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Psychological Education and Emotional Model Establishment Analysis Based on Artificial Intelligence in the Intelligent Environment

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Keywords: Emotion Model, Artificial Intelligence, Light Sensor, Psychological Education

Abstract: Emotion plays an important role in our daily life. It affects people's study and life in varying degrees. This study mainly discusses the psychological education and emotional model building based on artificial intelligence in intelligent environment. In this study, hidden Markov model (HMM) is used to recognize facial expression and describe the output probability of emotional state change. In the aspect of emotion feature extraction, acceleration sensor is used to judge the user's activity state, and optical sensor data and GPS data are used to collect environmental data. In order to reflect individual emotion and its intensity, emotion space method can be used to deal with the reflected emotion vector effectively. Because FACS system is too complex, this model simplifies it. The emotion reflected from emotion space corresponds to a series of AU parameters, which constitute the corresponding facial expression. The strength of these parameters is determined by the size of the emotion vector module. Finally, a sound processing module is added in front of the emotion parameter extraction module of the emotion model for better emotional interaction. In emotion recognition test, the accuracy rate of sensor data based on basic emotion model was 47.13%, 49.08% and 56.32%, respectively. The results show that the model attempts to achieve multi character expression by modifying the emotional space, and achieves the goal of multi modality of the model, which provides the possibility for personalized customization of emotional model in the future.

1. Introduction

Emotion, as a psychological form different from cognition and consciousness, affects people's learning, work efficiency and behavior patterns to varying degrees, and plays an important role in daily life. Emotion is a kind of instantaneous, spontaneous physiological and psychological process, which is often not controlled by subjective consciousness, but closely related to physiological changes. Usually, the change of emotion is affected by the outside world, and is often accompanied by the short-term changes of expression, voice and behavior. It is precisely because of these changes that emotions can be recognized through images and voice.

In the process of simulating the advanced intelligent behavior of intelligent virtual agent, the key is how to use the theoretical results of psychologists and behaviorists on human cognitive understanding, how to reflect the influence of motivation and synthetic emotion in the process of intelligent decision-making, so as to realize the real meaning of anthropomorphic decision-making process. Because of the diversity of the theory of emotional psychology, the methods of synthetic emotion theory are inconsistent, so it is difficult to find a unified theory and method of emotion which is suitable for information science. It is very important to build a set of effective emotion models which can be executed by computer by using the existing synthetic emotion models from different fields.

Emotion recognition aims to determine the emotional state contained in a person's speech or imitation. Turgut Özseven believes that emotion recognition from speech is a field related to signal processing and psychology. The speech parameters he obtained from speech signals through speech analysis is an objective evaluation method, which has been widely used in emotion recognition research. He has studied the success of emotion recognition from various aspects, and studied the influence of dimensional models on the success of independent emotion recognition. He uses support vector machines to classify acoustic parameters to determine whether emotion recognition is successful. His research process lacks data [1]. Ritblatt introduced the Early Childhood-Social Emotion and Behavior Regulation Intervention Expert (EC-SEBRIS) certification program model that integrates knowledge and practice. Contribute to the application of knowledge by integrating theories and practices that support young children and families, course work, videos, on-site guidance and reflection processes. The document will provide: research-based information to determine the demand for such training programs; the rationality of the conceptual framework of the EC-SEBRIS certification program; the description of the wrap-around training model, which he proposed uses a triple guidance and guidance method: reflection sexual supervision, video recording and on-site guidance to teachers. His research has no practical significance [2]. Yazdani AM proposed an implementation of an intelligent controller based on brain emotion learning (BELBIC), which can accurately track the speed of a hybrid stepping motor (HSM). In order to evaluate the performance of the BELBIC controller under actual conditions, he considered the system uncertainty due to changes in mechanical parameters and load torque disturbances. In order to verify the excellent dynamic performance and feasibility of BELBIC, he simulated the system in MATLAB Simulink, and compared the simulation results with the optimized proportional integral (PI) controller. His research is not novel enough [3]. Kotov A A believes that problems can be examined from the perspectives of philosophy, neuropsychology, and computer modeling. He solved the problem of the computational model of consciousness by designing computer agents designed to simulate "speech understanding" and irony. In addition, he looked for a "minimal architecture" that could mimic the effects of consciousness in computing systems. For the basic architecture, he uses a software agent, which is programmed to be used with scripts (generation or inference), to process the input text (or events) by extracting their semantic representation, and to select relevant responses. His research process lacks data [4].

This study uses Hidden Markov Model (HMM) to recognize facial expressions and describe the output probability of emotional state changes. In terms of emotional feature extraction, this study uses acceleration sensors to determine the user's activity status, and uses light sensor data and GPS data to collect environmental data. In order to reflect the individual emotion and its intensity, the emotion space method can be used to effectively process and reflect the emotion vector. Because the FACS system is too complex, this model simplifies it. The reflected emotion calculated from the emotional space corresponds to a series of AU parameters. These parameters form the corresponding facial expression. The intensity of these parameters is determined by the emotional vector. The size of the mold is determined. Finally, a sound processing module is added before the emotional parameter extraction module of the emotional model for better emotional interaction.

