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Research on Methods for Recognizing and Analyzing the Emotional State of College Students

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Abstract: *Based on the characteristics of how humans express emotions, emotion recognition methods include the use of body expressions and physiological signals. According to psychology and neurophysiology, the generation and activity of emotions are closely related to the activity of the cerebral cortex. Therefore, electroencephalographic (EEG) signals can effectively reflect brain activity and have been widely applied in fields such as cognitive behavior prediction, mental workload analysis, mental fatigue assessment, recommendation systems, and decoding visual stimuli. This study focuses on emotion state recognition and analysis methods for college students based on EEG signals under different external environmental stimuli. The research goal is to provide a fast and effective method for recognizing and analyzing the emotional state of college students to better understand and regulate their emotional states.*

Keywords: *Emotion recognition, EEG signals, College students*

1. Introduction

For college students, they are in what psychologist Jeffrey Arnett refers to as the "emerging adulthood" stage[1]. Individuals in this stage are physiologically mature but still retain many adolescent characteristics psychologically. They are open to multiculturalism, eager to try new things, and willing express their opinions. However, they also exhibit complex traits such as incomplete mental maturity, susceptibility to misleading influences, and weak resilience to setbacks. Studying and analyzing the emotional states of college students during sudden events is of great significance, as the recognition analysis of emotional states can provide a foundation for subsequent psychological adjustment and intervention measures for college students[2].

Based on the characteristics of how humans express emotions, emotion recognition methods can be categorized into two main types: body expressions and physiological signals[3]. Bodily expressions are physical manifestations that are easy to collect. Researchers believe that each emotion corresponds to unique body reaction. However, body expressions are often influenced by cultural backgrounds and social environments. According to Cannon's theory, changes in emotions are related to the rapid responses of physiological signals coordinated by the autonomic nervous system[4]. This makes physiological signals less controllable and helps overcome the limitations of body expressions. While physiological signals such as ECG and EMG have been widely used in emotion recognition studies[5], they are not direct responses to emotional changes.

Psychological and neurophysiological studies have shown that the generation and activity of emotions are closely related to the activity of the cerebral cortex. Therefore, electroencephalogram signals effectively reflect the brain's electrical activity and have been widely applied in various fields, including cognitive behavior prediction, mental workload analysis, mental fatigue assessment, recommendation systems, and decoding visual stimuli.

This study focuses on the recognition and analysis of college students' emotional states based on signals during sudden events. The research aims to provide a fast and effective method for recognizing and understanding the emotional states of college students in response to sudden events.

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2. Related Research and Value

2.1. Relevant Research

In recent years, emotion recognition based on EEG signals has attracted considerable attention from scholars. Russell's Valence-Arousal emotional model[6] is widely used in emotion recognition due to its ease of establishing evaluation criteria. Advances in EEG-based emotion recognition technology include feature extraction, feature selection, dimensionality reduction, and classification algorithms. After preprocessing the raw EEG signals, the current focus is on extracting and selecting information features to enhance signal differentiation. Traditionally, feature extraction and selection have been based on neuroscience and cognitive science.

In addition to neuroscience-based assumptions, computational methods from machine learning have also been applied to feature extraction and selection in EEG-based emotion recognition. Numerous studies have transformed preprocessed EEG signals into various analytical domains, including time, frequency, statistical, and spectral domains. However, a single feature extraction method is not suitable for all applications and brain-computer interface (BCI) systems[7]. Although researchers continue to explore the most effective EEG features for emotion classification, energy features are widely regarded as the most reliable. Among these, the Power Spectral Density (PSD) of EEG signals has proven effective in recognizing emotional states. However, feature extraction often results in high-dimensional and rich features.

Feature selection and dimensionality reduction are essential to avoid overfitting and reduce computational overhead. Compared to filter and wrapper methods used for feature selection, dimensionality reduction methods are more efficient. Various machine learning algorithms have been introduced as classifiers for EEG-based emotion recognition, such as Support Vector Machines (SVM), Naive Bayes, K-Nearest Neighbors, Linear Discriminant Analysis, Random Forests, and Artificial Neural Networks[8]. Among these methods, SVM based on spectral features is the most widely used. For example, a study classified happiness, sadness, anger, and pleasure using SVM based on EEG signals from 12 symmetric electrode pairs. The SVM achieved accuracy rates of 32% and 37% for the valence and arousal dimensions, respectively. Another study found that Gaussian Naive Bayes achieved accuracies of 57.6% and 62.0% for classifying low/high valence and arousal emotions, respectively.

