

Retraction

Retracted: Multimodal Emotion Recognition Algorithm for Artificial Intelligence Information System

Wireless Communications and Mobile Computing

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Wireless Communications and Mobile Computing has retracted the article titled “Multimodal Emotion Recognition Algorithm for Artificial Intelligence Information System” [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process and the article is being retracted with the agreement of the Chief Editor.

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Research Article

Multimodal Emotion Recognition Algorithm for Artificial Intelligence Information System

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Emotional expression is an essential and important link in human social activities and daily communication activities. Emotion recognition is a technology that uses computer technology to recognize the emotion of recognized objects. When emotion recognition technology was born, the research on human emotion recognition mainly focused on single-modal emotion recognition. Single-modal emotion recognition has been the most commonly used emotion recognition method. However, in recent years, with the continuous development of science and technology and the continuous improvement of people's awareness of the defects of single-modal emotion recognition, the research on multimodal emotion recognition is increasingly emerging. This paper is aimed at analyzing and studying the multimodal emotion recognition algorithm in artificial intelligence information system. Based on this research topic, this paper designs a single-modal and multimodal emotion recognition comparison simulation experiment for the four emotional characteristics of happiness, sadness, shock, and anger extracted from artificial intelligence information systems. The experiment concluded that the comprehensive emotion recognition accuracy rate of the multimodal emotion recognition algorithm in the artificial intelligence information system reached 93%. Compared with single-mode emotion recognition, the comprehensive recognition accuracy is improved by 7%.

1. Introduction

In people's interpersonal communication and daily life, the expression of emotion is of self-evident importance. People can convey a lot of information that is beneficial to interpersonal communication through emotional expression [1]. For example, people can judge the emotional state of the other party by analyzing the changes in the conversation object's words, facial expressions, and body language. They thus make adjustments at any time and respond accordingly to make the conversation and relationship more enjoyable for both parties. Therefore, emotion recognition has high social significance. Emotion recognition refers to the appropriate analysis and processing of emotional signals collected by sensors through a computer, thereby judging the current emotional state of the emotion recognition object. At present, the most common emotion recognition is single-mode

emotion recognition. From the perspective of three characteristic expressions of emotional information, language, facial expression, and body posture, because body posture includes different changes in body language and posture, and its change rules are generally difficult to follow [2, 3]. Therefore, single-modal emotion recognition has some shortcomings. In order to improve the overall recognition performance of emotion recognition and solve the shortcomings of single-mode emotion recognition methods for human emotion recognition, multimodal emotion recognition algorithms have high emotion recognition value. Multimodal emotion recognition refers to an emotion recognition method with strong inclusiveness and better recognition effect formed by fusing a variety of different emotional features. Multimodal emotion recognition has a great positive effect in the practical application of emotion recognition. With the development of artificial intelligence, multimodal

emotion recognition has also begun to be applied in artificial intelligence information systems. This paper mainly analyzes and studies the multimodal emotion recognition algorithm in artificial intelligence information system.

The innovation of this paper are as follows: (1) It analyzes and researches the application of multimodal emotion recognition algorithm in artificial intelligence information system, which is still less researched at present. (2) It conducts a comparative simulation experiment of single-mode and multimode emotion recognition of emotional features in artificial intelligence information systems. It judges the effectiveness of the multimodal emotion recognition algorithm and draws valid conclusions.