2. Establishment of Emotional Model

2.1. Psychological Education

Psychological education is necessary for most people. Generalized Anxiety Disorder (GAD) is a serious debilitating disease characterized by high comorbidities, which has a negative impact on overall health [5-6]. Cognitive behavioral therapy is recognized as GAD psychotherapy. Although CBT has been well established, it also shows that not all people can benefit from it [7]. It is important to highlight emerging models of collaboration with GAD patients from an emotionally focused treatment perspective. It can be compared with the mainstream CBT theory because it suggests that the experimenter is not to avoid emotional experience or its overall processing [8]. Contrary to the mainstream CBT theory, change is not achieved through emotional habit of habitual triggers (or emotions), but through a series of emotional processing steps to reorganize and transform problem emotional solutions. These steps include overcoming emotional avoidance, distinguishing and enduring core painful feelings, expressing unsatisfied needs in those feelings, and expressing emotional response feelings or needs to these feelings [9-10].

2.2. Emotional Model

In recent years, robotic systems have been mature enough to perform simple home or office tasks, guide visitors in environments such as museums or shops, and provide assistance in people's daily lives [11]. In order to make the interaction with services and even industrial robots as fast and intuitive as possible, researchers strive to create a transparent interface close to human-to-human interaction. Because facial expressions play a central role in human-to-human communication, the realization of robot faces has different levels of portrait and expression expression capabilities. There is an emotion model that is used to parameterize screen-based facial animation through inter-process communication [12-13]. The software will animate the transition and add other animations to make the digital face look "active" and equip the robot system with a virtual face [14].

Recent studies have shown that emotional dynamics such as inertia (ie, autocorrelation) can change over time [15-16]. Importantly, current methods can only detect gradual or sudden changes in inertia. This means that researchers must check whether they expect changes in inertia to be gradual or sudden. This will make researchers wonder when and how inertial changes occur. The time-varying change point autoregressive (TVCP-AR) model TVCP-AR can detect gradual and sudden changes in emotional dynamics. More specifically, there is a qualitative difference between the positive and negative inertia measured by a person over time. The inertia of positive effects only gradually increases with time, while negative effects gradually change with time [17]. This illustrates the need to be able to model gradual changes and sudden changes to detect meaningful quantitative and qualitative differences in temporal emotions [18-19].

The short-term energy calculation of the emotional speech signal at time n is defined as follows:

$$E_n = \sum_{m=-\infty}^{\infty}[x(m)\cdot w(n-m)]^2 \tag{1}$$

Among them, E_n is the energy value [20].

2.3. Hidden Markov Model

Hidden Markov model is built on the basis of hidden Markov chain. It is implicit, so it cannot be directly observed, and its existence can only be perceived through a random process. Human emotions are complex, it is a combination of uncertainty and inevitability. Emotional information is extremely rich, and its amount of information is huge. We study the emotional model. In the process, we can approximate the emotional process as a hidden Markov model to discuss [21-22].

With a random process $\{X_t, t = 0,1,2,\cdots\}$, there are:

$$P(X_{t+1} = x_{t+1}|X_0 = x_0,\ldots,X_t = x_t) = P(X_{t+1} = x_{t+1}|X_t = x_t) = a_{ij} \tag{2}$$

That is, the value of X_{t+1} only depends on the value of x_t and the state transition probability a_{ij}, so the basic equation of the hidden Markov chain can be obtained:

$$p^{(t+1)}{}_i = p_1^{(t)}a_{1i} + p_2^{(t)}a_{2i} + \cdots + p_N^{(t)}a_{Ni} = \sum_{j=1}^{N} p_j^{(t)}a_{ij} \tag{3}$$

Among them, $p_i^{(t)}$ and a_{ij} satisfy:

$$\sum_{i=1}^{N} p_i^{(t)} = 1 \tag{4}$$

$$\sum_{j=1}^{N} a_{ij} = 1 \quad \mathrm{a_{ij}} \geq 0, j = 1,2\ldots,N \tag{5}$$

