Emotional Computing and Emotional Measurement Methods Based on Intelligent Algorithms of Wireless Network Communication

Abstract: Emotion has always been a complex psychological and physiological phenomenon of people. In order to solve the problem of emotional calculation and emotional measurement methods, it will make people's research and understanding of emotion more meaningful in the future. This article aims to study the research of emotional computing and emotional measurement methods based on intelligent algorithms for wireless network communication. This paper proposes a modelling algorithm of physiological signal emotion based on random forest and LDA. After extracting the general features and proprietary features of the signal, the random forest algorithm is used to calculate the importance of these features under different labels, and the effective features are selected from all the features according to the order of importance. This article also realizes the process of establishing a complete emotional material database and physiological emotional database. Through multiple steps such as signal screening, material selection, emotion annotation and physiological data collection, the problem of missing physiological emotion database is solved. Experimental data shows that compared with other low-level feature classification, the recognition rate of the fusion method in this paper is 57.37% higher than other algorithms, the recognition rate of other behaviors is increased by 4.35%.

Keywords: Wireless Network, D2D, Emotional Computing, Feature Extraction

1.Introduction

At present, researchers at home and abroad have done a lot of research on human-computer interaction, among which the recognition of human behavior and posture and emotional computing are one of the research hotspots. Human behavior gesture recognition and emotion recognition show potential economic and social value in many fields such as intelligent monitoring, medical and health, so they are widely used in these fields. Emotion recognition is one of the most basic and important research contents in the field of emotional computing. In recent years, researchers have conducted extensive research on various modal information that can express emotions. Studies have found that changes in human emotions can cause changes in expression, behavior, psychology and physiology.

Emotion is a complex psychological and physical phenomenon of human beings. Emotion has penetrated into all aspects of human existence and life. The importance of emotion is self-evident. However, people's understanding of emotion is a long and tortuous process. The study of emotions has continued from ancient times to modern times. The process of cognition of emotion has gone through a process from denial to affirmation, and then to paying attention to it.

At present, there are many methods for affective calculation and affective measurement. The following people have their own views on affective calculation. Ren F proposed that emotional computing research has used advanced emotion recognition systems for facial expressions, voices, gait, and physiological signals, but these methods are usually impractical. He integrated mouse cursor movement analysis into emotional computing, and studied the idea that the movement of the computer cursor can provide information about the emotions of computer users. In the selection task, 16-26 trajectory features were extracted, and the relationship between emotion and cursor movement was examined. Participants were induced to have positive or negative emotions through music, movie clips or emotional pictures, and expressed emotions through questionnaires. Finally, it shows that cursor movement patterns such as the area under the curve and changes in direction help infer the emotions of computer users. Although he found that positive or negative emotions can be induced by induction, this induction is an acquired behavior, and it has not been induced by innate behavior [1]. Zhou Q analyzed the influencing factors and transformation of emotional state based on emotional psychology theory. After that, by establishing the mapping relationship between characters, emotions and actions, a multi-layer emotional decision-making model was proposed. This model reflects the changes in emotion and emotional space based on different characters. Experiments show that human emotional characteristics conform to theories and laws, and provide a reference for human-computer interaction system modeling. Although he puts forward a reference for the analysis of emotional state for human-computer interaction, the emotional characteristics of people are different and will vary from person to person, and it is not necessarily applicable to all kinds of machines [2]. Xin proposed an unsupervised framework to reduce reliance on human supervision. The proposed framework uses two stacked convolutional autoencoders to learn latent representations from wearable ECG and galvanic skin activity signals. These representations are used for binary arousal classification in the random forest model. This method reduces manual supervision and can aggregate data sets to achieve higher versatility. In order to verify the framework, the results of the proposed method are compared with methods using convolutional neural networks and using manual feature extraction. The method for fusing the two modes has also been studied. The results show that the stacked convolutional autoencoder has a wide range of applicability, and can be used in emotional computing together with machine learning. Although the unsupervised framework he proposed can be used for emotional computing, this framework is too monotonous and cannot meet today's market requirements [3].

The innovations of this paper are: (1) Realization of a physiological signal emotion modeling algorithm based on random forest plus LDA. After extracting the general features and proprietary features of the signal, the random forest algorithm is used to calculate the importance of these features under different labels, and the effective features are selected from all the features according to the order of importance. (2) Propose the research on the method of emotion calculation and emotion measurement based on the intelligent algorithm of wireless network communication. Use a multi-mode deep belief network to fuse the different features of the two modalities of physiological and video signals separately to obtain the fusion features of each mode, and then use the dual-mode deep belief network to finalize the fusion features of each mode. Fusion, get the features after high-level fusion, and use SVM for classification and recognition. (3) The process of establishing a complete emotional material database and physiological emotional database is realized. Through multiple steps such as signal screening, material selection, emotion annotation and physiological data collection, the problem of missing physiological emotion database is solved.

2. Methods of Sentiment Calculation and Sentiment Measurement Methods Based on Intelligent Algorithms of Wireless Network Communication

2.1 Data Collection of Physiological Signals in Emotional Computing

The key to the data basis of emotion recognition calculation through human physiological signals is to be able to collect the physiological signals corresponding to specific emotions [4]. In the laboratory, the key to the collection of the subjects' effective physiological signals is the method of inducing the subjects' emotions [5]. Therefore, before the physiological signal data collection, the subject's target emotion must be induced first. There are mainly two existing emotion induction methods: the first is to induce emotion by presenting emotion inducing materials to the subjects; the second is to induce emotion by setting up an inducing scene. Emotion induction through emotion induction materials has the advantage of the unity of emotion caused by the material, and the universality and standardization of emotion induction materials. The advantage of emotional induction through induced scenarios is that it has a strong sense of reality, and the induced emotions are highly similar to the emotions generated in real life [6].

The use of people's facial expressions as the material for emotion induction is mainly based on the fact that the emotional activities that individuals activate and experience when they feel the emotions of others and experience emotions are similar [7]. Inducing the emotions of the subjects through music materials also has a better effect. First, music has a higher success rate of emotional induction; secondly, unlike text materials, music has certain requirements for the subjects, and the appeal of music to the subjects is basically It crosses the culture and education level; again, music has a high consistency in the emotional stimulation of the subjects. Although music has the above advantages over other emotional materials, there is no widely recognized standardized music stimulus material library. Emotions induced by situation refer to the simulation of real scenes generated by emotions in the laboratory, and the relevant emotional experience of subjects is triggered by the manipulation of the scenes. One of the more commonly used methods in emotional situation induction is to set some scenes experienced by the subjects to cause the subjects' memories or imaginations, thereby causing the subjects' target emotions [8].