2. Related Work

Research on emotion recognition in academia has always been more and never stopped. Among them, Jenke et al. study emotion recognition in human-computer interaction. He combined neuroscience and EEG emotion recognition to explore the emotion feature extraction method of emotion recognition in human-computer interaction [4]. Xu et al. studied emotion recognition in emotion videos. They proposed a new technique to facilitate emotional expression in emotional videos by transferring emotional information from heterogeneous external sources including image and text data [5]. Menezes et al. mainly study emotion recognition in virtual environments. He uses the EEG as an emotional signal sensor and targets the emotional features extracted from the EEG signal. Based on Russell's Circumplex model, he modeled and analyzed emotional states in virtual environments [6]. Zheng's research proposed a new group-sparse canonical correlation analysis method for simultaneous EEG channel selection and emotion recognition [7]. Albornoz and Milone's research focuses on language emotion recognition. He developed a novel ensemble classifier to handle multiple languages. He combined the concept of emotional universality to map and predict emotional expressions in never-before-seen languages [8]. Zhu et al. studied the importance of intelligent service applications such as intelligent medical care and intelligent entertainment based on speech emotion recognition. He discussed how to improve the accuracy of speech emotion recognition from the aspects of speech signal feature extraction and emotion classification methods [9]. Although the above researches are all related to emotion recognition, they are not practical enough for the research of multimodal emotion recognition algorithms in artificial intelligence information systems, and the research process is also complicated and difficult to operate.

3. Artificial Intelligence Information System and Multimodal Emotion Recognition Algorithm

3.1. Artificial Intelligence Information System. First of all, artificial intelligence technology is a technology that uses computer means to realize human-like intelligence. That is to say, artificial intelligence technology is a technology that

simulates human intelligence [10–13]. Artificial intelligence technology is highly comprehensive, integrating the development and contributions of psychology, mathematics, philosophy, and other disciplines and has powerful technical functions. Since the birth of artificial intelligence technology, its research and application fields have become more and more extensive. The main application fields of artificial intelligence technology are industry, service industry, medical industry, and financial industry. Its main technical fields include pattern recognition, automatic programming, natural language processing, intelligent decision-making, and intelligent information systems. The artificial intelligence information system is an intelligent information system that is constructed based on artificial intelligence technology and knowledge engineering technology and takes knowledge processing as the main method. The artificial intelligence information system is constructed based on artificial intelligence technology and knowledge engineering technology. It takes knowledge processing as the main method and is an intelligent information system generated on the basis of ordinary information system. Compared with general information systems, artificial intelligence information systems have a more complete hierarchical structure and more powerful functions. For example, artificial intelligence information systems are highly intelligent in terms of information storage and information processing and analysis, which greatly improves the efficiency of information processing [14, 15]. The architecture of artificial intelligence information system is shown in Figure 1.

The main structural levels of the artificial intelligence information system are shown in Table 1.

3.2. Multimodal Emotion Recognition. Multimodal emotion recognition means that emotion recognition can be performed on multiple emotional features at the same time. With the rapid development of science and technology, people and computers have become more and more inseparable, and the ability of human-computer interaction has become more and more important [16]. Emotion recognition is an important aspect of computer intelligence in human-computer interaction. In order to achieve a more harmonious and natural human-computer interaction experience, the computer must have the ability to "perceive." For humans, in the process of communication, emotions are mainly conveyed to the outside world through carriers such as expressions, voices, and gestures. The information conveyed in various ways is inclusive and complementary to each other. If the computer has the ability to "perceive," it must learn to imitate the human interaction with the outside world in the abovementioned ways. Many previous researchers have mainly focused on how to use single-modal information (such as facial expressions, speech, and gestures) to judge the current emotional state. They have proposed many excellent algorithms and achieved good research results. Although the results are ideal, they all have a drawback. Because the emotional transmission is carried out in many ways simultaneously, the emotional result is the result of the joint fusion of many ways. Emotion recognition only through a single vector or pattern has obvious