Introduce the state probability vector:

$$p^t = [p_1^t, p_2^t,\ldots,p_N^t] \tag{6}$$

The basic equation can be expressed as:

$$p^{(t+1)} = P^{(t)}A \tag{7}$$

2.4. Sensor

The sensor node is responsible for collecting human body motion posture information, and simulates the human body movement through the information data collected by each sensor node. Each sensor node is an independent individual, which corresponds to the key joint points of the human body, and the human skeleton model plays an intermediary role [23]. Conversion of quaternion and rotation matrix:

$$yaw = \tan^{-1}\left(\frac{2(q_0 q_1 + q_3 q_2)}{q_3^2 - q_2^2 - q_1^2 + q_0^2}\right) \tag{8}$$

$$q = e \sin\left(\frac{\partial}{2}\right) \tag{9}$$

Among them, ∂ represents the angle of rotation. The expression method of signal amplitude area is as follows:

$$SMA = \frac{1}{w}\int_0^w \left(|x(t)| + |y(t)| + |z(t)|\right)dt \tag{10}$$

Among them, w is a parameter. The division of the joints in the human skeleton model is the process of extracting the key joint points of the human body, and the movement posture information of the human body is obtained by sensors bound to the key joint points. The motion posture information at each key joint point of the human body can effectively reflect the motion posture of the entire human body after processing. Through the analysis of the human skeleton model, this system simplifies the human body model into 17 key joint points. A micromechanical sensor is placed at each key joint point to form a sensing node, and the sensing node uses the built-in acceleration of the micromechanical sensor. The data fusion filtering of the meter, gyroscope and magnetic sensor obtains the movement information of the key joint points. Arranged between the 17 sensor nodes of the human body, there is no strict control center.Due to environmental and usage reasons, individual nodes may have poor communication effects.Each node can join and leave the network at any time. The sensor node failure will not affect the operation of the system [24-25].

3. Emotional Model Building Experiment

3.1. Emotional Feature Extraction

(1) Feature extraction of acceleration sensor

The activity state data is obtained by simple calculation based on the acceleration sensor, which can determine the user's specific state. The sensor calculates the data at a frequency of one minute per minute to determine whether the user's state within this minute is stable, slow or fast.

(2) Extraction of environmental perception data

Environmental perception data includes two types of light sensor data and GPS data, and a total of 6 feature values are extracted.

1) Light sensor data collection information includes time and corresponding light intensity; GPS data collection information includes longitude, latitude, altitude, GPS speed, time, accuracy, positioning method (GPS positioning or network positioning).

2) GPS feature extraction. We hope to know the number of locations the user has visited every day and the length of stay in each location through GPS information, and use this as a basis for judging user activity. Therefore, in order to record the user's trajectory more accurately, GPS uses high frequency for data collection (recording once every 30s). The collected data is parsed by JSON to obtain the latitude and longitude of each sampling point, and use them as the x-axis and y-axis to

plot the data.

3.2. Emotional Parameter Extraction

According to the design of the input signal of the emotion model, this model divides external stimuli into three types: object, event and action, which correspond to the three types of evaluations that the emotional subject should have, standards and preferences. Standard, each category has its corresponding feature description, these feature descriptions will be used as the processing parameters of this module. The stimuli that cause emotional reactions are divided into three categories: Object, Event, and Action. Each feature description corresponds to three components: arousa (stimulus size), Valence (stimulus pleasure), Stance (friendly or not). (The understanding of the meaning of these three components is an important issue considered when establishing many emotional models.) For example: feature description "Danger" (Fatalness), corresponding to strong incentive value (High Arousal), negative pleasure stimulation value (Negativevalence) , and the introverted friendly value (stance). After designing a suitable feature description, this module processes and produces a series of feature descriptions (avs values) over a period of time, which becomes the processing output of the emotional parameter extraction module of this module, which will be processed by the emotional feature value analysis module of the next module.

3.3. Facial Expression Recognition

Using differential equations for emotional modeling can only qualitatively study the changing trend of emotional dynamics, but it cannot quantitatively study the possibility of emotional state changes. This study uses Hidden Markov Model (Hidden Markov Model, HMM) to recognize facial expressions and describe the output probability of emotional state changes. When the state output probability takes a larger or smaller value, the result of the cumulative calculation may exceed the range of the floating point number of the computer, causing an overflow problem. This study proposes to use a computer to automatically calculate the scale factor coefficient instead of manual adjustment, and derives the method to automatically calculate the scale factor coefficient. The method of automatically calculating the scale factor reduces the error rate, improves the correct rate, and frees people from the training calculation process.

3.4. Emotional Space Design

Using the emotional space method, it can effectively process the emotional vector that reflects the specific individual emotion and its intensity. The emotional space method has been used by many existing emotional models, and the space itself has developed from the original one-dimensional to the present multi-dimensional, but there is no criterion for judging whether they are correct and effective. In order to make the emotional space simple and effective, the space established by this emotional model refers to the six basic emotions of Ekman, and the positive and negative principles of the OCC model. This emotional space is represented by a three-dimensional space, and the three dimensions are respectively represented: Arousa (stimulus size), Valence (stimulus pleasure), Stance (friendly or not). Each vector in the space represents an emotion, the modulus of the vector represents the intensity of the emotion, and the direction of the vector represents the type of emotion. The distribution of emotional points in the space follows the principle of positive and negative opposition, placing the opposing emotions in the opposite direction and evenly covering the entire space. Evenly covering the entire space with emotional points means that this emotional model does not have outstanding personality characteristics. If the distribution is uneven, it will have outstanding personality characteristics, such as "irritability" and so on.

