The Recognition of Multiple Anxiety Levels Based on Electroencephalograph

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Abstract—Anxiety is a complex emotional state that has a great impact on people's physical and mental health. Effectively identifying different anxiety states is very important. By inducing various anxiety states of 12 healthy college students with electroencephalograph (EEG) recording, comprehensive EEG features, including not only commonly used frequency domain features but also the time domain, statistical and nonlinear features were extracted from different EEG bands and brain locations. Next, correlation analysis was performed between various features and anxiety level changes that were predetermined at each stage of the experiment using a 5-point Likert scale, and the most relevant features were collected. Then, different classifiers were applied to classify four anxiety levels using different features alone or together to explore their anxiety recognition ability. Based on our dataset, the highest accuracy of identifying four anxiety states reached approximately 62.56 percent using the Support Vector Machine (SVM), which improved the classification accuracy compared with previous studies. The results also revealed the importance of EEG linear features (especially for features including total power, mean square and variance) in anxiety recognition. Furthermore, it suggested that EEG features in the beta band and the frontal lobe contributed to anxiety recognition more than the features in the other bands or other brain locations. In short, this study improves the accuracy of multi-level anxiety recognition and helps in choosing better features for anxiety recognition, which lay the foundation for the detection of continuous anxiety changes.

Index Terms—Electroencephalography (EEG), anxiety, multi-level, recognition, expressive writing, public English speech

1 Introduction

Anxiety is a complex psychological process and a compound emotional state that is always caused by imminent risk and threat [1]. Studies [2], [3] have shown that although moderate anxiety can stimulate potential and help meet challenges, excessive anxiety often has adverse impacts on attention bias [2], sleep [3], [4], [5] and working memory capacity [2].

Presently, the diagnosis of anxiety disorder mainly relies upon clinical symptoms or a series of questionnaires [6], [7], [8], [9], [10], e.g., the Manifest Anxiety Scale [6], the Hamilton Anxiety Scale [7], the State-Trait Anxiety Inventory [8], the Self-Rating Anxiety Scale [9] and the Beck Anxiety Inventory [10]. However, this diagnosis method is not objective enough, and it has a risk of subjective bias, affecting the quality of evaluation [11]. Because of its high accuracy and relatively objective evaluation, neuroimaging technologies, e.g., magnetic resonance imaging (MRI) and electroencephalograph (EEG), have been widely used in emotion assessment [12], [13], [14], [15]. Particularly, due to the instantaneous nature of emotion generation, EEG has obvious advantages in comparison with other neuroimaging techniques because of its high temporal resolution [16]. To date, there are many kinds of quantitative anxiety studies based on EEG [16], [17], [18], [19], [20], [21], [22], [23], [24], [25]. These studies show that anxiety is mainly manifested as changes in mood and cognitive ability, which affect the fluctuation of EEG.

At present, most quantitative studies on anxiety focused on the associations between EEG features and anxiety changes [17], [18], [19], [20], [21], [22], [23], [24], [25]. Hardt et al. [17] observed that anxiety level changes were proportional to changes in alpha waves in high anxiety subjects. Furthermore, extensive literature has revealed that EEG asymmetry is related to changes in emotion-related traits and states [18], [19], [20]. Davidson et al. suggested that frontal EEG asymmetry may reflect the strategic brain activity in response to emotional stimuli [18]. The decrease in anxiety level caused by certain methods is always accompanied by a larger left-sided shift of alpha asymmetry compared to that on the right side [19]. Several studies [21], [22], [23], [24], [25], [26] also have confirmed that EEG asymmetry increases as anxiety levels decrease. In addition, previous research has successfully differentiated three anxiety states using a machine learning method [11]. Zheng et al. designed a riding task with data recording via photoplethysmogram (PPG monitors physiological signals, such as heart rate, breathing and so on) and EEG to elicit competitive anxiety in 20 participants. Then, three anxiety levels (low/ moderate/ high anxiety) were distinguished. When combining PPG and EEG linear features,

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including the Hjorth parameter, mean and power of wavelet coefficients, the accuracy reached approximately 60 percent through training k-nearest neighbor (kNN) [11].

It can be easily found that most of these anxiety studies focused on the analysis of EEG linear features, but past theoretical and experimental studies have also shown that the complex electrical activities in the brain are irregular and nonlinear [27]. These linear analyses may be limited in characterizing brain activity, and it was difficult to completely describe the intrinsic mechanism of brain activity [28]. Numerous studies have confirmed the feasibility of applying nonlinear features in EEG signal classification [28], [29], [30], [31], [32], [33], [34]. Peng et al. [29] collected EEG signals at prefrontal sites (Fp1, Fp2 and Fpz) from two groups (high versus moderate stress groups). Different nonlinear features, including C0 complexity (C0), LZ complexity (LZC), correlation dimension (D2), Renyi entropy (RE), the first positive Lyapunov exponent (L1), and linear features (power and alpha asymmetry score) in each EEG band (theta, alpha and beta), were analyzed for the identification of two stress states. Guo et al. [30] acquired 6-channel EEG data, calculated approximate entropy (ApEn) and proposed an immune feature weighted SVM for classification of five different mental tasks. Wang et al. [31] systematically compared three kinds of EEG features, including power spectrum, wavelet and nonlinear dynamical (ApEn, Hurst exponent) features, and employed them for emotion classification. Due to the nonstationary nature and randomness of EEG signals, the nonlinear features used in these studies provided a better description of the signals' characteristics, which offered more robust identification of different EEG signals and may also be valuable for anxiety level recognition. Regrettably, there were no nonlinear features (such as C0 and entropy) that showed a direct correlation with anxiety changes. They were only used for EEG signal classification [32], [33], [34], [35], and anxiety recognition ability of these nonlinear features has not been further explored. Therefore, it is indispensable to explore the influence of commonly used nonlinear features on anxiety recognition.