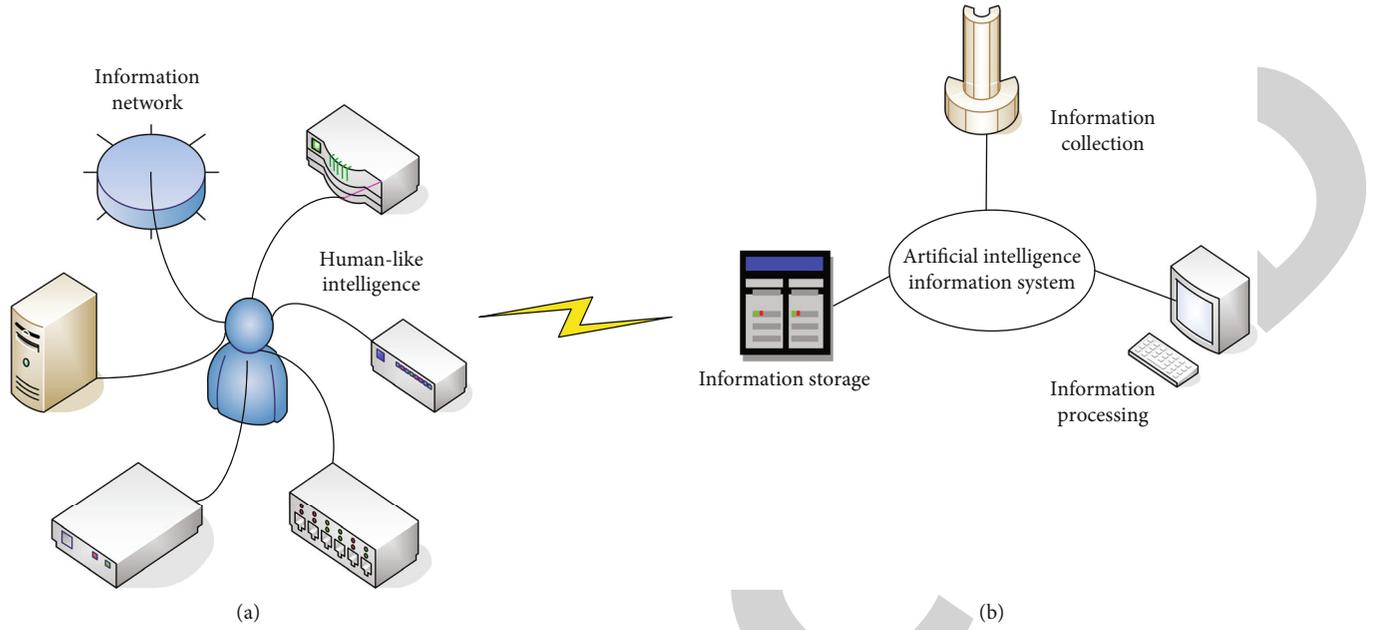


FIGURE 1: AI information system architecture.

TABLE 1: Structure hierarchy of AI information system.

Organizational level	System type	Typical function
Strategic layer	Decision support systems	Trend forecasting and planning
Management	Information management system	Information storage, information processing
Knowledge layer	Knowledge work system	Computer aided design, virtual reality
Operation layer	Information processing system	Computer aided design, virtual reality

limitations. Because the recognition of human emotion is a more complex problem. Research also shows that accurate and reliable emotion recognition results need to simultaneously consider the information of emotional features of multiple patterns. To achieve more perfect emotion recognition, the exploration of multimodal emotion recognition is crucial.

3.3. Several Multimodal Emotion Recognition Algorithm Models

3.3.1. Bayesian Network. Bayesian network, also known as belief network, is a directed acyclic graph labeled with conditional probability based on Bayes' theorem. Its essence is to comprehensively utilize prior knowledge and data sample information. This effectively avoids the subjective bias of prior information and the noise influence of data sample information [17]. It establishes an association constraint relationship between random variables and finally achieves the purpose of facilitating the calculation of conditional probability [18]. The basic structure of the Bayesian network model is shown in Figure 2.

Among them, the feature node $\{A, B, D, E\}$ represents the four features of the sample, and the class node C represents the category of the sample. For all feature nodes, when satis-

fying the conditions independently of each other, the following formula relation exists [19].

$$C(n) = \sum_{i=0}^{N-1} S(i) \frac{\pi n}{i}. \quad (1)$$

According to Bayes' theorem, the joint probability distribution of the above feature node variable set can be obtained as follows:

$$P = P(C) \prod_{i=1}^{\pi} P(x_i|C). \quad (2)$$

In essence, Bayesian network observes variables through feature node variable sets, so as to obtain the posterior probability of class node C . According to Bayes' theorem and its conditional independence [20], the posterior probability of class node C can be obtained as follows:

$$P(C) = \frac{P(C) \prod_{i=1}^n P x_i C}{x_n}. \quad (3)$$

Bayesian network is an easy-to-build classification method, which has high efficiency in dealing with weakly