There are nine points in the space, including six basic emotions and two other emotion points ("unhappy", "tired"). The origin is used to express "calmness". Although it does not represent emotion, it is also necessary. Each emotion is divided into its own independent area, as shown in Table 1. E represents the three-dimensional vector, which is calculated in the previous step. Changing the size of the area division can get a change in the robot's personality. The districts of each emotional point in the emotional space of this model are uniformly divided, and there is no obvious personality characteristic. From this emotional space mapping, we can find out which specific emotion the emotion vector E represents and how strong it is.

Table 1: Regional division

Emotion Area	Valence- x axes	Arousal- y axes	Stance- z axes
Calm	Ex<1	Ey<1	Ez<1
Joy	Ex>1	Ey>1	Ez>1
Unhappy	Ex<-1	Ey>1	Ez<1
Surprise	Ex<1	Ey>1	Ez<1

3.5. Facial Expression Design

Emotions have various influences on individual behaviors, such as direct influences such as emotions directly triggering behaviors; indirect influences such as: behavioral motivation and cognitive results of robots controlled by emotions. Emotion is considered to be a mediation medium between environmental input and behavioral output. The output of this model focuses on the influence of emotions on facial expressions. In order to express facial expressions, this model refers to Ekman's FACS system. Each facial expression is composed of a series of AU parameters (including its intensity). Because the FACS system is too complex, this model simplifies it. The design of the facial expression system of this model is shown in Table 2. The reflected emotion calculated from the emotional space corresponds to a series of AU parameters. These parameters form the corresponding facial expression. The strength of these parameters is determined by the model of the emotion vector,the size is determined.

Table 2: Design of facial expression system

AU	Description	Facial muscle
1	Inner Brow Raiser	Frontalis, pars medialis
2	Outer Brow Raiser	Frontalis, pars lateralis
3	Brow Lower	Corrugator supercilii, Depressor supercilii
4	Upper Lid Raiser	Levator palpebrae superioris

5	Cheek Raiser	Orbicularis oculi, parsorbitalis

3.6. Sound Processing Module Design

Among many voice emotion parameters, some are difficult to detect, and some require professional analysis, so it is not practical to use them all. According to the feasibility of operation, this model adopts three reference quantities of average fundamental frequency, sound intensity, and fundamental frequency range when improving. As a preliminary attempt to simulate sound emotion, these three quantities can basically meet the requirements and are easy to obtain and detect. This research refers to the conclusions of psychological sound statistics, collects the sound signals in language expression, processes the signals, extracts the average fundamental frequency, sound intensity, and fundamental frequency range data, comprehensively designs, and obtains an emotional model that can process sounds. Although this emotional model cannot reach the level of understanding the meaning of the speaker's words (the understanding of robotic language has yet to be developed), the emotions aroused by sounds can be simulated.

Add a sound processing module before the emotional parameter extraction module of the emotional model. The main task of this module is to extract the sound intensity and audio value of the sound file, filter out the interference value, and determine the corresponding audio and sound intensity value within 0.5 seconds. Look up a table designed based on the results of psychological statistical research and find the emotional parameters corresponding to the two averages.

3.7. Realization of Emotional Interaction

The overall structure of the emotional virtual model is shown in Figure 1. The perception system obtains and processes sensor information, mainly voice recognition and facial expression recognition, and effectively transforms the recognition results into emotional measures and transmits them to the emotional system to stimulate the appearance and changes of emotions. The emotional system is composed of three related subsystems: needs, emotions, mood, and personality. The module needs to evaluate the type and importance of perceptual events to determine the type and intensity of emotional responses; the emotional module experiences emotional stimulation and emotional updates Two processes, the updated emotional state is output to the behavior module; the personality module is used to change the threshold of emotional excitation and the rate of attenuation, which affects emotional excitation and emotional changes. The behavior system relies on the information delivered by the emotional system to select appropriate behaviors.