Overall, this paper mainly focuses on realizing the identification of multiple anxiety levels and is dedicated to exploring the impact of different features on anxiety recognition.

The contributions of the paper can be summarized as follows:

1. Not only EEG frequency-domain features, but also time-domain, statistical and nonlinear features were used for four-level anxiety recognition. Compared with the previous study, the classification accuracy was improved with comprehensive EEG information.
2. The recognition ability of different features (different EEG bands/ different brain locations/ different types) was quantitatively explored to choose better features for multi-level anxiety recognition, which will help in future anxiety studies.

The remainder of this paper is organized as follows: Section 2 describes experimental materials, Section 3 provides experimental methods including data preprocessing and analysis techniques, Sections 4 and 5 present results and discussion, respectively, and conclusions are discussed in Section 6.

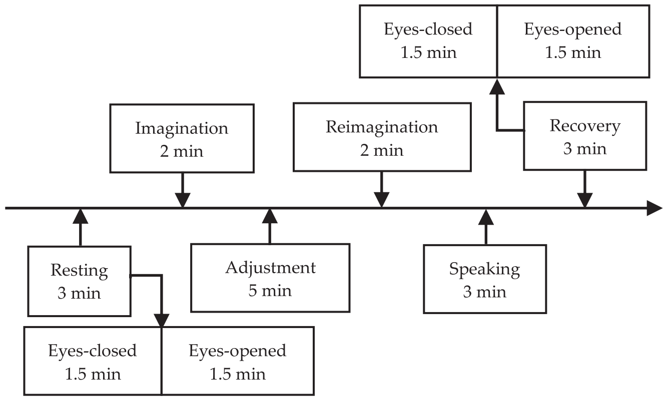


Fig. 1. A sketch map of the experimental process.

2 Materials

2.1 Participants

A total of 12 university students (all were native Chinese speakers and 19–28 years of age) participated as paid volunteers. All participants had normal or corrected-to-normal vision, and they were right-handed, as assessed by a handedness questionnaire [36]. They reported no history of mental health problems or neurological disorders. Written informed consent was obtained from all of the participants. All study procedures were conducted in accordance with the current version of the Declaration of Helsinki.

2.2 Experimental Paradigm

In this study, the experiment involves two kinds of stimulation to induce different levels of anxiety. One is public English speech. Public English speech has successfully induced the anxiety of speakers in previous studies [37], [38], [39]. It is easy to operate and is therefore used to arouse the social anxiety of the participants. The other is expressive writing [40], [41], which is the way people express their emotion, feelings or way of thinking about things through writing. As early as 1986, Pennebaker and Beall [42] had been confirmed the positive effect of expressive writing on mental health, especially for the regulation of emotions. Considering the application of expressive writing in emotional regulation [43], it was used to alleviate participants' anxious emotions.

The experiment was divided into six stages. The experimenter (female) introduced the experimental process briefly to participants before the experiment started. Fig. 1 shows the procedures of the experiment. The first stage consisted of eyes-closed and eyes-opened resting, which lasted 1.5 min each to calm down the moods of the participants. Then, the subjects were asked to imagine an embarrassing experience during an English speech for 2 min. The participants relieved their anxiety by expressive writing, namely, writing down their anxiety state for 5 min afterwards, and next, their anxiety was evoked again by 2 min of awkward English speech reimagination. After that, subjects were required to give an English speech in front of 3 experimenters for 3 min and finally recovered by relaxing with their eyes closed for 1.5 min and then open for 1.5 min. EEG data were collected simultaneously throughout the entire experiment.

Previous studies [37], [38], [39] have shown that anxiety induced by imagining an awkward situation during an

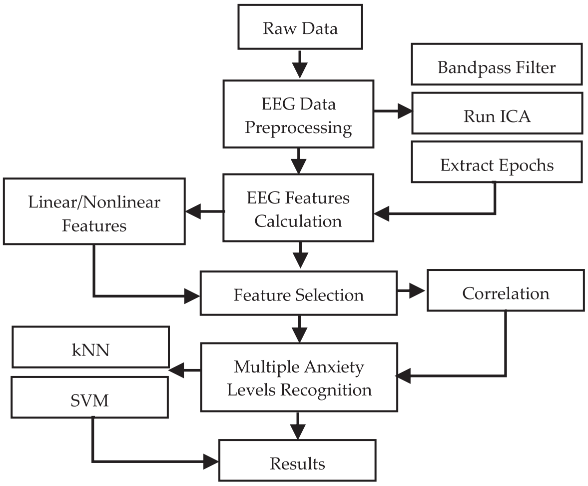


Fig. 2. The flowchartof the study.

English speech will be alleviated through expressive writing. Additionally, the delayed effect of expressive writing [40], [41], [42], [43] is able to improve the subjects' anxiety state effectively so that they will not feel so anxious when they once again imagine the awkward situation. In addition, the elicited anxiety by public English speech may take some time to subside. According to these points, a 5-point Likert scale was applied to presuppose the anxiety level of participants in different experimental stages ("1" = not anxious, "2" = mildly anxious, "3" = moderately anxious, "4" = very anxious, "5" = extremely anxious) [44]. In one stage (Resting Stage), participants perceived themselves as experiencing the non-anxiety level, three stages were associated with mild anxiety (Adjustment Stage, Reimagination Stage and Recovery Stage), one stage was associated with moderate anxiety (Imagination Stage) and one stage was associated with very anxious state (Speaking Stage).