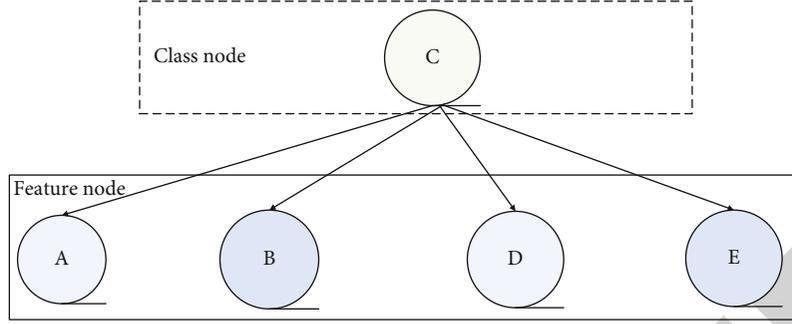


FIGURE 2: Basic structure of Bayesian network.

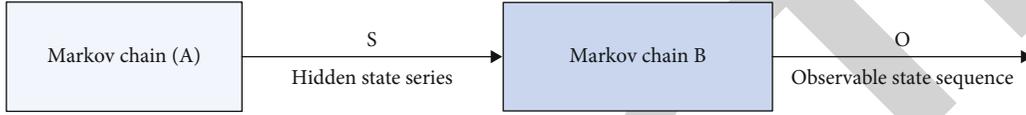


FIGURE 3: Hidden Markov model process.

correlated features. But when the input features are correlated, the assumption of strong independence of Naive Bayesian network is violated, and the classification effect is not good [21].

3.3.2. Hidden Markov Model. Hidden Markov model is used to describe a Markov process with hidden unknown parameters, which is a statistical model. As a directed graph model, it is widely used in fields such as emotion recognition and language processing. A hidden Markov model can be described by a quintuple. It includes 2 state sets and 3 probability matrices, namely, $\gamma = (S, O, \pi, A, B)$. Among them, the elements in the state set S usually cannot be directly observed, and it belongs to the hidden state. The elements in the state set O can be directly observed, because it belongs to the observable state associated with the hidden state, which belongs to the hidden state. The probability matrix represents the initial state probability matrix. The probability matrix A represents the hidden state transition probability matrix. The probability matrix B represents the observed state transition probability matrix [22, 23]. A complete hidden Markov process is shown in Figure 3.

It can be seen from Figure 3 that the hidden Markov model includes two parts: Markov chain and random process. It is determined by the initial probability distribution, the state transition probability distribution, and the observation probability distribution. According to the state sequence, a Markov chain can obtain the joint probability distribution of all variables as [24]:

$$P(S, O) = P(S_1)P(O_1, S_1) \prod_{i=2}^r P(S_i, O_i, S_{i-1}). \quad (4)$$

Among them, $P(S_1)P(O_1, S_1)$ is the initial condition, $P(S_i)$ is the transition condition, and $P(O_i)$ is the observation condition. This lets $F = \{f_1, f_2, \dots, f_n\}$ be the set of all possible states, and $K = (k_1, k_2, \dots, k_n)$ is the set of all possible observa-

tions. Among them, N is the number of states, and M is the number of observations [25].

First, the implicit state transition probability matrix is as follows:

$$A = (a_{ik})N, 1 \leq i \leq N, 1 \leq k \leq N, \quad (5)$$

where $a_{ik} = P(s_{i+1} = q_k, s_i = q_i)$ is the probability of transitioning to state q_i at time $t + 1$ while being in state q_i at time t .

The observed state probability transition matrix is

$$B = (b_i)K, 1 \leq k \leq N, \quad (6)$$

where $(b_i)K = P(O_t = v_k | s_t = q_i)$ is the probability of generating observations under the conditions at time t .