Recently, deep learning (DL) methods[9] have been introduced for EEG-based emotion classification. Unlike traditional shallow methods, DL models eliminate the need for signal preprocessing and feature extraction/selection processes, making them more suitable for emotional representation. However, DL methods cannot reveal the relationship between emotional states and EEG signals. Additionally, training DL networks is computationally intensive, which limits their practical application in real-time emotion recognition.

Overall, the field of affective computing has seen significant research, including the integration of deep learning methods. However, modeling and recognizing emotional states remain underexplored areas. EEG-based emotion recognition still faces challenges, such as the fuzzy boundaries between emotions.

Logistic Regression (LR)[10] has been widely used as a statistical learning model in pattern recognition, machine learning, and EEG signal processing. Current studies have employed LR trained on EEG power spectral features for automatic epilepsy diagnosis. Other researchers have used wavelet transformations to extract effective representations from non-stationary EEG recordings and applied LR as a classifier to distinguish between epileptic and non-epileptic seizures. Some studies trained regularized linear LR on raw EEG signals without feature extraction to classify imagined motor activities.

In the memory domain, researchers have trained LR models with L2 penalties using spectral power features from intracranial EEG (iEEG) signals to analyze brain encoding states and memory performance. Others combined t-distributed stochastic neighbor embedding (t-SNE) to reduce the dimensionality of iEEG signals and used the learned L2-regularized LR classifier to predict successful memory encoding. Research in this area is still in its early stages, and the potential of LR models in EEG-based emotion recognition has not been fully explored.

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2.2. Applications and Theoretical Value of Research

This research holds significant practical application value. Strengthening the construction of a social psychological service system and fostering a confident, rational, and positive societal mindset are essential goals. Leveraging psychological research outcomes to predict, guide, and improve the emotions and behaviors of individuals, groups, and society can effectively contribute to building a robust social psychological service system. This, in turn, enhances the psychological well-being of the population and promotes mental health.

For university students, who are in a critical period of physical and mental development, such research is particularly valuable. With rapid economic development comes intense social competition, and college students face immense academic, graduation, and employment pressures. Studying emotion recognition among university students, summarizing their psychological and behavioral characteristics, and actively implementing targeted intervention measures can help establish the "awareness-psychology-behavior" cultivation framework for students. This contributes to improving their mental health, fostering personal growth, and supporting their academic and career success.

This research also holds substantial theoretical value. Emotions play a central role in people's attention, decision-making, and communication. Due to the application of brain-computer interfaces and their effectiveness compared to human expressions and other physiological signals, emotion recognition based on electroencephalograms (EEG) has seen significant advancements.

Despite major progress in affective computing, emotion recognition remains an underexplored field. This study seeks to advance research into emotion state recognition and analysis using EEG signals. Specifically, it aims to apply Logistic Regression (LR) based on Gaussian kernels and Laplacian operators for EEG-based emotion recognition. The Gaussian kernel enhances the separability of EEG data in the transformed space, while the Laplacian prior promotes the sparsity of the learned LR regressor, thus avoiding overfitting.

The study will further investigate key frequency bands in emotion recognition. Experimental data will be used to analyze the performance of the LORSAL method and compare it with recent deep learning (DL) approaches. This research is expected to contribute valuable insights into the field of emotion recognition.

3. Recognizing and Analyzing the Emotional State of College Students

The research on emotion state recognition and analysis methods for university students based on EEG signals aims to provide a fast and effective method for understanding and recognizing the emotional states of college students.