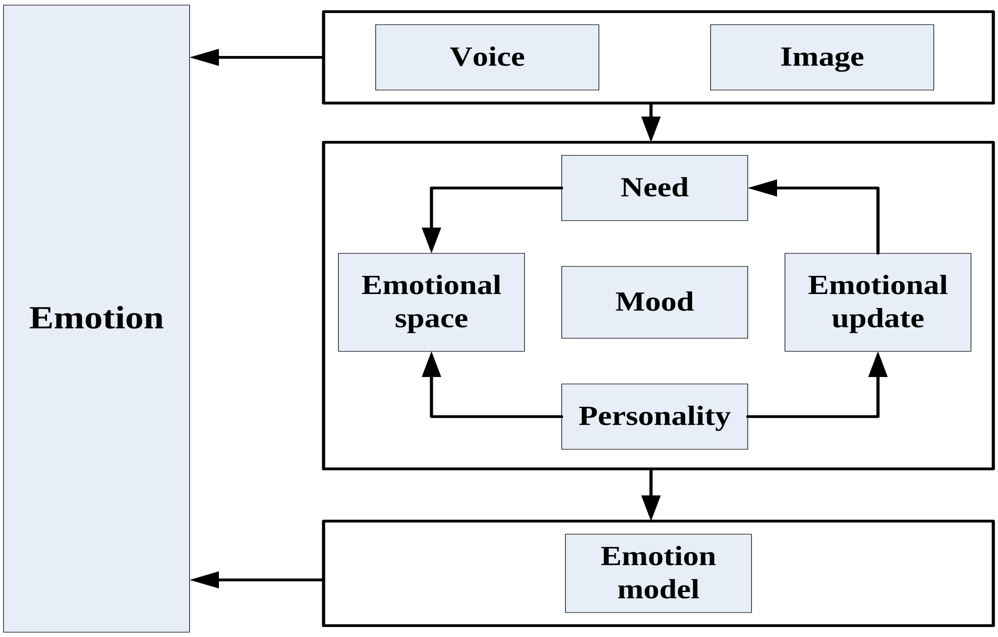

Figure 1: Overall structure of emotional virtual model

4. Emotion Model Analysis

4.1. Emotion Recognition Analysis

The results of emotion recognition accuracy are shown in Table 3. The accuracy here refers to the average accuracy, that is, the percentage of the total test data whose classification result matches the actual label in the test data. We have obtained three types of different sensor data test samples. The accuracy rates based on the basic emotion model are 47.13%, 49.08%, 56.32%, and the accuracy rates based on the emotion model are 59.77%, 60.92%, and 64.37%, respectively. Next, the results are fused according to the classification results of the feature vectors of these three types of sensors. It can be seen that the accuracy of emotion recognition after the result fusion is higher than that of the single-category data, which is 58.62% and 58.62% based on the basic emotion model. 67.82% based on the ring emotion model. Through the analysis of the data, we conclude that the mixed data will often have higher recognition accuracy than the single category of sensor data feature vector after the result fusion. The recognition accuracy of the ring emotion model is generally higher than that of the basic emotion model. It can be seen from Table 3 that although the specific emotion classification probabilities of various types of perception data are not completely the same, the overall trend is consistent, that is, the emotion type with the highest probability after the same sample data is classified by different feature vectors is basically the same. Whether it is in sports perception data, environmental perception data, mobile phone usage data, or after the results are fused, the probability of being "happy" is the greatest. This result also verifies the reliability of the result fusion experiment from the side, that is, the three types of sensor data are the same regardless of the individual judgment before fusion or the overall judgment classification result after fusion, but the specific values are different.

Table 3: Results of emotion recognition accuracy

P / Data	P1	P2	P3	P4	P5
Data A	0.0	0.033	0.8875	0.0795	0.0
Data B	0.0	0.1	0.867	0.033	0.0
Data C	0.067	0.12	0.677	0.17	0.033
Data D	0.0	0.244	0.567	0.089	0.033
Data E	0.0	0.6	0.233	0.167	0.0

4.2. Emotional Response Analysis

This model simulates the emotional response of a child. The simulation example designs the following sequence of events to trigger the model, so as to achieve the purpose of checking the validity of the model. The emotional response results are shown in Figure 2. The simulation effect of the model output is shown in Figure 2. From Figure 2 it can be clearly seen the reaction emotion and the intensity of emotion calculated by the emotion model at each stage. Comparing the emotional response of real children triggered by the same event, it can be seen that the emotional expression is basically normal. Since the emotion of the child is simulated, many parameters in the model are designed to represent the child's emotional characteristics, such as: the parameter δt that marks the memory effect is small, which means that it is basically not affected by the previous emotions, which is in line with the general emotional changes of children and sudden changes. When there is no new stimulus, the original emotional intensity will slowly fall back, indicating that it gradually becomes calmer. The emotional response of fear in Figure 2 begins to weaken when there is no trigger event for two consecutive periods of time, and the weakening amplitude is very fast, which also shows the characteristics of rapid emotional changes in children. Different emotions correspond to different line types. Thin lines indicate mild and low emotions, and thick lines indicate strong and excited emotions. For example, the bold solid line indicates "happy", and the thin line and dotted line indicate "sadness". It can be seen from the experimental results that when the initial emotion is calm and external rewards and punishment stimuli act on the emotion agent at the same time, the output of the emotion model changes with the ratio of the two joint inputs. When $V1/V2>1$, the final emotional state output is 1, which is a positive emotional output; when $V1/V2<1$, the final emotional state output is -1, which is a negative emotional output. It can also be seen from the output curve that the emotional output does not change immediately with the input, but has a time delay, which shows that the emotional change of the virtual person is gradually changed under the action of emotional energy. This result is consistent with emotional psychology. Theory, common sense of life and experience are consistent.