The final initial state probability matrix is

$$\pi = (\pi)_i, 1 \leq i \leq N. \quad (7)$$

Among them, π refers to the initial state probability, and $\pi_i = P(s_i = q_i)$ refers to the probability of being in the state at time $t = 1$.

At this point, the hidden Markov model can be modeled, but the following three problems still need to be solved in the modeling process. The first is the problem of how to calculate the conditional probability γ given $P(O|\gamma)$ and the observation sequence O . This is followed by the problem of how to find the optimal sequence that maximizes the value of $\gamma = (S, O, \pi, A, B)$ given $P(O|\gamma)$ and the observation sequence O . This is finally given the observation sequence O , how to adjust $S = (s_1, s_2, s_3, \dots, s_n)$ to make $\gamma = (S, O, \pi, A, B)$ get the maximum value $P(O|\gamma)$ [26].

3.3.3. Gaussian Mixture Model. Gaussian mixture models are a widely used clustering algorithm. It uses multiple Gaussian probability density distribution functions to describe the

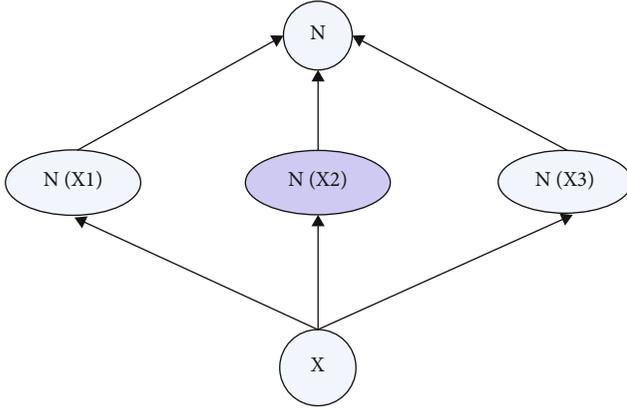


FIGURE 4: Gaussian mixture model.

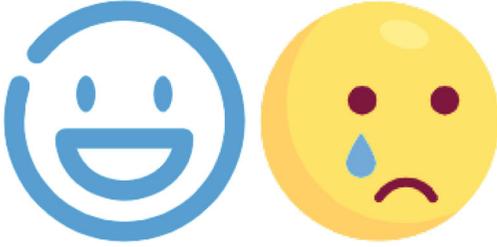


FIGURE 5: Happy and sad emotions.

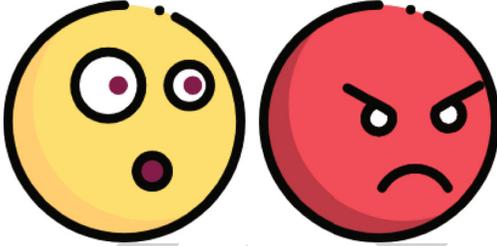


FIGURE 6: Shocked and angry emotions.

data sample distribution [27]. The schematic diagram of its model is shown in Figure 4.

It can be seen from Figure 4 that the Gaussian mixture model is essentially the weighted sum of several Gaussian probability density distribution functions, which is defined as follows:

$$P(X|\theta) = \sum_{i=1}^N \pi_k N(X, \mu_k). \quad (8)$$

Among them, X represents the N -dimensional feature vector of the sample, $\{\pi_k | \sum_{k=1}^N \pi_k = 1\}$ represents the corresponding weight of each distribution function, and μ_k represents the expectation vector. σ_k^2 is the variance vector, $\sum k = \rho_k^2 I$ is the covariance matrix, and $N(X, \mu_k, \sum k)$ is called

TABLE 2: Single-modal emotion recognition rates when normalized and unnormalized.