The main research content includes the following four aspects: (1) Studying the characteristics of the emotional states of university students; (2) Investigating models that effectively reflect the emotional states of university students, modeling and analyzing emotional states, focusing on analyzing the fuzzy boundaries between emotions, and exploring the characteristics and patterns of university students' emotional states; (3) Researching the extraction of various features from EEG signals, introducing the LR model with Gaussian kernel and Laplacian prior, and the learned LORSAL algorithm LR regressor for EEG-based emotion recognition and analysis algorithm research; (4) Studying the key frequency bands for emotion recognition based on EEG signals: extracting features from different frequency bands (Delta, Theta, Alpha, Beta, Gamma, and Total) to analyze emotional states; studying the effectiveness of emotional recognition using different EEG signal features, including PSD, DE, DASM, RASM, and DCAU.

3.1. Research Approach and Methods

This study analyzes the characteristics of various biological signals and assesses the feasibility and effectiveness of EEG signals for analyzing the emotional dynamics of university students. Based on the Russell Model of Emotions, the SAM Self-Assessment Model, and signal feature extraction, the EEG signals are analyzed. By proposing an emotion classification method based on a Logistic Regression (LR) classifier combined with Gaussian kernels and Laplacian priors, this study aims to improve the accuracy and effectiveness of emotion recognition and analysis in university students. The results will provide a basis for subsequent psychological adjustment and intervention measures for university students.

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By reviewing relevant literature, a comprehensive understanding of the current status and guiding directions of emotional changes in university students is obtained. Relevant concepts and theoretical models are defined, and the characteristics of university students' psychological and emotional states, as well as adjustment strategies, are thoroughly studied. EEG signal data from university students are collected through random sampling surveys. After analyzing and organizing the data, scientific feature extraction methods are applied to analyze the data, summarize the overall emotional state changes of students, and identify the emotional state characteristics of individuals with emotional disturbances. Comparative experiments are conducted between the proposed LORSAL method[11] and four other classifiers: Naive Bayes (NB), Support Vector Machine (SVM), linear Logistic Regression with L1 regularization (LR_L1), and linear Logistic Regression with L2 regularization (LR_L2), to verify the advantages of the proposed method. The average accuracy and standard deviation obtained from five different classifiers, using features extracted from five frequency bands (Delta, Theta, Alpha, Beta, and Gamma), are compared in two dimensions. These include the average precision and standard deviation of LV/HV emotional classification, and the average precision and standard deviation of LA/HA emotional classification.

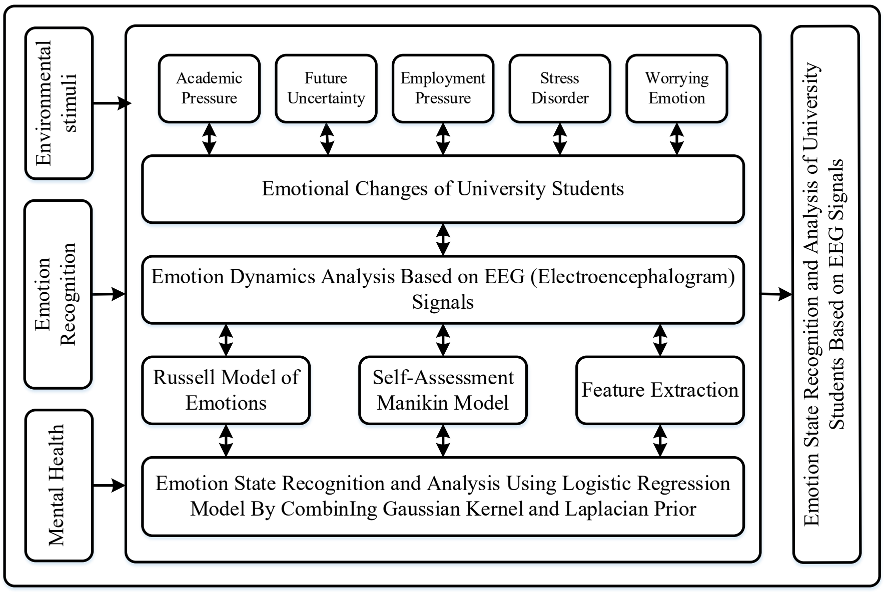

Figure 1: Framework of Research Implementation Steps

3.2. Research Implementation Steps

The research is carried out in four stages, as shown in Figure 1:

Stage 1: Collect relevant literature extensively, read and investigate in depth, establish the research direction, clarify the research objectives and significance, and conduct a literature review on the current related research. This stage primarily uses the literature research method.