2.3 EEG Recording

The EEG data were recorded through a 128-channel Electrical Geodesic Instrument system (https://www.egi.com/research-division/geodesic-sensor-net). The input impedance of amplifier was 200 kΩ. Electrodes were placed in an expanded 10-20 International system and referenced to Cz during the recording process, and impedances of all electrodes were kept below 50 kΩ. The EEG data were sampled at 500 Hz and filtered in a range of 0.01-200 Hz with a bandpass filter at each electrode site.

3 Methods

The method section is organized as follows: Section 3.1 describes the EEG data preprocessing and EEG data segmentation, and the key techniques, including calculation of various EEG features, feature selection and classification, are presented in Sections 3.2, 3.3, 3.4, respectively. The entire method is depicted as follows, and subsequent data processing is illustrated by a block diagram in Fig. 2.

3.1 EEG Data Preprocessing

Original EEG signals were first filtered (bandpass, Hamming window) in the frequency range of 0.5–50 Hz. EEG signals are often influenced by a series of artifacts, such as muscular movements, eye blinks and eye movements [45], hence, artifact removal is essential. Independent component analysis (ICA) [46] is a useful statistical method for signal separation. Therefore, it was employed for manually separating artifacts from EEG signals [47]. Next, all EEG activities were rereferenced to the global average reference.

Based on previous studies, EEG data from three homologous electrode pairs of the International 10–20 system (F3 and F4 at the frontal region, C3 and C4 at the parietal region, and P3 and P4 at the occipital region) were representative at different brain locations [48]. Selected EEG data from three homologous electrode pairs were then segmented into six epochs (Resting stage, Imagination stage, Adjustment stage, Reimagination stage, Speaking stage and Recovery stage) for subsequent processing, according to the experimental stage. All of the above operations were performed in a MATLAB-based open-source toolbox, EEGLAB 13.4.4b [49].

The preprocessed EEG data were band-pass filtered (Hamming windowed, Fast Fourier Transform) into five frequency bands (delta: 0.5–4 Hz; theta: 4–8 Hz; alpha: 8–13 Hz; beta: 13–30 Hz; gamma: 30–45 Hz) for subsequent processing. The EEG signal of each stage in each band was then split into segments. Each segment was 5000ms in duration, and the EEG signal of each person was divided into 216 segments (Resting stage: 36 segments, Imagination stage: 24 segments, Adjustment stage: 60 segments, Reimagination stage: 24 segments, Speaking stage: 36 segments, and Recovery stage: 36 segments), and a total of 2592 segments (Resting stage: 432 segments, Imagination stage: 288 segments, Adjustment stage: 720 segments, Reimagination stage: 288 segments, Speaking stage: 432 segments, and Recovery stage: 432 segments) were obtained from 12 subjects, which contained a total of four different levels of anxiety (not anxious: 432 segments, mildly anxious: 1440 segments, moderately anxious: 288 segments, and very anxious: 432 segments). In addition, in order to maintain the objectiveness and balance of the data, the 20 segments of the different stages in each subject were randomly selected. Therefore, four different anxiety levels could be identified through these segments.

3.2 EEG Feature Extraction

This study mainly extracted two types of features, including linear and nonlinear features. The specific types and quantities of features calculated are shown in Table 1.

TABLE 1
The Features Collected in Our Study

390 Linear and Nonlinear Features		
300 Linear Features		90 Nonlinear Features
Time Domain Features	Hjorth parameter Activity/Mobility/Complexity	Approximate entropy (ApEn)
Frequency Domain Features	total power (sumPower)	C0 complexity (C0)
	maximum power spectral density (maxs)	Correlation dimension (D2)
	frequency at maximum power density (f0)	**Note:** For each electrode, ten linear features were obtained in five bands; thus, a total of 300 (10×5×6) linear features were extracted. In a similar manner, 90 (3×5×6) non-linear features were extracted.
	Hemispherical Asymmetry (HA)	
Statistical Features	Mean absolute amplitude (Ppmean)	
	Mean square	
	Variance	

The features were extracted as follows and the variables declared below will be used throughout the paper. The EEG data of each subject was denoted as a matrix $X(t)$, the size of which is $\mathrm{c} \times \mathrm{N}$, where N represents the number of time sample, and c is the number of EEG channels. The data can also be expressed by a time course ($X(t) = [x_1(t), \ldots, x_C(t)]^{\mathrm{T}}$), where $x_c(t)(c = 1, \ldots, C)$ implies the time series of the cth channel. For convenience, in the following, $x(t)$ will be used to demonstrate a time series of a single-channel (Noting that the notations of calculated features are in italics for differentiation).

3.2.1 Linear Features

To explore the anxiety recognition ability of various EEG features, different types of linear features were extracted as follows.

- *Time domain features.* Hjorth parameters [50], [51], one of the most documented statistical properties of EEG signals, were calculated. Hjorth parameters include three kinds of parameters $(Activity, Mobility, Complexity)$, which reflect three characteristics of signals: amplitude, slope and slope rate of change. Specifically, *Activity* is the mean power of signals, *Mobility* represents the mean frequency and *Complexity* approximates the change in frequency. They are defined as follows:

$$Activity(x(t)) \ = \ var(x(t)) \tag{1}$$

$$Mobility(x(t)) = \sqrt{\frac{Activity(x'(t))}{Activity(x(t))}} \tag{2}$$

$$Complexity(x(t)) = \frac{Mobility(x'(t))}{Mobility(x(t))}, \tag{3}$$

$x'(t)$ is the first derivative of $x(t)$.