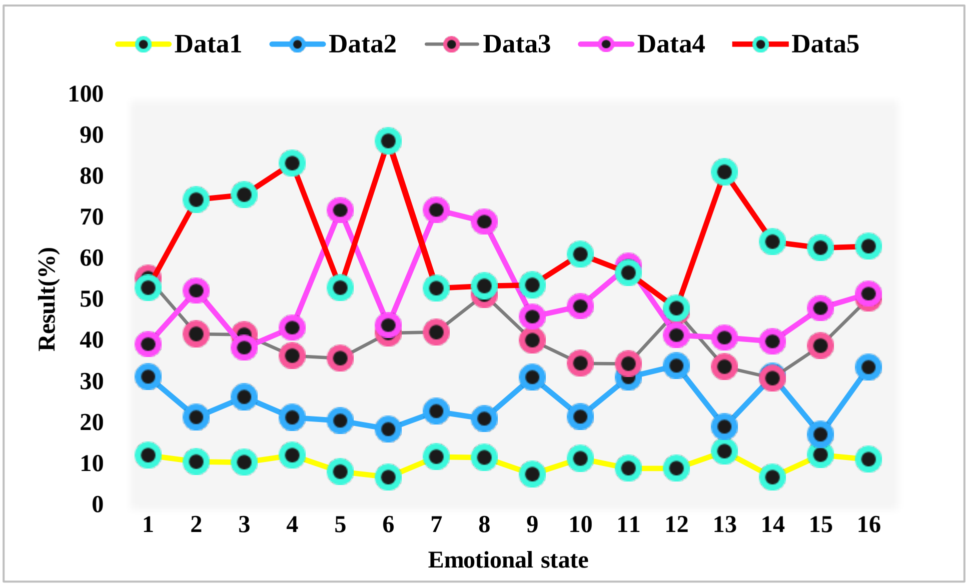

Figure 2: Emotional response results

4.3. Trigger Event Analysis

The emotional response under the trigger event sequence after the model is modified is shown in Figure 3. Another event trigger sequence was designed to cover several emotional points not involved in the emotional response simulation example. The trigger event sequence is as follows: 1. Say hello to him; 2. Give him a toy he is not familiar with; 3. He will not Play with this toy; 4. Change a toy that he likes; 5. If you have a favorite toy, throw away the previous toy and criticize him; 9. Say goodbye to him. The analysis result of the trigger event is shown in Figure 3. It can be seen from Figure 3 that the simulation result has a greater change than the simulation result of the trigger event sequence 1. Not only is the design of the event sequence changed, the model itself has also been modified, and the emotional model is realized by modifying the emotional space. Purposes with different personality characteristics. The emotional model of this simulation is based on the previous model, modified the emotional space, and removed the emotional point of "sadness". Therefore, it can be obtained that the emotion model did not express "sorrow" in the last step, but only the previous emotion slowly weakened. This shows that it is not easy to be sad or optimistic. This model uses an extreme method of removing emotional points to express personality characteristics, and the effect is very obvious, that is, the removed emotions are no longer displayed, but this is not in line with reality. The method of reducing certain emotional point areas and expanding certain emotional point areas can be adopted to reflect personality characteristics, which is more in line with reality.