Stage 2: Develop or adopt an appropriate sampling strategy and use the sampling survey method to collect EEG signal data from university students. The main task of this stage is data collection for the research.

Stage 3: Use analytical tools to process the collected data. Based on the preset research hypotheses, transform the issues into abstract data analysis, assess the feasibility of analyzing the emotional states of university students using EEG signals, and analyze the differences and patterns in the data before and after processing.

Stage 4: Based on the survey and research conclusions, and combining the characteristics of university students' psychological and emotional states, propose an EEG signal-based method for the recognition and analysis of emotional states in university students.

3.2.1. Russell's Emotion Model

It is assumed that the emotional state of university students follows Russell's Model of Emotion, which can quantitatively describe emotional states based on this model. Russell's Model divides emotions into two dimensions: Valence and Arousal. Valence is categorized into pleasant and

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unpleasant, while Arousal is categorized into low and high intensity. This results in four quadrants of emotional types, as shown in Figure 2.

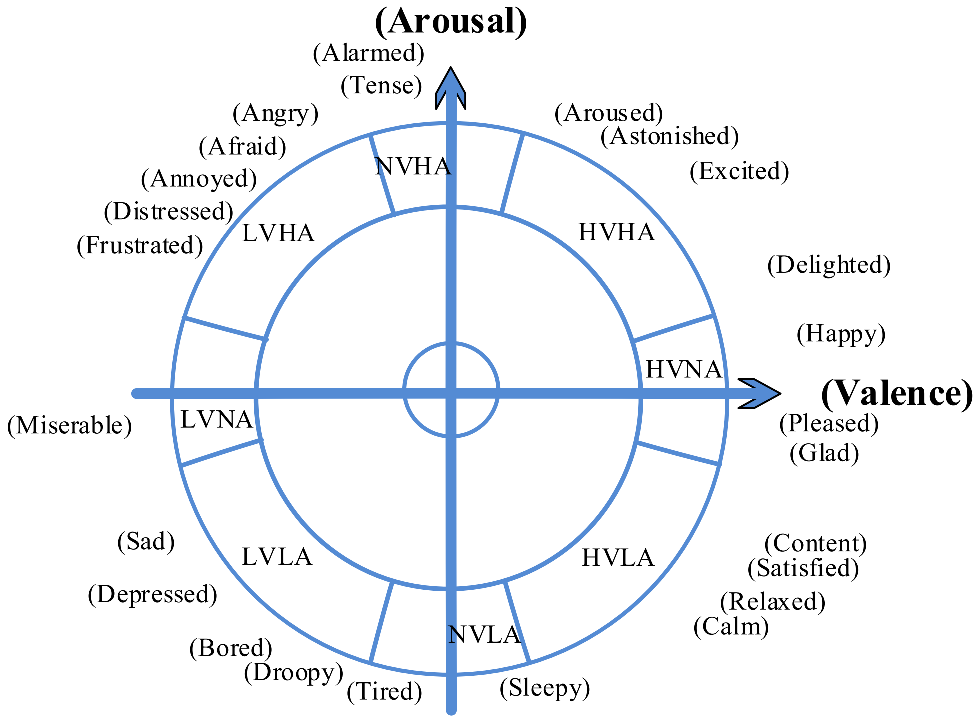

Figure 2: Russell's Valence-Arousal Model of Emotion

3.2.2. Self-Assessment Manikin Model

The SAM (Self-Assessment Manikin) model uses two dimensions: Valence and Arousal, with corresponding discrete values ranging from 1 to 9. These values can be used as recognition labels in emotion recognition and analysis tasks, as shown in the Figure 3. Two different binary classification problems are proposed for emotion recognition: low/high valence (LV/HV) recognition and low/high arousal (LA/HA) recognition. In the experiment, the SAM model uses the emotional subject's ratings (from 1 to 9) as basic data, with a threshold of 5 applied to classify the self-assessment results into LV/HV and LA/HA categories.