The content mentioned in the above part is the emotional induction method. After the subject is caused to produce the corresponding specific emotion through the emotional induction method, the physiological signals in this process need to be effectively collected in time [9]. The following will take the acquisition of EEG signals as an example to briefly explain the methods of acquiring physiological signals. EEG signal is a kind of brain signal obtained by non-invasive monitoring. It records the electrical signal generated by brain activity through multiple electrodes placed on the scalp. EEG signals reflect the sum of postsynaptic potentials produced by thousands of neurons in the brain [10]. Because the EEG signal is measured on the scalp, it cannot monitor the specific location of the EEG signal source, but the time resolution of the EEG signal is very good, usually reaching the millisecond level of recording accuracy. The variation range of the original EEG signal is within a range of tens of millivolts, so signal amplification and signal filtering techniques are generally used in the acquisition of EEG signals [11].

2.2 Affective Computing Model

There are two common types of human emotion classification models, namely basic emotion theory and dimensional emotion theory [12].

The dimensional emotion theory believes that emotion has a multi-dimensional structure. Different emotional dimensions represent a characteristic of emotion. Different emotions can be expressed as points in the emotional dimension space, and each point has specific emotional dimension coordinates. The theory regards different emotions as continuous and gradually changing, and the difference between different emotions can be measured and calculated by the position of specific emotions in space [13].

(1) Basic emotion theory and basic emotion model

Basic emotion theory believes that human emotion is composed of several basic emotions, and these basic emotions are shared by people across races and cultures. Different cultural backgrounds may have different interpretations of basic emotions, and different basic emotions can produce complex emotions after being mixed [14].

Ekman, who proposed the basic emotion theory, believes that basic emotions must have the following characteristics: first, basic emotions must come from human instinct; second, all people can produce the same basic emotions in the same situation; third, everyone has the same basic emotions. The expressions are the same, and everyone expresses the same semantics; fourth, these emotions must have the same expression pattern for everyone. These emotions determine the comparison and evaluation between individual behavior and objective standards; the fourth category is the emotions related to others, which can be divided into love and hate according to positive and negative.

(2) Dimensional Emotion Theory and Dimensional Emotion Model

The dimensional emotion theory believes that emotion has a variable amount in a certain inherent nature, and the different nature of emotion forms different dimensions of emotional description, and the combination of dimensions forms the dimensional emotional space. The dimensional emotion theory does not exclude the existence of basic human emotions. In different dimensional emotion theories, people map basic emotions in the dimensional emotional space. For example, in the two-dimensional emotional space, "happiness" belongs to a high degree of arousal and high positive effect. The emotion of valence, and "sadness" belongs to the emotion of low arousal and high negative valence. So far, researchers have proposed different dimensional emotion theories based on different understandings of emotions.

2.3 Wireless Network D2D Communication Model

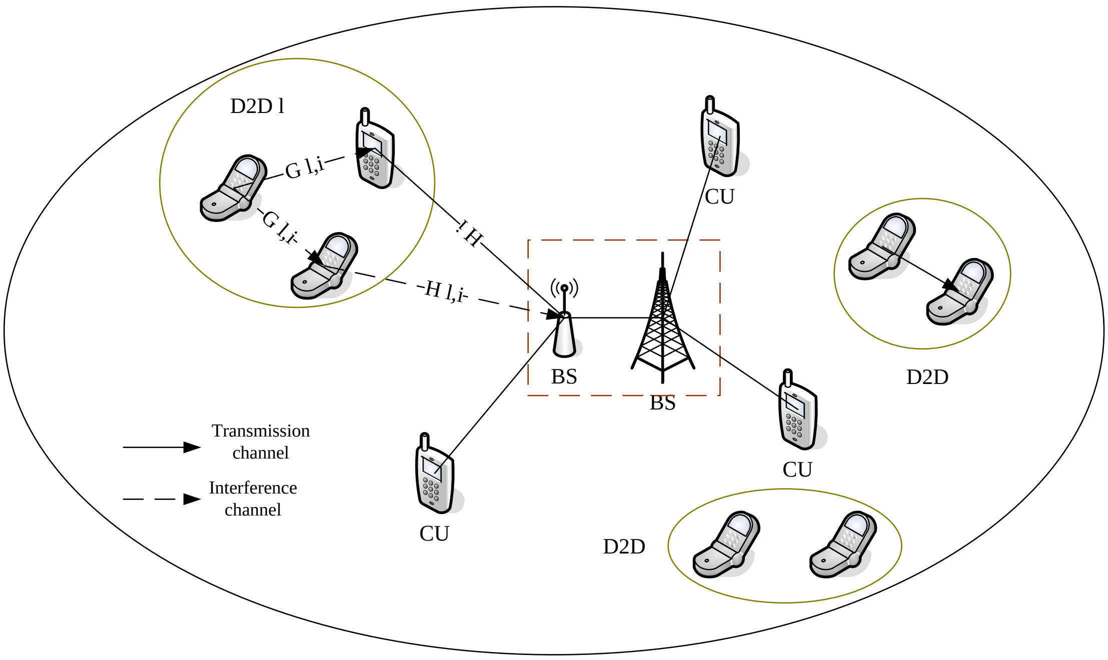

Figure 1: Downlink communication model for deploying D2D heterogeneous network

As shown in Figure 1, there is a single-cell hybrid network downlink communication scenario where D2D users and cell users share downlink resources. The network contains L pairs of D2D users and K cell users. Each pair of D2D users consists of a transmitter and Consists of a receiving end.

Since this chapter mainly studies the energy-efficient resource reuse scheme for D2D users, it is assumed that the resource allocation of cell users is predetermined. That is, there are a total of K downlink resource blocks in the cell, and cell users occupy RBs for data transmission [15].

Based on this, the transmission rate of the first pair of D2D users can be expressed by the following formula:

$$R_l^i = \sum_{l=1}^{K} x_{l,i} \log_2(1+\frac{p_{l.i} g_{l,i}}{1+p_l h_{l,i}^L}) \quad (1)$$

Among them, $p_{l,i}$ and p_l respectively identify the transmit power of the transmitting end of the 1-th pair of D2D users performing data transmission on the 1-th RB and the downlink transmit power used by the base station to communicate with the 1-th cell user. The transmission rate of cell users must meet the following conditions:

$$R_l = \sum_{i=1}^{I} x_{l,i} \log_2(1+\frac{p_l h_l}{1+p_{l.i} g_{l,i}^L}) \geq \mathrm{R}_c \quad (2)$$

The optimization problem of this paper is modeled as follows:

$$\{\max_{x_{l,i}, p_{l,i}, p_l}\}^{\eta_{ee}} = \frac{\sum_{i=1}^{I}\sum_{l=1}^{K} x_{l,i} \log_2(1+\frac{p_l h_l}{1+p_{l.i} g_{l,i}^L})}{\sum_{i=1}^{I}\sum_{l=1}^{K} x_{l,i} p_{l,i} + \sum_{i=1}^{I} 2p_c^i} \quad (3)$$

$$\sum_{i=1}^{I} x_{l,i} \leq 1) \quad (4)$$

$$\sum_{l=1}^{\mathrm{K}} x_{l,i} p_{l,i} \leq P_i^{\max} \quad (5)$$

$$\sum_{\mathrm{i}=1}^{L} \mathrm{p}_l \leq P_{BS}^{\max} \quad (6)$$

Inequality constraints are used to ensure that D2D users do not exceed the maximum transmit power limit $\mathrm{P}_i^{\max}$ when sharing downlink resource blocks with cell users for data transmission.