	Not normalized	Normalized	Comprehensive
Happy	72.97%	92.65%	87%
Sad	73.78%	90.18%	84%
Shock	77.62%	91.54%	86%
Anger	75.16%	93.12%	88%

the k th submodel. It is defined as follows:

$$N(X, \mu_k, \sum k) = \frac{1}{\sqrt{(2\pi)^N |\sum k|}} \exp \left\{ -\frac{1}{2} (x - \mu_k)^T \sum k^{-1} (x - \mu_k) \right\}. \quad (9)$$

According to Bayesian theory, the posterior probability 1 can be expressed as follows:

$$p(x|\theta) = \prod_{t=1}^T P(x_t|\theta). \quad (10)$$

In

$$P(X|\theta) = \prod_{t=1}^T \log P(x_t|\theta). \quad (11)$$

Then, take its logarithm:

$$\log P(X|\theta) = \prod_{t=1}^T \log P(x_t|\theta). \quad (12)$$

The prior probability $P(\theta_k)$ is unknown, so it is assumed that each feature is independent of each other; that is, the prior probability of each feature is equal: $P\theta_k = 1/N$. The feature vector X is determined; then, $P(X)$ is a constant, which is equal for all categories, and the sample classification can be performed.

3.3.4. Model Evaluation Criteria. In emotion recognition, appropriate evaluation criteria are usually used to evaluate the effectiveness of the model. Next, the algorithm evaluation criteria in discrete and continuous emotion models are introduced, respectively.

First, in the discrete emotion model, the unweighted average recall rate and the weighted average recall rate are used as the evaluation criteria of the algorithm, which can be calculated by the following formula:

$$UAR = \frac{1}{K} \sum_{i=1}^k \frac{N_r^i}{k}, \quad (13)$$

$$WAR = \frac{\sum_{i=1}^k N_r^i}{N}. \quad (14)$$

Among them, N_r^i represents the number of correctly identified samples of the i -th class, N_r^t represents the total number of samples of the i -th class, N represents the total

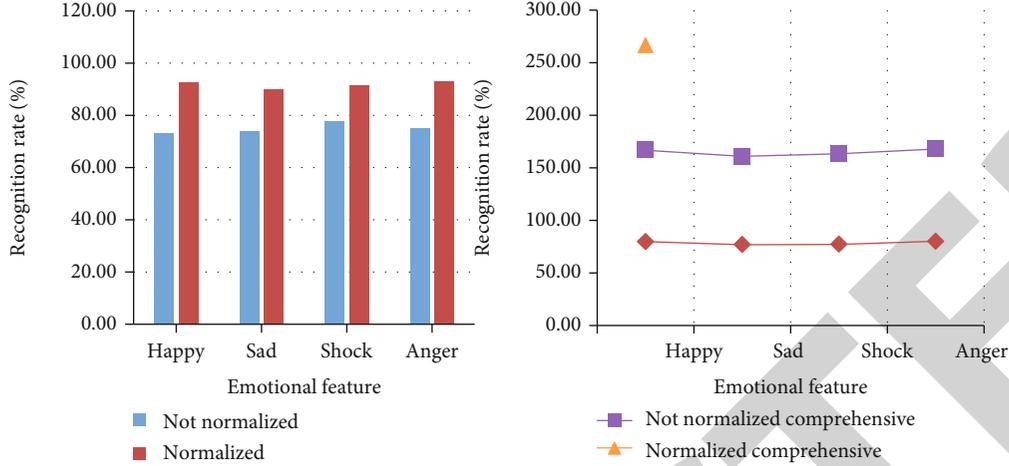


FIGURE 7: Single-modal emotion recognition results: (a) recognition rate when normalized and unnormalized; (d) comprehensive recognition rate.

number of samples, and K represents the number of sample categories to be identified. The weighted average recall rate, also known as the correct recognition rate, represents the correct rate of recognition of a certain category. But in some cases, the correct recognition rate cannot effectively evaluate the effectiveness of the algorithm. For example, if only one sample of a certain type is identified and the identification is correct, it means that the identification accuracy rate has reached 100%. But at this time, the classification algorithm cannot effectively identify other samples. Therefore, researchers often use the unweighted average recall rate to assist in evaluating the effectiveness of the algorithm.

In the continuous emotional model, the Pearson product-moment correlation coefficient is used as the evaluation criterion of the algorithm, which can be calculated by the following formula:

$$C = \frac{\sum_{i=1}^N (y_i - \bar{y})}{\sqrt{\sum_{i=1}^N y_i}}, \quad (15)$$

where y represents the mean of the sample labels $\{y_1, y_2, \dots, y_n\}$ and N represents the total number of samples. The correlation coefficient is used to measure the correlation between y and N , and its positive and negative values indicate positive and negative correlations, respectively.