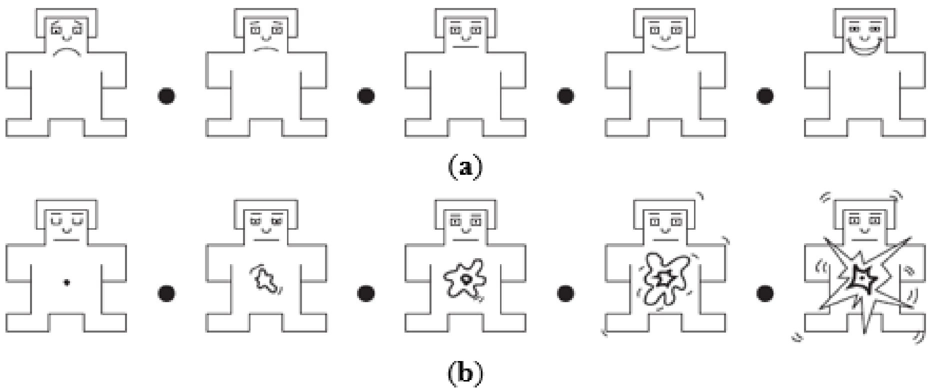

Figure 3: Self-Assessment Manikin Model

3.2.3. Feature Extraction Methods

Various power spectral features and electrode combination features were extracted from the constructed EEG signals in the frequency domain[12], as shown in Figure 4. The extraction of discriminative statistical features is crucial for emotion recognition, as EEG signals exhibit high complexity and non-stationarity. Power Spectral Density (PSD) is one of the most commonly used statistical features in emotion recognition and analysis tasks.

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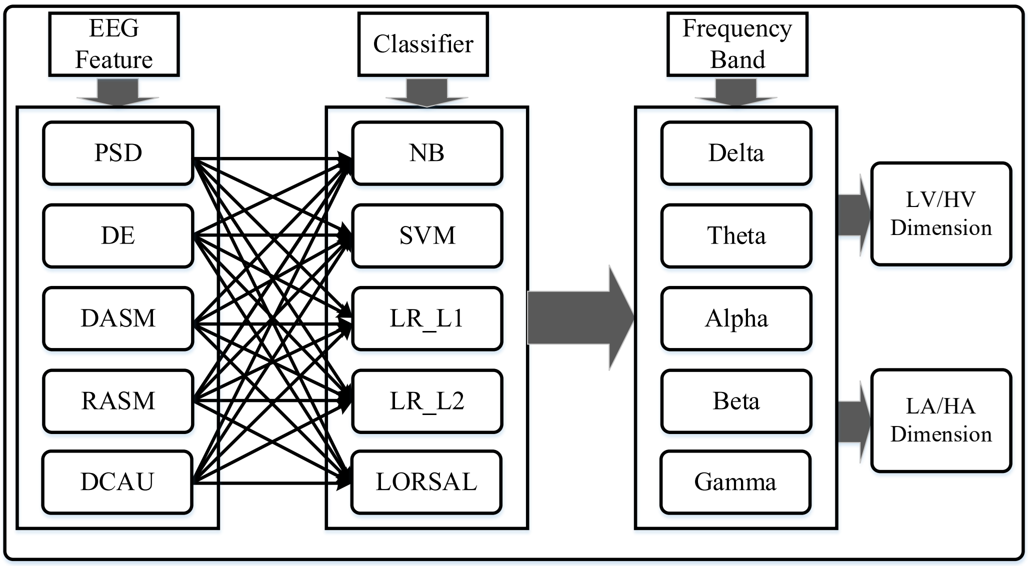

Figure 4: Feature Extraction of Different Frequency Bands

Numerous studies in neuroscience and psychology have identified five frequency bands closely related to psychological and emotional activities: Delta (1 Hz–3 Hz), Theta (4 Hz–7 Hz), Alpha (8 Hz–13 Hz), Beta (14 Hz–30 Hz), and Gamma (31 Hz–50 Hz).