Assuming that the 1-th D2D user reuses the RB of the 1-th cell user for data transmission l, the following inequality about the base station transmit power can be obtained:

$$p_l \geq \frac{\delta_c(1+p_{l,i} g_{l.i}^I)}{h_i} \quad (7)$$

If you want to get the best state, you should take the minimum that can be obtained. Based on this, the optimization problem can be written in the following equivalent form:

$$\{\max_{x_{l,i},p_{l,i},p_l}\}^{\eta_{ee}} = \frac{\sum_{i=1}^{I}\sum_{l=1}^{K} x_{l,i}\log_2(1+\frac{p_{l,i}d_{l,i}}{1+p_{l.i}g_{l,i}^{L}})}{\sum_{i=1}^{I}\sum_{l=1}^{K} x_{l,i}p_{l,i}+p_c} \quad (8)$$

$$\sum_{i=1}^{I} x_{l,i} \le 1 \quad (9)$$

$$\sum_{l=1}^{K} x_{l,i}p_{l,i} \le P_i^{\max}, \forall l, \quad (10)$$

$$\sum_{l=1}^{K}\sum_{i=1}^{L} x_{l,i}\frac{\delta_c}{h_l}p_{l,i}g_{l,i}^{L} \le P_{BS}^{\max} - \sum_{l=1}^{K}\frac{\delta_c}{h_i} \quad (11)$$

In order to obtain the optimal parameter value, then the optimization objective function can be written as:

$$\eta_{ee}^{*} = \{\max_{x_{l,i},p_{l,i},p_l}\}\frac{B_{D2D}(x_{l,i}^{*},p_{l,i}^{*})}{P_{D2D}(x_{l,i}^{*},p_{l,i}^{*})} \quad (12)$$

Based on the theory of nonlinear fractional programming, it can be equivalently transformed into:

$$T(x_{l,i},p_{l,i}) = \{\max_{x_{l,i},p_{l,i},p_l}\}B_{D2D}(x_{l,i}^{*},p_{l,i}^{*}) - \eta_{ee}^{*}P_{D2D}(x_{l,i}^{*},p_{l,i}^{*}) \quad (13)$$

In order to facilitate the observation of its unevenness, it is redefined as:

$$B_{D2D} = \sum_{i=1}^{I}\sum_{l=1}^{K} x_{l,i}\log_2(1+\omega(p_{l,i})) \quad (14)$$

Next, find the second derivative of the function $\omega(p_{l,i})$ with respect to it:

$$\omega^{''}(p_{l.i}) = -\frac{2p_{l.i}d_{l.i}f_{l.i}}{(e_{l.i}+f_{l.i}p_{l.i})^3} \le 0 \quad (15)$$

Since the logarithmic function is also an increasing concave function, according to the judgment of the convexity and convexity of the compound function in convex optimization, it can be inferred that the function is convex.

2.4 Evaluation Method of Sentiment Measurement

After stimulating the subjects through emotion-inducing materials and inducing corresponding emotions, the effectiveness and reliability of emotion-inducing must also be ensured [16]. The effect of emotion induction is affected by multiple factors, such as the individual differences of the subjects, the order of the experimental materials, the experimental environment, etc. Therefore, after collecting the physiological data of the subjects, the validity of the experiment needs to be verified [17].

The evaluation methods for the effect of emotion induction include the subject's self-evaluation report, the emotional scale test and the interview records of the subjects. At the same time, the evaluation of the effect of emotion induction should be carried out immediately after the end of the emotion induction experiment, so as to ensure the timeliness of the evaluation [18].

In terms of effect evaluation through the affective scale, the more commonly used affective scales include: self-report evaluation, PAD scale, SAM scale and so on. The self-evaluation report is mainly for the subjects themselves to evaluate the degree of several basic emotions listed in the report. The measurement of each basic emotion is divided into 5 levels, or more detailed is divided into 9 levels [19]. For example, for the emotion of joy, if there are 5 levels, the emotion without joy is defined as 1, the mild joy is defined as 2, the moderate joy is defined as 3, the more intense joy is defined as 4, and the very strong Joy is defined as 5, then the degree of joy that the subjects feel about themselves during the self-report assessment needs to choose a value from 1-5 to describe their emotional state. The advantage of self-report evaluation is that, the disadvantage is that some mixed emotions cannot be described by this method [20].

In view of the complexity of emotions, the methods and methods tend to be diversified when evaluating the effects of emotion-induced materials, so there is no unified standard for the evaluation of the inducing effects [21].

2.5 Physiological Signal Feature Extraction and Expression Methods

EEG signal is a kind of complex physiological electrical signal. For emotion classification and recognition through EEG signal, it is first necessary to extract and describe the relevant features of EEG signal [22]. Previous research on the feature extraction of EEG signals mainly focused on the time domain and frequency domain. There are not many studies on the spatial characteristics of EEG signals. The feature extraction and expression methods of EEG signals are generally studied in the time domain or frequency domain. As for the spatial characteristics of EEG signals, the previous research basically did not have more research besides comparing the asymmetry of EEG feature values extracted by symmetric electrodes. At the same time, traditional research believes that the EEG signal contains less spatial information, and the EEG signal is weak in spatial display [23]. The method proposed in this paper is mainly to map the frequency domain characteristics of EEG signals to a two-dimensional plane through the international 10-20 system to form EEG feature frames, and then generate a series of sequential feature frame sequences according to different time windows. These feature frame sequences are used to extract the corresponding features of the picture through the convolutional neural network, and the extracted picture features are sent to the recurrent neural network for emotion recognition analysis.