- *Frequency domain features.* Using a parametric approach, an adaptive autoregressive model (AAR) estimates the power spectrum density (PSD) of signals. Because of the strong nonstationary nature of EEG signals, the AAR model has an advantage over the classic spectral estimation method, which is only applicable to stationary random processes [52]. A p-order AAR model with time-varying parameters describes the EEG signal x_t in the following form:

$$x_t = \phi_0 + \phi_{1,t}x_{t-1} + \phi_{2,t}x_{t-2} + \cdots + \phi_{p,t}x_{t-p} + e_t, \tag{4}$$

x_t is a function of the linear combination of the top p time series and the error term of one electrode; $\emptyset_{i,t}, i = 1, \ldots, p$ is the autoregressive parameter that changes over time; $\emptyset_0$ is a constant, and e_t is the white noise with zero mean and variance σ^2.

Selecting the proper model order is critical as high order will induce false peaks in the spectra and low order will produce smooth spectra, so the order of the AAR model is adaptively chosen by the Akaike information criterion (AIC) [53]. Next, Lenvinson-Durbin recursion [54] was employed to find model parameters and variance of white noise. After these parameters were determined, the spectrum estimation of the time series could be easily obtained. With spectral estimation of time series, four linear features (*frequency at maximum power density (f0), maximum power spectral density (maxs), total power (sumPower), and hemispherical asymmetry (HA)*) were extracted. Among them, *hemispherical asymmetry (HA)* [21], [22], [23], [24], [25], [26] is typically calculated by subtracting the natural log of left hemispherical power from that of right hemispherical power (ln (right power)–ln (left power)).

- *Statistical features.* Three basic statistical features were also considered, including *mean absolute amplitude* (Ppmean), *mean square*, and *variance* to obtain the statistical characteristics of the EEG signals, which were calculated as follows:

$$\begin{aligned} Mean\ absolute\ amplitude &= E(|x(t)|) \\ &= \tfrac{1}{N}\textstyle\sum_{i=1}^{N}|x_i| \end{aligned} \tag{5}$$

$$Mean\ square = E(x(t)^2) = \frac{1}{N}\sum_{i=1}^{N}x_i^2 \tag{6}$$

$$Mean\ square = E\{(x(t) - E(x(t))^2)\}. \tag{7}$$

Through the above process, ten linear features were obtained, consisting of three time domain features, four frequency domain features and three statistical features. A total of 300 linear features (10 linear features $\times$ 5 bands $\times$ 6 electrodes) were ultimately collected for each segment.

3.2.2 Nonlinear Features

Because the application of nonlinear system theory to EEG has been shown to provide more information than that offered by traditional EEG measures, $C0$ [28], [55], [56], $ApEn$ [29], [30], [57], [58] and $D2$ [59], [60], [65] were calculated as strong nonlinear features. In the same way as described above, these nonlinear features were obtained for each EEG segment in each EEG band.

ApEn [29], [30], [57], [58] is a preferred measure of complexity or regularity owing to taking the temporal order of points in a time sequence into consideration. To extract ApEn, first the time series $\{x(t), t = 1, 2, \ldots, N\}$ is transformed to the m-dimensional vector $\mathrm{X_t}$,

$$X_t = \{x(t),\ x(t+1),\ \ldots, x(t+m-1)\}. \tag{8}$$

Then, the distance between the arbitrary vectors X_t and X_j $(j = 1, 2, \ldots, N-m+1, j \neq t)$ was computed,

$$\begin{gathered} d_{tj} = \max|x(t+j) - x(j+k)| \\ k = 0,\ 1,\ \ldots,\ m-1. \end{gathered} \tag{9}$$

Given a threshold of r ($r = 0.2$ in this work), the number of $d_{tj}\ \leq R(R\ =\ r \times \mathrm{SD})$ is counted for each vector X_t (SD is the standard value of the sequence), and the ratio of the number to the total distance N-m is $C_t^m(t)$.

Next, through $C_t^m(t)$, we can define $\varphi^m(r)$,

$$\varphi^m(r) = \ \frac{1}{N-m+1}\sum_{t=1}^{N-m+1} lnC_t^m(t). \tag{10}$$

Let m = m + 1 and repeat the above process to obtain $C_t^{m+1}(t)\varphi^{m+1}(r)$. Then, $ApEn$ is calculated as

$$ApEn = \sum_{N\to\infty} \varphi^m - \varphi^{m+1} \tag{11}$$

For EEG time series, the larger $ApEn$ values are associated with higher complexity or irregularity of EEG signals.

$C0$ [28], [55], [56] characterizes the complexity of signals, for time series $x(t)$, $t = 1, 2, \ldots, N$, the Fourier transform of this sequence is expressed as follows:

$$F_N(j) = \frac{1}{N}\sum_{t=1}^{N} x(t)W_N^{-tj},\ j = 1, 2, \ldots, N \tag{12}$$

$$W_N = e^{-2\pi i/N}. \tag{13}$$

Then the mean square of $F_N(j)(j = 1,\ 2, \ldots,\ N)$, G_N is calculated,

$$G_N\ =\ \frac{1}{N}\sum_{j=1}^{N} |F_N(j)|^2 \tag{14}$$

$$\bar{F}_N(j) = \begin{cases} F_N(j),\ |F_N(j)|^2\ >\ G_N \\ 0,\qquad\quad |F_N(j)|^2\ >\ G_N \end{cases}. \tag{15}$$

The inverse Fourier transform of $\bar{F}_N(j), j = 1, 2, \ldots, N$, is $\bar{x}(t)$. Thus, $C0$ is defined as

$$A_1 = \sum_{t=1}^{N} |x(t) - \bar{x}(t)|^2 \tag{16}$$

$$A_0 = \sum_{t=1}^{N} |x(t)|^2 \tag{17}$$

$$C0 = \frac{A_1}{A_0}. \tag{18}$$

Similar to $ApEn$, the larger $C0$ corresponds to higher signal complexity, and $C0$ complexity ranges between 0 (e.g., periodic signal) and 1 (e.g., pure random signal) according to the above formula.