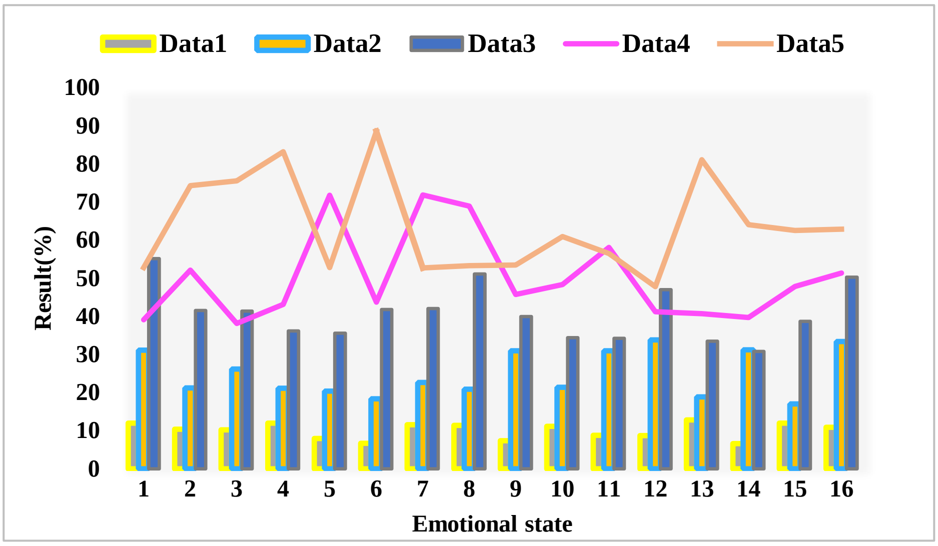

Figure 3: Emotional response under the sequence of triggering events

4.4. Emotional Response to Individual Stimulation

Individual stimulation of emotional response is shown in Figure 4. It can be seen from Figure 4 that the emotional model restores the emotional point of "sorrow"; and adds the emotional point of "tired". When the model waited for a long time without stimulation, fatigue began to appear, which made the model enter a dormant state. When this model deals with the emotion of fatigue, it is different from other emotions. Because the emotion of fatigue is usually caused by the absence of external stimuli for a long time, or the running time of the whole system is too long, two internal timers are used to trigger the emotion of fatigue. When the system starts a timer, another timer is started when there is no stimulus. When any timer reaches a predetermined value, the fatigue emotion is triggered. By satisfying a certain stimulus, the triggered timer is cleared to stop the fatigue emotion. For example: when there is a new stimulus, the fatigue in Figure 4 will disappear immediately. It can be seen from the experimental results that when the initial emotion is in a calm state, when the outside world gives a reward stimulus, the emotional model output changes with the input, and finally is 1, which is the happy emotional output; when the outside world gives a punishment stimulus, the emotional model The output changes with the input, and finally is -1, which is the emotional output of anger. This result is consistent with the theory, common sense and experience of emotional psychology. Therefore, it is feasible to use this model to simulate human emotion changes and use it in the emotional agent of human-computer interaction.

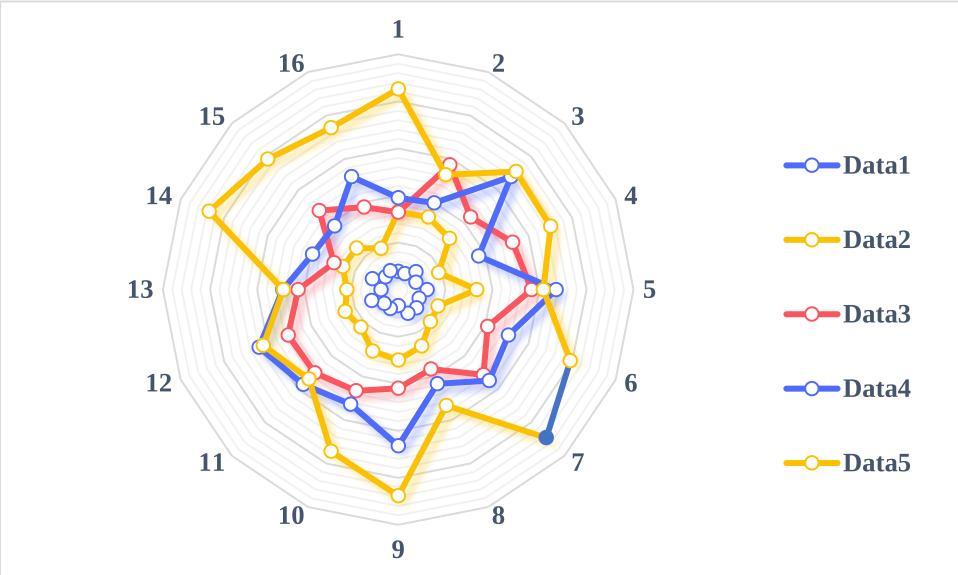

Figure 4: Stimulating emotional response alone

4.5. Personality and Needs on Emotional State

Each emotion has a certain inducement or stimulus. These stimuli can be auditory, visual, verbal, or other. Different types of stimuli can cause different emotional states. With the disappearance of external stimuli, the emotional state should gradually tend to the initial state. According to the response characteristics of emotional bell ringing, it is assumed that the stimulus type is an emotional stimulus with an emotional intensity of 0.8. A stimulus signal with an intensity of (0.8,0) is applied at equal time intervals, and the personality parameter is [0,0,0,0,0]. Under the same stimulation state, the personality parameter is P=[0.4,0.5,0.25, 0.8, 0.2], that is, the emotional change of the emotional state change process model produced in the case of introverted personality is shown in Figure 5. It can be seen from Figure 5 that personality parameters change the intensity of emotion and the duration of change. The emotional intensity of introverted personality decreases, but the duration of emotional state changes increases, which reflects that the emotional state of introverted personality is more stable and less affected by external stimuli, which is basically consistent with the law of human emotional changes. Set the initial need state D=0, and the external stimulus is the stimulus signal that meets the need state. Personality parameter P=[0.4,0.5,0.25,0.8,0.2]. It can be seen from Figure 5 that the emotional intensity of the first few times increases gradually, but under the repeated stimulation, the emotional intensity of the virtual person will decrease. This is more consistent with the weakened response under repeated stimulation in physiology and psychology. After the virtual human needs to meet the threshold, it needs to be switched to another state. Keep other parameters unchanged, and still apply the stimulus signal with equal time interval intensity (0.8, 0). This is because the stimulus signal is judged as an interference signal by the need module at this time, and the number of needs satisfaction cannot be increased. The number of needs satisfaction is in a spontaneous attenuation state, and the stimulation signal will aggravate the generation of negative emotions. This is also consistent with the psychological mechanism of emotions, that is, the polarity of a person's emotions is determined by the relationship between objective things and individual needs. Satisfying needs produces positive emotions, and dissatisfied needs produce negative emotions.