In previous experimental studies, most of the physiological signal data collected multi-modal physiological signals. For example, in several well-known open source data sets (such as DEAP, etc.), the collection experiments involved collected the subjects' brain electrical signals, ocular electrical signals, electromyographic signals, and skin conductance signals, etc. [24]. Therefore, in the subsequent physiological signal analysis process, a wide variety of feature vectors are often generated after feature extraction, and the dimensionality of feature vectors is huge. How to perform information fusion and information compression on the feature information of multimodal physiological signals is directly related to the accuracy of subsequent emotion classification and recognition and the execution efficiency of the classification method. This paper proposes a method of using a stacked self-encoding neural network to losslessly compress the eigenvalues of multi-modal physiological signals, and then send the fused and compressed physiological eigenvalues to the recurrent network for emotional state recognition. The results show that the Stacked self-encoding neural network fusion and compressed multi-modal fusion feature values have achieved good classification results in sentiment classification and recognition [25].

3. Experiments on Emotional Computing and Emotional Measurement Methods Based on Intelligent Algorithms Based on Wireless Network Communication

3.1 Subjects

The test is carried out in a relatively quiet room. The light in the room is appropriately reduced to facilitate the subjects to watch the material. At the same time, the temperature is adjusted to the standard room temperature. The test time period is fixed between 6 pm and 10 pm to ensure the outside world The influence caused by the factor is within an acceptable range. The preparation stage of the experiment is mainly aimed at the inspection of the material data playback material and the debugging of the equipment to ensure that no special failures occur. Before the experiment, give the participants an explanation of the experiment process and some precautions to prevent the participants from fluctuating mood due to sudden playback and other reasons, and also give the participants enough time to calm down before the experiment.

3.2 Experimental Data Set

Table 1: Experimental data set

Behavior category	Behavior label	Training set data volume	Test set data volume
walk	1	18000	2400
Fall down	2	156	2400
Run	3	18000	2400
still	4	18000	2400
Go upstairs	5	18000	2400
Go downstairs	6	18000	2400

As shown in Table 1, it is a sample record of 6 behaviors. This stage has officially entered the measurement of physiological signals. After sorting out the materials, synchronously collecting the emotional physiological signals generated by the participants' resonance with the contents of the materials, the key is the way of preparing the emotional inducing materials.

3.3 Experimental Procedure

(1) The basic signal acquisition time of 2 minutes. This part does not play the material but only records the basic physiological signals of the subjects, and is used to eliminate the influence of personal differences in the subsequent;

(2) Start playing the evoked material. There are four types of materials. The duration of each type of material is 1 minute and 4 minutes in total. At the same time, after each type of material is played,

there will be a 1-minute rest time to relieve the physiological signal of the previous material. The impact. The playing sequence of the material is: high price and low arousal degree, high price and high arousal degree, low price and low arousal degree, and low price and low arousal degree.

(3) At the end of the experiment, the equipment was dismantled and the subjects were asked whether there were any test problems during the experiment, such as whether the material was successfully played, and whether there was strong external interference during the play that caused the diversion of attention.

After the experiment officially started, the operator of the experiment should not interfere with the subjects in any form before the end. During the experiment, the state of the subjects should be continuously monitored. If problems are found, the experiment should be stopped in time.

4. Sentiment Calculation and Sentiment Measurement Methods Based on Intelligent Algorithms of Wireless Network Communication

4.1 Comparative Analysis of the Performance of Wireless Network Communication Algorithms

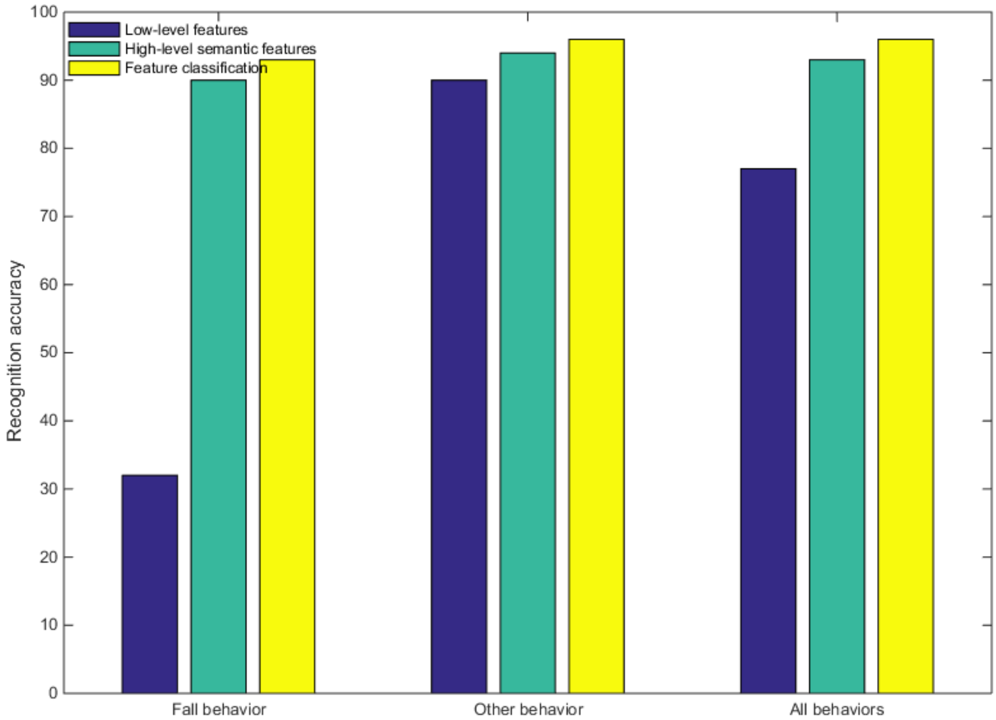

Figure 2: Comparison of the recognition performance of the three methods

As shown in Figure 2, it is the overall performance comparison of the three recognition methods, in which the behavior of falling, other behaviors and all behaviors are in contrast. Compared with other low-level feature classifications, when the fall behavior sample data is 10, the recognition rate of the fusion method in this paper is 57.37% higher than other algorithms, the recognition rate of other behaviors is increased by 4.35%, and the average recognition rate of the 6 behaviors is improved. That’s 17.4%. It shows that the recognition performance of the classification method in this paper is improved for both low-level feature classification and high-level semantic feature classification, which verifies the effectiveness of the feature fusion method.