$D2$ [59], [60], [65] is mainly used to approximate the dimension of a phase space, which indicates the dynamic complexity of the EEG signal. The larger correlation dimension corresponds to the more complex EEG time series. The value of the $D2$ is determined as shown in the following steps. A time series $x(t)$, which contains N points, is used to reconstruct the phase space Y_i by Takens principle [61]. Then, the distance between every pair of points was measured, and the correlation integral was computed as follows:

$$C(r) = \lim_{n\to\infty} \frac{1}{N(N-1)} \sum_{i\neq j} \theta\big(r - |Y_i - Y_j|\big), \tag{19}$$

where M is the data points' number, r denotes the radial distance of each reference point, and $\theta(x)$ represents the Heaviside step function that is defined as

$$\theta = \begin{cases} 0,\ (x \leq 0) \\ 1, (x\ >\ 0) \end{cases}. \tag{20}$$

Then,

$$D2 = \lim_{r\to 0} \frac{lnC(r)}{lnr}. \tag{21}$$

In summary, each segment finally extracted 90 nonlinear features (3 nonlinear features $\times$ 5 bands $\times$ 6 electrodes).

3.3 EEG Feature Selection

As mentioned above, each linear or nonlinear feature was calculated for each segment. However, it is unclear which features are most relevant to anxiety changes, and irrelevant features could be noisy for classification tasks [62]. Thus, feature selection is useful for improving classification accuracy. Pearson correlation [63] was employed to characterize the correlation degree between changes in each feature and predetermined anxiety levels. The features whose correlation coefficients were greater than $0.8\,(|\mathrm{r}|\ >\ 0.8$, according to p value $(p\ <\ 0.05))$ were selected for the subsequent process.

3.4 Classification

In this study, to evaluate whether different EEG features provide useful information for anxiety recognition, two popular classifiers named SVM and kNN were applied for classification. The following is a brief introduction to these classifiers.

SVM [64], [65] is a supervised learning model that is usually applied for pattern recognition, classification and regression analysis. It maps the sample space into high-dimensional feature space by nonlinear mapping (kernel function) so that the nonlinear separable problem in the original sample space is transformed into a linear separable problem in a new feature space. The radis based kernel function of SVM was chosen for its good effect on most classification problems.

kNN [65], [66] is also a supervised learning algorithm, its core idea is that a sample is similar to k samples in feature space. If most of the k samples belong to a certain class, the sample also belongs to this class. In this work, we varied $\mathrm{k} = 2$ to 10 to obtain maximum accuracy. The similarity was computed using Euclidean distance.

Classifications were executed by means of the following aspects. Initially, the selected linear and nonlinear features were individually and jointly used for classification for the sake of quantitatively evaluating the anxiety recognition ability of linear features and nonlinear features in different bands. Next, all linear and nonlinear features in each band were combined for separate classification. Finally, all features were united for classification. Furthermore, by exploring the impact of different brain location features on classification, features in different brain locations (frontal region: F3 and F4 electrodes, parietal region: C3 and C4 electrodes, occipital region: P3 and P4 electrodes) were applied for classification.

The data were divided into four parts, three parts were used for the training model and the remaining parts were used as the testing set. Feature selection was employed in the training set, and in the interest of developing robust classifiers, each classification was performed one hundred times (the final result is the average of 100 classification results), which made the classification results more objective. After all classifications were implemented, a two-sample t-test was

TABLE 2
Statistics on the Number of Features That Highly Correlated with Predetermined Anxiety Levels

	Delta	Theta	Alpha	Beta	Gamma	**Total**
Frontal Electrodes	0	1	0	8	5	14
Parietal Electrodes	0	0	3	7	1	11
Occipital Electrodes	0	1	1	2	1	5
Total	0	2	4	17	7	30

(Representative electrode of different brain locations: frontal electrodes - F3, F4, parietal electrodes – P3, P4, occipital electrodes – C3, C4).

performed multiple times to compare the differences between different classification results. And when the p value was less than 0.05, the difference was considered significant. When it was less than 0.01, the difference was extremely significant.

4 Results

4.1 Correlation Analysis Between EEG Features and Predetermined Anxiety Levels

30 features (for each segment) significantly correlated with different anxiety levels were extracted (Table 2) in six experimental stages (2 features in the theta band, 4 features in the alpha band, 17 features in the beta band and 7 features in the gamma band). For the spatial domain, the number of selected features extracted from different brain regions (frontal electrodes: 14 features; parietal electrodes: 11 features; occipital electrodes: 5 features) were almost identical (Table 2). Moreover, 23 linear and 7 nonlinear features, as shown in Table 3, were selected for subsequent analysis. And the recognition ability of different features will be further explored.

4.2 Classification Performance

Through feature selection, 30 features (each segment) were chosen for classification. Two classifiers (SVM, kNN), as mentioned earlier, were employed. A two-sample t-test was used to analyze the differences in various classification results at the group level.