4. Multimodal Emotion Recognition Simulation Experiment of Artificial Intelligence Information System

4.1. Experimental Design. The purpose of this multimodal emotion recognition simulation experiment of artificial intelligence information system is to judge the recognition effect of multimodal emotion recognition on emotional features in artificial intelligence information system. This paper mainly conducts a comparative experiment of single-modal emotion recognition and multimodal emo-

tion recognition of artificial intelligence information system. It compares and calculates the recognition accuracy of the multimodal emotion recognition algorithm to the emotional features in the artificial intelligence information system to achieve the experimental purpose. The multimodal emotion recognition algorithm is compared and calculated to achieve the experimental purpose of judging the effectiveness of the multimodal emotion recognition algorithm. First of all, this paper extracts the emotion information of three modes, including the eyes, expressions, and body gestures, including four emotion feature categories including happy, sad, shocked, and angry, from the artificial intelligence information system as the emotion recognition object of this experiment. Sample examples of these four sentiment feature categories are shown in Figures 5 and 6:

4.2. Single-Modal Emotion Recognition. In this single-mode emotion recognition experiment, the emotion features of each sample extracted are combined and normalized. It then divides all samples into two parts: training samples and test samples. It then obtains the class label values that correspond to the training samples. The category label values are represented by 1, 2, 3, and 4, respectively. In the whole experiment process, the method of automatic optimization is adopted; that is, grid division is used to determine the best parameters in the classifier. It saves the obtained parameter values for later emotion recognition. In the experiment, the 16560-dimensional Gabor feature was extracted from the expression signal, and then, the dimensionality was reduced to 131 by the principal component analysis method. For the extraction of posture features, the EyeWeb platform is used to track the posture. It obtains several indicators such as exercise quantity QoM, limb contraction index CI, exercise rate VEL, exercise acceleration ACC, and palm motion line FL, as well as their respective minimum, maximum, mean, median, and standard deviation. It finally obtains 80-dimensional gesture emotion features. The experimental results described below

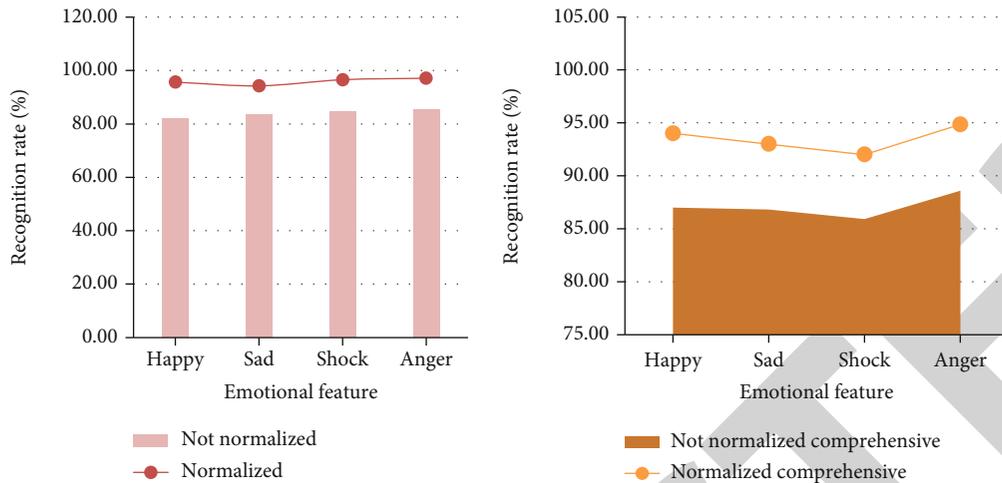


FIGURE 8: Multimodal emotion recognition: (a) recognition rate when multimodality is not normalized and normalized; (f) comprehensive recognition rate of multimodal emotion recognition.

are the average recognition rates obtained after 10 times of 10-fold cross-validation. The following compares the difference between the emotion recognition rates of each pattern when the data is normalized and when the data is not normalized. The simulation results are shown in Table 2.