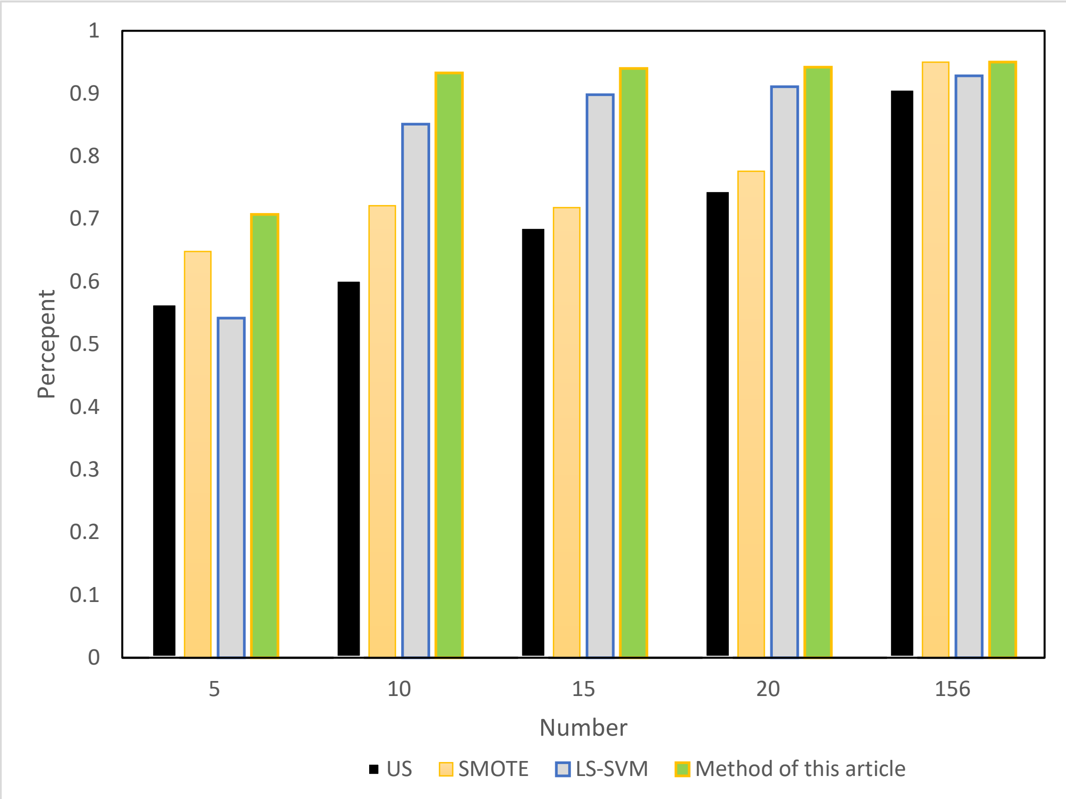

Figure 3: Comparison of average recognition rates of methods

As shown in Figure 3, it can be seen that when the number of collected behavior samples changes, the average recognition rate of the method used in this article is significantly improved compared to other methods. The average recognition rate of this method is compared with other methods. The algorithm has improved by 33.05%, 21.2% and 8.21% respectively.

4.2 Emotion Signal Analysis

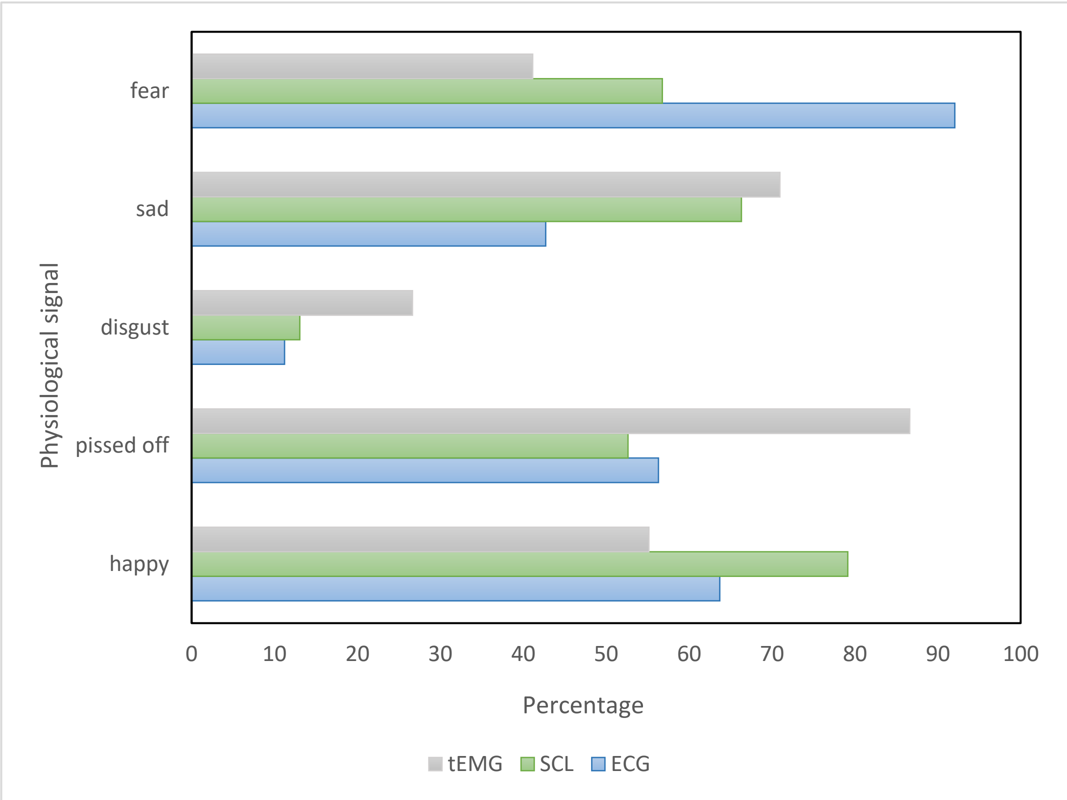

Figure 4: Classification and recognition rate of three physiological signals

As shown in Figure 4, in order to observe the performance capabilities of the three signals for each emotion, the initial features extracted by the three signals are classified using SVM respectively, and the classification accuracy of the three physiological signals for each emotion is obtained. It can be seen that the different signals The degree of response to different emotions is different, and the recognition effect of the emotion of disgust is poor.

Table 2: Inception-ResNet-v2 network output feature recognition rate of each layer

Features of each layer output	Recognition rate(%)
Convolution layer features	60.62
AvgPool layer features	58.43
Dropout layer features	43.91
Fully Connected layer features	69.74

As shown in Table 2, in the deep feature extraction part of the single-mode video signal, in order to be able to select better output features in the Inception-ResNet-v2 network, this paper classifies the output features of each layer and compares the recognition performance of each layer. As shown in Table 2, it can be seen that the output feature recognition effect of the fully connected layer is the highest, which shows that compared to other layer features, the fully connected layer has a higher ability to express emotions.