4.2.1 Using Linear or Nonlinear Features

Since there are no features that are highly associated with anxiety changes in delta band, classifications were first carried out several times using the involved linear features (23 for each segment) and nonlinear features (7 for each segment) in the theta (2 nonlinear features for each segment), alpha (3 linear and 1 nonlinear features for each segment), beta (16 linear and 1 nonlinear features for each segment) and gamma (4 linear and 3 nonlinear features for each segment) band (as shown in Table 3). The classification results are shown in Fig. 3. Classifications were performed in each EEG band using the features selected by the correlation calculation, when applying linear features in different bands (accuracy using SVM: alpha-55.69 percent, beta-59.72 percent, gamma-58.61 percent; accuracy using kNN: alpha-49.39 percent, beta-52.82 percent, gamma-52.53 percent), accuracy in the beta band (SVM: 59.72 percent) was superior to that of the other bands ($p < 0.01$). Using nonlinear features in the corresponding band (accuracy using SVM: theta-52.78 percent, alpha-52.67 percent, beta-50.00 percent, gamma-50.78 percent; accuracy using kNN: theta-50.00 percent, alpha-50.94 percent, beta-52.56 percent, gamma-48.41 percent), the highest classification accuracy is obtained in theta band (SVM: 52.78 percent).

TABLE 3
Statistics on the Number of Linear or Nonlinear Features That Highly Correlated with Predetermined Anxiety Levels

			Feature Number	**Total**
Linear Features	Time Domain Features	Activity	5	23
		Mobility	3	
		Complexity	1	
	Frequency Domain Features	f0	1	
		maxs	2	
		sumPower	3	
		HA	1	
	Statistical Features	Ppmean	3	
		Mean square	2	
		Variance	2	
Nonlinear Features	ApEn		1	7
	C0		2	
	D2		4	
Total			30	

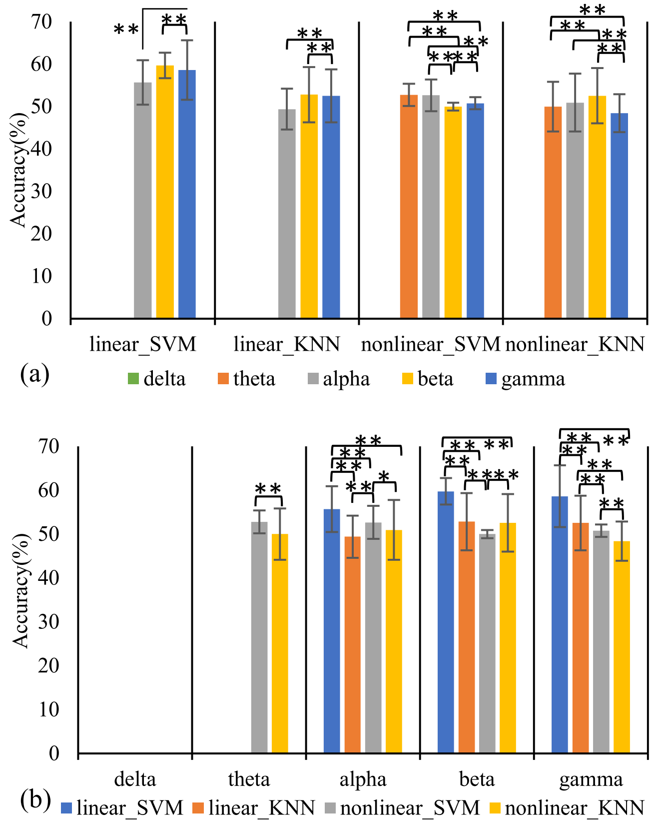


Fig. 3. Classification accuracy and significance analysis presented by different classifiers using linear or nonlinear features, respectively. (a) shows classification results and the significance analysis using the same classifier in different bands; (b) exhibits classification results and the significance analysis using different classifiers in the same band. $(* : p < 0.05, ** : p < 0.01)$

4.2.2 Combining the Linear and Nonlinear Features of Each Band

To further explore the recognition ability of features in different bands, linear and nonlinear features were combined in each band (theta band-2 for each segment, alpha band-4 for each segment, beta band-17 for each segment, gamma

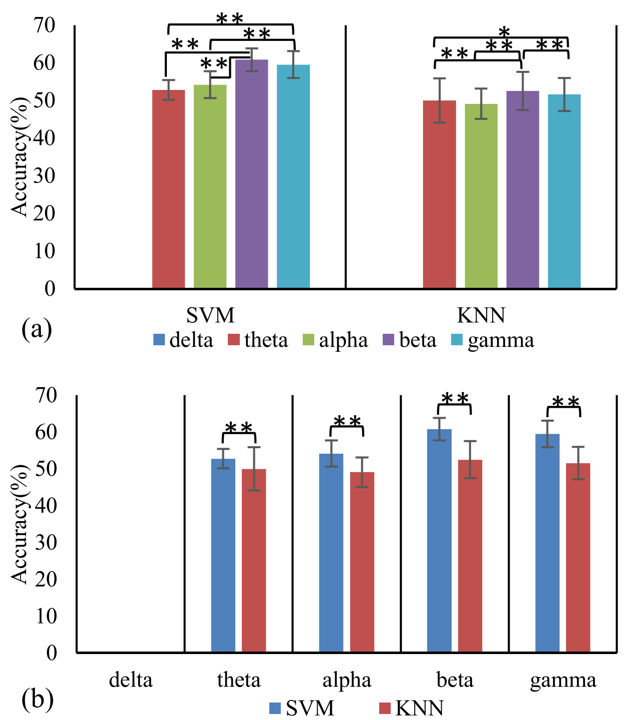


Fig. 4. Classification accuracy presented by different classifiers combining linear and nonlinear features in each band, respectively. (a) displays classification results using the same classifier in different bands; (b) shows classification results and the significance analysis using different classifiers in the same band. $(* : p < 0.05, ** : p < 0.01)$.