In this study, the differential entropy (DE) of EEG signals was used:

$$h(X) = -\int_X f(x)\log(f(x))dx \tag{1}$$

When the random variable X follows a Gaussian distribution N(μ， σ ²), the Differential Entropy (DE) can be simply expressed as:

$$h(X) = -\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\frac{(x-\mu)^2}{2\sigma^2} \log\frac{1}{\sqrt{2\pi\sigma^2}} \exp\frac{(x-\mu)^2}{2\sigma^2} dx = \frac{1}{2}\log 2\pi e\sigma^2 \tag{2}$$

Where π and e is a constant. The DE can be calculated as the logarithmic spectral energy of a fixed-length EEG record for a given frequency band. Therefore, similar to the PSD feature, DE features are computed for the five frequency bands:

$$DASM = DE(X_{left}) - DE(X_{right}) \tag{3}$$

$$RASM = DE(X_{left}) \big/ DE(X_{right}) \tag{4}$$

$$DCAU = DE(X_{frontal}) - DE(X_{posterior}) \tag{5}$$

According to this method, the dimensions of PSD, DE, DSAM, RASM, and DCAU are 160 (32 channels * 5 frequency bands), 160 (32 channels * 5 frequency bands), 70 (14 electrode pairs * 5 frequency bands), 70 (14 electrode pairs * 5 frequency bands), and 55 (11 electrode pairs * 5 frequency bands), respectively. For simplicity, the features extracted above are directly used as inputs for the recognition methods being compared in this study.

4. Conclusions

In-depth study of the impact of different environmental stimuli on the emotional states of university students has clear relevance and practical significance for how to quickly and systematically carry out mental health education activities for students. Quantitative analysis of university students' emotional states using the Russell Model, scoring emotional subjects with the SAM self-assessment model for emotional state recognition labels, and using feature extraction methods to represent EEG signal frequency bands for effective emotion differentiation. By abstracting emotional state issues into

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mathematical problems using scientific research methods, an effective research plan can be designed. In-depth exploration of the emotional state information contained in EEG signals and its advantages over other biological signals. The use of the LORSAL method can effectively improve the accuracy of emotion recognition while ensuring recognition efficiency.

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References

[1] Arnett J J. Emerging adulthood: What is it, and what is it good for? [J]. Child development perspectives, 2007, 1(2): 68-73.
[2] Schutz P A, Pekrun R E. Emotion in education[M]. Elsevier Academic Press, 2007.
[3] Cacioppo J T, Gardner W L. Emotion[J]. Annual review of psychology, 1999, 50(1): 191-214.
[4] Kołakowska A, Landowska A, Szwoch M, et al. Emotion recognition and its applications[J]. Human-computer systems interaction: Backgrounds and applications 3, 2014: 51-62.
[5] Agrafioti F, Hatzinakos D, Anderson A K. ECG pattern analysis for emotion detection[J]. IEEE Transactions on affective computing, 2011, 3(1): 102-115.
[6] Russell J A. Emotion, core affect, and psychological construction[J]. Cognition and emotion, 2009, 23(7): 1259-1283.
[7] Garcia-Molina G, Tsoneva T, Nijholt A. Emotional brain–computer interfaces[J]. International journal of autonomous and adaptive communications systems, 2013, 6(1): 9-25.
[8] Suhaimi N S, Mountstephens J, Teo J. EEG-based emotion recognition: a state-of-the-art review of current trends and opportunities[J]. Computational intelligence and neuroscience, 2020, 2020(1): 8875426.
[9] Jafari M, Shoeibi A, Khodatars M, et al. Emotion recognition in EEG signals using deep learning methods: A review[J]. Computers in Biology and Medicine, 2023: 107450.
[10] Hosmer Jr D W, Lemeshow S, Sturdivant R X. Applied logistic regression[M]. John Wiley & Sons, 2013.
[11] Bioucas-Dias J, Figueiredo M. Logistic regression via variable splitting and augmented Lagrangian tools[J]. Instituto Superior Técnico, TULisbon, Tech. Rep, 2009.
[12] Pan C, Shi C, Mu H, et al. EEG-based emotion recognition using logistic regression with Gaussian kernel and Laplacian prior and investigation of critical frequency bands[J]. Applied sciences, 2020, 10(5): 1619.