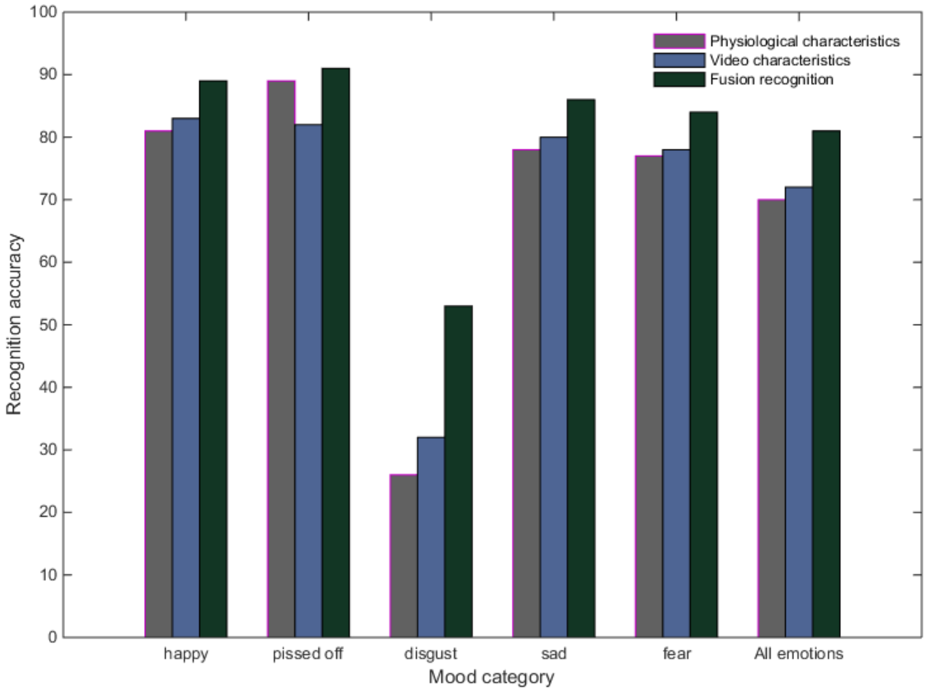

Figure 5: The accuracy of emotion recognition by different signal characteristics

As shown in Figure 5, it is the classification result after fusion of physiological features and video features. From this, the features extracted by the model proposed in this paper can effectively perform emotion recognition, and the average recognition rate is 80.89%. It can be seen from the classification performance of physiological signals and video signals that both have their own advantages and disadvantages.

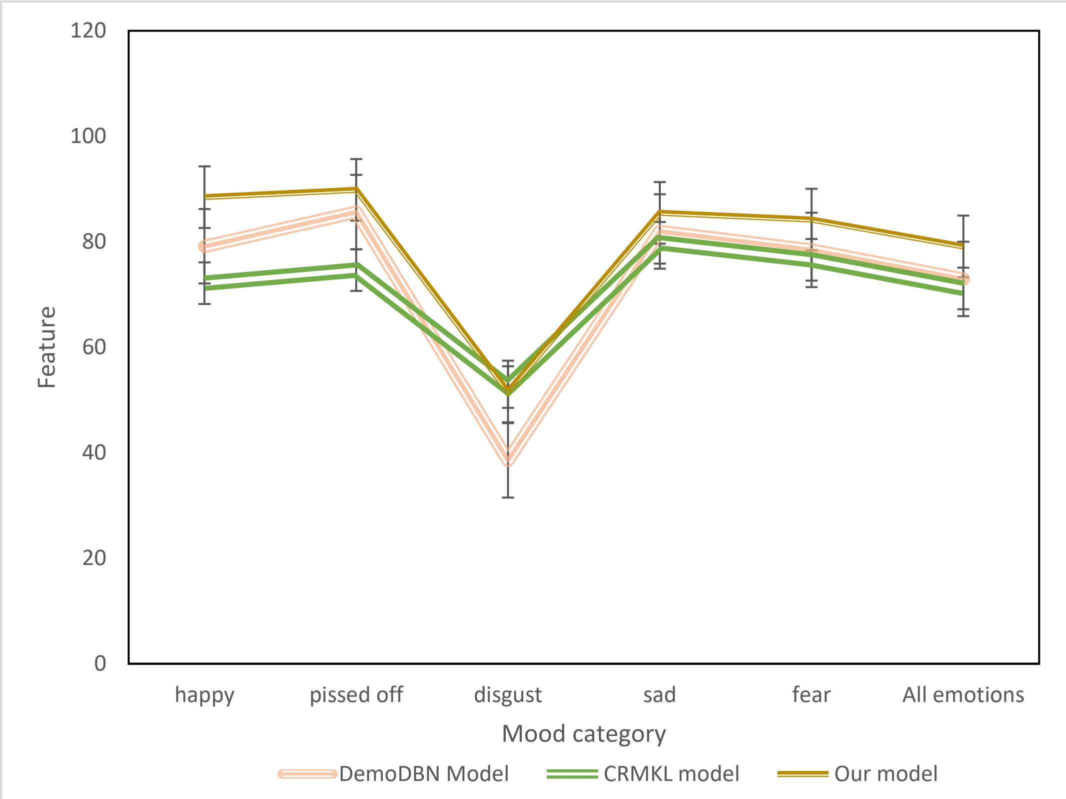

Figure 6: Classification results of different models

As shown in Figure 6, in order to verify the effectiveness of the method in this paper, the two method models are classified and identified under the Bio Vid Emo DB data set. Compared with other methods, the multi-modal fusion features obtained by fusing each modal feature separately have a better performance in emotion recognition, which shows that the classification of each emotion is reduced while the cost of multi-modal feature selection is reduced. Performance has also been improved.