band-7 for each segment) as the inputs of classification. Fig. 4 displays the classification results. Through combination, the classification accuracies in some bands declined instead of increasing (accuracy using SVM: alpha-54.17 percent; accuracy using kNN: alpha-49.10 percent, beta-52.51 percent, gamma-51.59 percent). There were still several classification improvements, but the improvements were unstable when different classifiers were applied (accuracy using SVM: beta-60.80 percent, gamma-59.52 percent). Moreover, the joint of linear and nonlinear features in the beta band achieved the highest accuracy (SVM: 60.80 percent) among all bands $(p < 0.01)$.

4.2.3 *Combining Linear and Nonlinear Features of All Bands*

Next, for the purpose of specializing linear and nonlinear recognition ability of different anxiety levels, linear (23 for each segment) and nonlinear features (7 for each segment) of all bands were combined separately for classification. The results revealed a significant difference $(p < 0.01)$ in classification accuracy between applying linear features (accuracy using SVM: 61.35 percent; accuracy using kNN: 54.42 percent) and nonlinear features (accuracy using SVM: 53.97 percent; accuracy using kNN: 49.21 percent).

Finally, by combining all features of all bands, the classification accuracy exhibited the best performance. The performance of different classifiers is summarized in Fig. 5. Considering the effects of classifiers on classification, the accuracy using SVM (up to 62.56 percent) was approximately 9 percent higher than that of kNN (53.23 percent) $(p < 0.01)$.

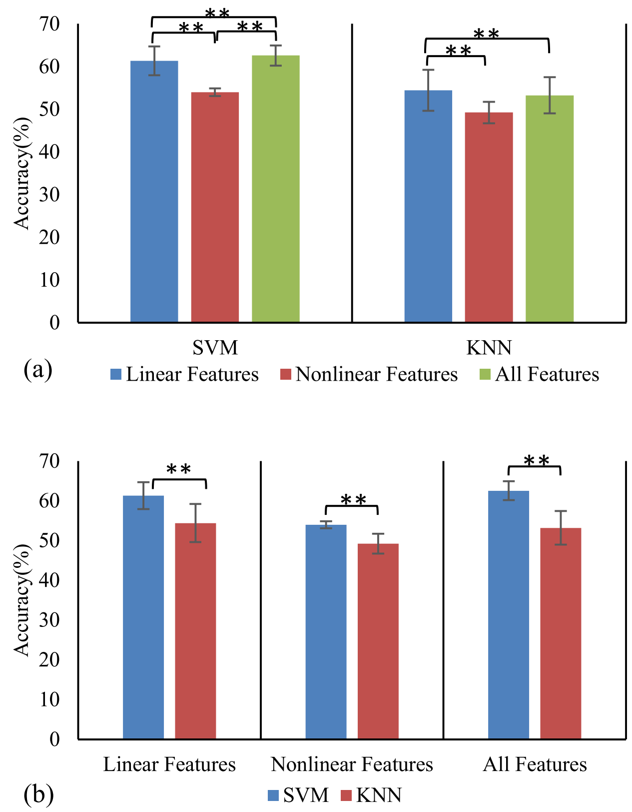


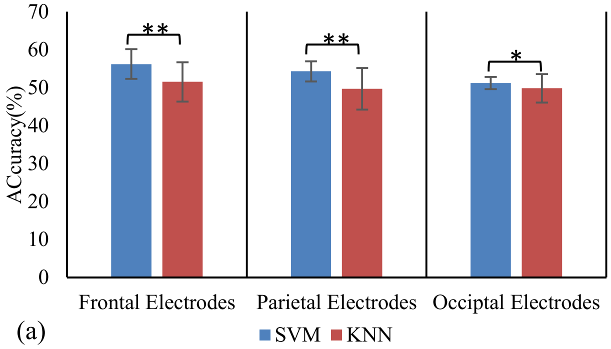
Fig. 5. Classification accuracy presented by different classifiers combining linear and nonlinear features. (a) displays classification results using different types of features with the same classifier; (b) shows classification results and the significance analysis using linear or nonlinear or all features with different classifiers. $(* : p < 0.05, ** : p < 0.01)$

5 Features from Different Locations

Moreover, the classification results obtained when features were extracted from different spatial locations of the brain (Frontal Electrodes: 14 for each segment; Parietal Electrodes: 11 for each segment; Occipital Electrodes: 5 for each segment), as shown in Fig. 6. The classification accuracy exhibited by the features of frontal electrodes (SVM: 56.23 percent; kNN: 51.52 percent) had better recognition of anxiety relative to the features of the parietal (SVM: 54.29 percent; kNN: 49.71 percent) and occipital (SVM: 51.24 percent; kNN: 49.83 percent) regions $(p < 0.01)$.

