusions

Starting from the EEG data of the three modalities (neutral audio stimulation, negative audio stimulation, and positive audio stimulation), the entire classification algorithm was divided into three stages in this study. The first stage was the feature extraction. In this stage, the EEG data from 86 depressed patients and 92 healthy subjects were recorded under three modalities and the EEG features were extracted, including linear features, such as EEG relative power and absolution power, and nonlinear features, such as c0-complexity and correlation dimension. The second stage was feature fusion. In this stage, the EEG features extracted under different modalities were combined linearly using the feature-level fusion technique and selected new features as input to the classifier in the linearly combined features matrix using the t-test. The third stage was classification. Three well-known classifiers, KNN, DT, and SVM, were evaluated and compared using tenfold cross-validation in this stage. Furthermore, GA was applied for feature weighting. On comparing the classification accuracy among all classifiers in different fusion modalities, the KNN classifier was found to perform the best in the fusion of positive and negative audio stimuli, with the highest accuracy rate of 86.98%.

Compared with previous studies, the present study found a new way to identify depression using modality fusion and three-electrode EEG data and achieved a higher classification accuracy. In conclusion, the EEG signal can be a useful tool for studying depression and discriminating between depressed patients and normal controls.

Declaration of Competing Interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

Acknowledgment

This work was supported in part by the National Key Research and Development Program of China (Grant No. 2019YFA0706200), in part by the National Natural Science Foundation of China (Grant No.61632014, No.61627808, No.61210010), in part by the National Basic Research Program of China (973 Program, Grant No.2014CB744600),and in part by the Program of Beijing Municipal Science & Technology Commission (Grant No.Z171100000117005).

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