4.3 Sentiment Calculation Analysis

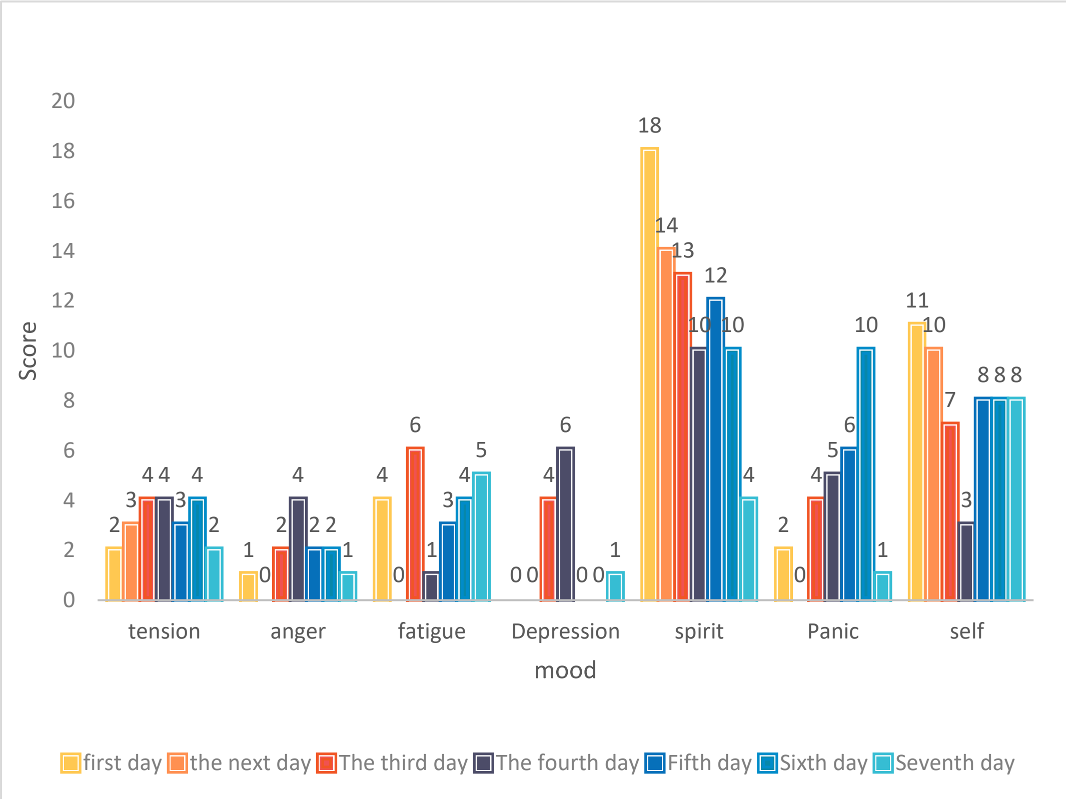

Figure 7: Statistical histogram of the POMS scale of subjects in 7 days

As shown in Figure 7, the data that needs to be processed is the POMS scale data collected by the subjects during the experiment. According to the calculation method of the POMS component in the basic principle, the value of the mental component of each subject can be calculated. Its POMS statistics are shown in Figure 7 in the form of a histogram. It can be seen that the proportion of positive emotions of the subjects is a little stronger than negative emotions. At the same time, emotions fluctuate over time in 7 days, which indicates whether the mental "energy" component is obtained during the week. The score is relatively high, and the "depression" component has no corresponding feeling in three days of the seven-day test.

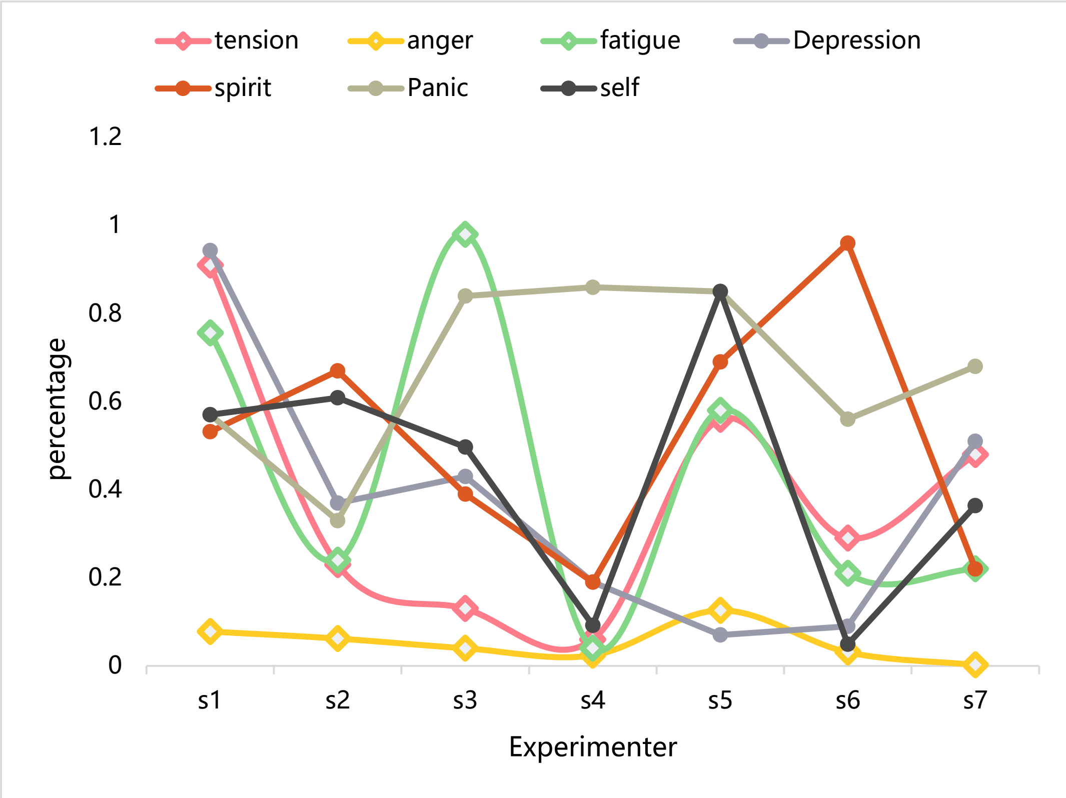

Figure 8: IMF1 Volatility Index Characteristics and POMS Scale Significantly Correlated Indicators

As shown in Figure 8, in order to more intuitively show the relationship between the IMF1 features of the EEG signal and the POMS component, the abscissa in the figure is the number of the 7 subjects, and the ordinate is the bilateral significance index in the correlation analysis result., Different series represent different POMS components. From the figure, it can be seen that the correlation between the EEG characteristics of the 7 subjects and the anger component is more significant, and the correlation between the EEG characteristics of the 4th subject and the 6th subject is more significant.