It can be seen from Table 2 that the single-pattern recognition rate with normalization is significantly higher than the single-pattern emotion recognition rate without normalization. The comprehensive accuracy of the recognition of the four types of emotional features in this single-mode emotion recognition is 87%, 84%, 86%, and 88% from happy to angry, respectively. The specific results are shown in Figure 7.

From the single-mode emotion recognition simulation experiment results shown in Figure 7, it can be seen that the improvement of the recognition rate by data normalization is quite obvious. Normalization removes the influence of dimensions on the data and limits the variation range of the data to a small range, which is simple and accurate. In summary, in the single-mode emotion recognition mode, the recognition rate is higher when normalized, and the comprehensive recognition accuracy of the selected four types of emotional features is 86%.

4.3. Multimodal Emotion Recognition. In multimodal emotion recognition, the emotional features of each mode are first unified and normalized. At the same time, the Bayesian network model is used for feature dimension reduction for the collected emotional features. It then uses the hidden Markov model to fuse the emotional features of the two modes for object feature selection. It then uses the Gaussian mixture model to fuse the multimodal emotional features with the normalized emotional features and the facial expression emotional features and gesture emotional features reduced by the Bayesian network model. Finally, the multimodal emotion recognition simulation experiment can be carried out according to the model evaluation standard. The experimental results are shown in Figure 8.

It can be seen from the simulation experiment results in Figure 8 that the accuracy of emotion recognition is improved to a certain extent after all the selected emotional features are fused with each other. The comprehensive recognition accuracy rate has reached 93%, which is 7% higher than that of single-mode emotion recognition. This fully demonstrates the effectiveness of the multimodal emotion recognition algorithm for artificial intelligence information systems.

5. Discussion

Emotional expression is an important part of people's daily communicative life. People's emotional expression is mainly reflected by emotional features such as speech, facial expressions, and body language. Emotion recognition refers to judging the emotional state of a person by identifying these emotional characteristics. This adjusts communication behavior at any time to promote the harmonious development of interpersonal communication. Emotion recognition mainly includes single-modal emotion recognition and multimodal emotion recognition [28].

Compared with single-mode emotion recognition, multimodal emotion recognition breaks the recognition limitation of ever-changing and difficult-to-see emotional features and has a better recognition effect on emotion recognition. Therefore, the research and application of multimodal emotion recognition are also increasing day by day such as the application of multimodal emotion algorithm in emotion feature recognition of artificial intelligence information system. This paper mainly analyzes and studies the application of multimodal emotion recognition in artificial intelligence information systems [29].

In order to judge the effect of multimodal emotion recognition algorithm on emotional features in artificial intelligence information systems, this paper designs a single-modal and multimodal emotional recognition comparison experiment. The experiment concluded that the comprehensive recognition

accuracy rate of multimodal emotion recognition algorithm for emotional features in artificial intelligence information system reached 93%, which was 7% higher than that of single-modal emotion recognition. This shows that the multimodal emotion recognition algorithm of artificial intelligence information system has better emotion recognition effect and can play a positive role in complex human emotion recognition.

6. Conclusion

This paper mainly analyzes and studies the application of multimodal emotion recognition algorithm in artificial intelligence information system. The four emotion features of happiness, sadness, shock, and anger extracted from the artificial intelligence information system were compared, and simulated experiments of single-mode and multimode emotion recognition algorithms were carried out. The research conclusions drawn prove that the multimodal emotion recognition algorithm has a better recognition effect than the single-modal emotion recognition for the emotional features in the artificial intelligence information system. The research conclusions of this paper have certain reference significance for promoting the application and development of multimodal emotion recognition algorithms in artificial intelligence information systems. However, the research of this paper still has some shortcomings, such as the research method is not innovative enough, and the angle is not comprehensive enough. The author hopes to make improvements in the future to make more contributions to the research of multimodal emotion recognition algorithms.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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