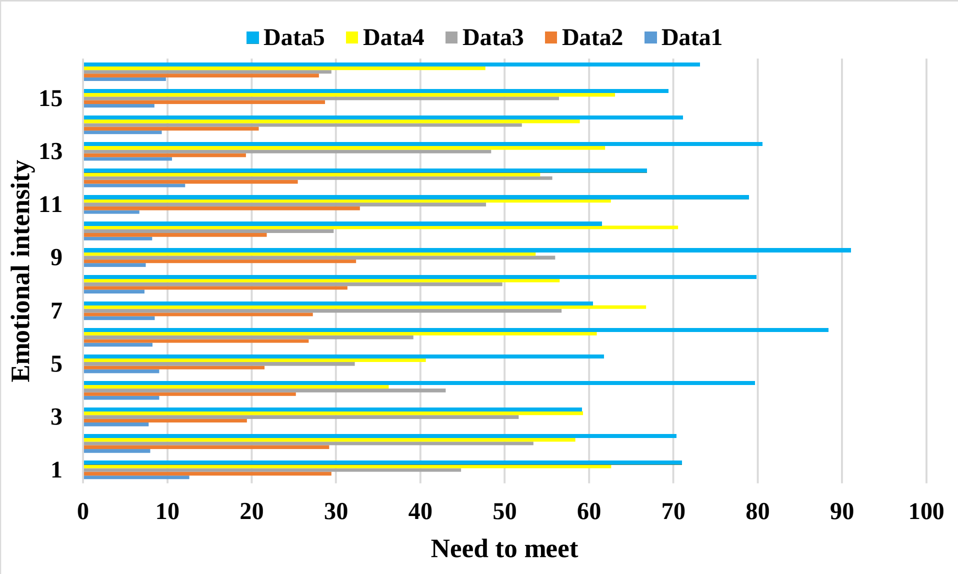

Figure 5: Emotional changes of the model of emotional state changes in the case of introverted personality

5. Conclusion

Among many voice emotion parameters, some are difficult to detect, and some require professional analysis, so it is not practical to use them all. According to the feasibility of operation, this model adopts three reference quantities of average fundamental frequency, sound intensity, and fundamental frequency range when improving. As a preliminary attempt to simulate sound emotion, these three quantities can basically meet the requirements and are easy to obtain and detect. This research refers to the conclusions of psychological sound statistics, collects the sound signals in language expression, processes the signals, extracts the average fundamental frequency, sound intensity, and fundamental frequency range data, comprehensively designs, and obtains an emotional model that can process sounds. Although this emotional model cannot reach the level of understanding the meaning of the speaker's words (the understanding of robotic language has yet to be developed), the emotions aroused by sounds can be simulated.

This research uses hidden Markov model to recognize facial expressions and describe the output probability of emotional state changes. In terms of emotional feature extraction, this study uses acceleration sensors to determine the user's activity status, and uses light sensor data and GPS data to collect environmental data. In order to reflect the individual emotion and its intensity, the emotion space method can be used to effectively process and reflect the emotion vector. Because the FACS system is too complex, this model simplifies it. The reflected emotion calculated from the emotional space corresponds to a series of AU parameters. These parameters form the corresponding facial expression. The intensity of these parameters is determined by the emotional vector. The size of the mold is determined. Finally, a sound processing module is added before the emotional parameter extraction module of the emotional model for better emotional interaction.

The perception system obtains and processes sensor information, mainly speech recognition and facial expression recognition, and effectively transforms the recognition results into emotional measures and transmits them to the emotional system to stimulate the appearance and changes of emotions. The emotional system is composed of three related subsystems: needs, emotions, mood, and personality. The module needs to evaluate the type and importance of perceptual events to determine the type and intensity of emotional responses; the emotional module experiences emotional stimulation and emotional updates Two processes, the updated emotional state is output to the behavior module; the personality module is used to change the threshold of emotional excitation and the rate of attenuation, which affects emotional excitation and emotional changes.

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