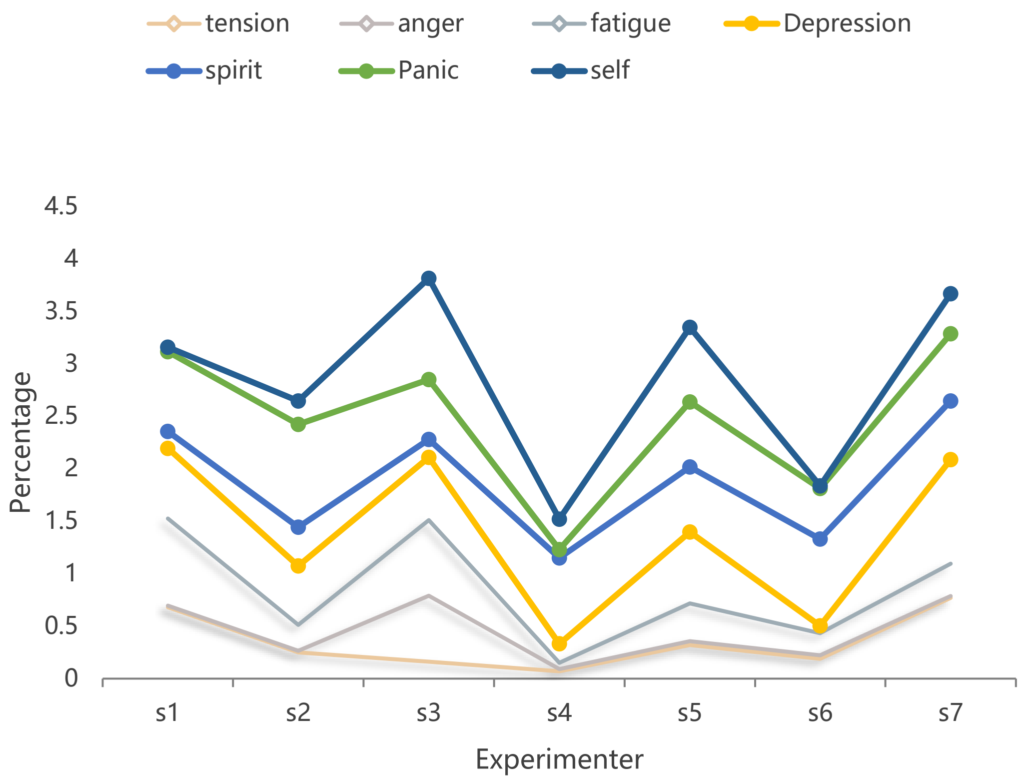

Figure 9: IMF2 Volatility Index Characteristics and POMS Scale Significantly Correlated Indicators

As shown in Figure 9, it is a significant indicator display of the correlation analysis between the IMF2 component features of the EEG signal and the POMS scale component. It can be seen from the figure that the IMF2 component characteristics of the 7 subjects' EEG signals still have a significant relationship with the anger component, while the correlation between the EEG characteristics of the 4th subject and the 6th subject and the self component is more significant.

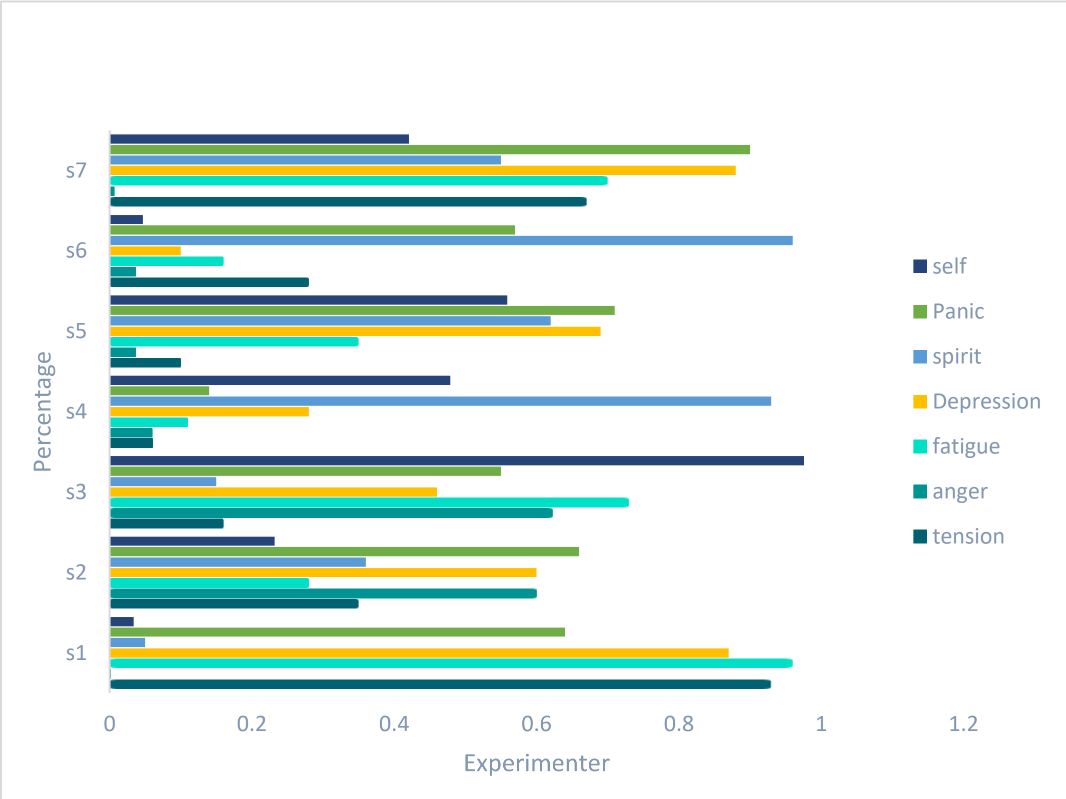

Figure 10: IMF3 Volatility Index Characteristics and POMS Scale Significantly Correlated Indicators

As shown in Figure 10, it is a significant indicator display of the correlation analysis between the IMF3 component features of the EEG signal and the POMS scale component. It can be seen from the figure that the relationship between the IMF3 component characteristics of the 7 subjects' EEG signal and the anger component is more significant, the correlation between the energy component of the No. 1 subject and the self component of the No. 6 subject and the EEG IMF3 is more significant.

5. Conclusion

With the rapid development of artificial intelligence technology, people's lives are becoming more and more intelligent, mainly in human health monitoring, behavior recognition, intelligent monitoring robots, natural language processing, emotion detection, computer vision and many other fields. At present, the functions of mobile smart devices are constantly being improved and developed. These devices can not only be carried around without affecting the movement and beauty, but also can directly obtain body-related sensor information, and perform daily behavior recognition on these sensor information, especially fall detection. It can play a preventive role in the health and safety of the elderly. Although the method in this paper improves the accuracy of human behavior recognition and emotion recognition to a certain extent, it still has some shortcomings. Based on the research work of this article, it can also be supplemented and extended in the following aspects: (1) This article is carried out. Although the data of human behavior recognition is collected by people of different age groups, the number of collectors of different age groups is not balanced, and the data of the elderly are insufficient. In future research, we should balance the number of collectors of different ages, increase the number of collectors as much as possible, and obtain more reasonable data sets. (2) The attribute learning added in human behavior recognition is still in the research stage. Further exploration of attribute learning and classification methods, and enhancing the semantic complement of attributes to categories are the focus of future research. In this paper, binary attributes are used for attribute representation, but the relative attributes are developing rapidly at present. Although relative attributes do not have semantic meanings, the subsequent comparative research on the behavioral representations of binary attributes and relative attributes still has practical application significance.

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