6 Discussion

In this study, a practical approach was presented for anxiety recognition, and different EEG features that were highly correlated with predetermined anxiety levels were selected to identify different anxiety levels elicited in different experimental stages. The classification results highlighted the importance of this study, which investigated the potential value of EEG measurement in the objective evaluation of distinct anxiety levels. By integrating EEG linear and nonlinear features, we determined a series of quantitative anxiety indicators and enhanced the accuracy of anxiety recognition. The highest accuracy, approximately 63 percent, was achieved using all selected features as input. As for previous studies, most of them focused on the identification of two anxiety levels [67], [68], [69]. For example, Feng et al.



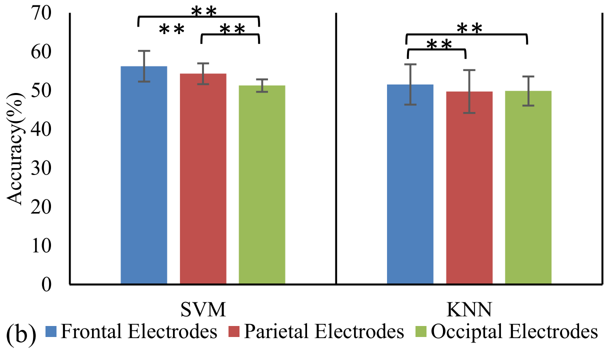


Fig. 6. The classification accuracy presented by different classifiers in different electrodes. (a) displays the results of classification and the significance analysis using the same classifier in different electrodes. (b) exhibits the results of classification and the significance analysis using different classifiers in the same electrodes $(* : p < 0.05, ** : p < 0.01)$.

TABLE 4
The Recognition Rate (Mean ± SD) of Four Anxiety Levels When Applying the Method Proposed by Zheng et al. to the Data Our Study Collected

Accuracy(%)	Zheng et al.	Our Method
SVM	44.44±15.80	**62.56 ±2.37**
KNN	58.94±8.81	53.23 ±4.23

[67] constructed functional connectivity (fMRI data) of normal people and patients of anxiety disorder, and achieved classification accuracy of 82.5 percent using SVM [64], [65]. Mokatren et al. [68] exploited the convolutional neural network (CNN) to identify normal people and anxiety patients (EEG data), achieving 87 percent recognition accuracy. Besides, a few studies have achieved the recognition of multiple anxiety levels. Zheng et al. realized three-level anxiety recognition. Compared with these studies, our approach not only achieved multi-level anxiety classification but also improved the classification accuracy (approximately 4 percent) over the method proposed by Zheng et al. [11] (using our data with their method), which proved the validation of our methods. The specific results are displayed in Table 4.

Previous quantitative studies on EEG signal recognition have demonstrated the feasibility of using linear EEG features [11], [20], [21], [22], [23], [24], [25], especially for EEG frequency domain features, hence, in our study, we applied not only the EEG frequency domain features as classification input but also the time domain and statistical linear features [28], [29], [30], [31], [32], [33], [34], which may contain more information about EEG signals to further strengthen the classification results. In addition, based on our data set, several nonlinear features were calculated: C0 characterized EEG signal complexity, D2 characterized EEG dynamic characteristics and functional connections, and ApEn characterized fluctuation and unpredictability of signals. Further, anxiety identification ability of these features was explored. The results showed that, the anxiety recognition ability of the selected linear features (especially for features including sumPower, meanSquare and variance-) were better than the selected nonlinear features by comparing feature weights (as displayed in appendix). Furthermore, our research also exhibited that when combining linear and nonlinear features for classification, the accuracy improvement generated by nonlinear features was limited, and even the effects they provided were negative. This may indicate that the correlation between nonlinear features and anxiety change is relatively weak. In other words, linear features may be better predictors of anxiety. More importantly, compared to nonlinear features, linear features with fast computing speed and small memory operation were conducive to further research on real-time tracking of anxiety changes [70]. However, it is worth noting that this was only observed in selected nonlinear features in this study, so whether other nonlinear features have better performance remains to be verified.

In previous quantitative studies of anxiety recognition, the feasibility of using EEG tools has been reported [11], [69]. In our study, considering future research on classification in different EEG bands, the results of feature selection indicated that there were more features associated with anxiety changes in beta and gamma bands and the result of classification validates that the beta band was always the best predictor of anxiety states when linear features were used and gamma was second to beta, which was consistent with the observations in the literature. That is, brain activities with higher frequency reflected emotional and cognition processes [16].

Furthermore, in terms of classifier performance, two classifiers, SVM and kNN, were applied. And in most cases, SVM has a better classification effect. Since classification was repeated many times using the resampling technique, the classifiers were more robust. It is noteworthy that the current study found that frontal EEG features have better capability for anxiety recognition, which was also in accordance with previous studies (Emotion is controlled by the forehead of the brain [71]).

There are also some limitations in this study. This study did not include enough subjects. A larger population would further validate the results. Another shortcoming of the study is that self-reported anxiety levels of participants were not measured through scales. Although the selected features highly correlated with predetermined anxiety levels and subsequent classifications using these features yielded relatively good experimental results, there should be some difference between predetermined anxiety levels and subjects' actual anxiety levels. However, according to previous studies, self-reported anxiety varies greatly because of individual differences, therefore, anxiety levels fluctuated significantly at the group level [72]. Hence, whether using self-reported anxiety can further improve the current results is still worth exploring.

In the future, more work should be implemented using larger data sets with more anxiety levels to realize real-time anxiety monitoring.

7 Conclusion

In this study, by eliciting different anxiety levels and collecting corresponding EEG data, we enhanced the accuracy of multi-level anxiety recognition and simultaneously revealed the impact of different features on anxiety recognition. These findings might provide new insights into anxiety study, lay the foundation for the detection of continuous anxiety changes and help people better understand anxiety.

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