EXPLORING THE DIRECTION OF THE ENGLISH TRANSLATION OF ENVIRONMENTAL PROTECTION ARTICLES BASED ON THE ROBOT COGNITIVE-EMOTIONAL INTERACTION MODEL

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Reception: 01/12/2022 **Acceptance**: 16/01/2023 **Publication**: 05/03/2023

Suggested citation:

S., Shuai. (2023). **Exploring the direction of the English translation of environmental protection articles based on the robot cognitive-emotional interaction model**. *3C TIC. Cuadernos de desarrollo aplicados a las TIC, 12(1)*, 222-246. https://doi.org/10.17993/3ctic.2023.121.222-246

ABSTRACT

To broaden the application area of the cognitive-emotional interaction model for robots. In this paper, an algorithmic model for the English translation of environmental articles based on a cognitive-emotional interaction model for robots is used to model the process of emotion generation using reinforcement learning. Similarly, positivity and empathy are used to quantify the reward function for emotional state assessment, and the optimal emotional strategy selection is derived based on the utility function. In the process of article translation by the robot, Lagrangian factors are introduced to make the translation probability maximum process transformed into the process of obtaining the highest value of the auxiliary function at a random state. Finally, the effectiveness of the robot's cognitive-emotional interaction model in the English translation of environmental protection articles is verified by the Chinese-English parallel question-and-answer dataset. The experimental results demonstrate that this model can not only be used for the English translation of environmental protection articles but also can give the corresponding English translation work similar to human emotions, which can better help people understand the meaning of English. It also provides a basis and direction for the subsequent in-depth application of the robot cognitive-emotional interaction model in various fields.

KEYWORDS

Robot cognitive model; Emotional interaction model; Optimal emotional strategy; Emotional state assessment reward function; Reinforcement learning model

https://doi.org/10.17993/3ctic.2023.121.222-246

PAPER INDEX

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1. INTRODUCTION

In recent years, with the introduction and implementation of the concepts of "smart home", "smart community" and "smart city", human-computer interaction has become an indispensable part of the public's daily life [1-4]. People expect robots to have the cognitive-emotional computing ability to generate advanced anthropomorphic emotions while satisfying daily interaction needs [5]. At the same time, as the intersection of psychology, cognitive science, and artificial intelligence has intensified, researchers have found that robot cognition should be reflected in both "intelligence" and "emotional intelligence" [6]. Therefore, robot cognition and computation of emotional interaction models have become a hot topic in the field of intelligent robot research [7].

Emotional interaction cannot be achieved without the technical means of artificial intelligence [8]. For nearly two decades, AI researchers have been trying to empower machines with cognitive abilities to recognize, interpret, and express emotions [9]. Artificial intelligence techniques simulate human emotional cognition and decision-making processes by correlating, analyzing and reconstructing data containing emotional information in different scenarios with each other, and eventually transforming the data into abstracted thoughts that computers can understand [10-12]. The affective interaction process uses the user's modal data to achieve recognition of the user's affective state and uses the feedback information from the affect recognition to perform affective modeling based on cognitive analysis and to guide the interaction behavior [13-14]. Thus, the sentiment recognition process and the sentiment modeling process are the two most important steps of sentiment interaction [15].

In recent years, numerous valuable research approaches have emerged in the field of cognitive and affective interaction modeling for robots. The literature [16] argues that cognitive-emotional computing is about giving computers the human-like ability to observe, understand, and generate various emotional states so that they can interact in a naturally intimate, lively, and interesting way like humans. The literature [17] proposed an emotional interaction model based on guided cognitive reassessment strategies GCRs, which can reduce the robot's dependence on external emotional stimuli and promote positive emotional expression of the robot to some extent. The literature [18] proposed a personalized emotion model based on PAD and established a three-level mapping relationship between personality space, mood space and emotion space to describe the human emotion change pattern. The literature [19] used electrophysiological techniques and MRI to study the expression of cognition and emotion in the brain during behavior. In the literature [20], cognitive feelings were identified as an emotional experience, and this was confirmed by observing changes in the physiological and behavioral representations of validity and arousal in a cognitive task. In [21], a willingness-based interpretable and computational emotion model and CASE, a personality model to measure robot differences, were proposed to improve the performance of multiple robots in pursuit of tasks by using a willingness to quantify the effect of emotional factors on task assignment through an emotional contagion model to compute inter-robot emotional interactions. In the literature [22], by conducting emotion-cognition-related experiments, it was found that emotional

https://doi.org/10.17993/3ctic.2023.121.222-246

states affect the input of cognitive control in the brain and the associated metacognitive experience. The literature [23] established a multi-emotion dialogue system MECs by multi-task Seq2Seq learning, and after multi-task learning based on question-answer datasets, the candidate answer with the most similar emotion to the input interrogative was selected as the output of the robot, which achieved better results in a single round of dialogue. The literature [24] proposed an integrated framework for emotion computation, which firstly considers personality traits, social content and other factors for the evaluation of external emotional stimuli, secondly considers mood states, internal memories and other factors for the generation of emotions, and finally performs the expression of intelligent behaviors based on the generated emotions. The literature [25] assesses students' interest in learning events based on a combination of OCC affective modeling and fuzzy reasoning, which is a means of using affective modeling as an aid to affect recognition prediction. The literature [26] implements the process of natural change in robot emotions, which for interactive behavior is still based on discrete rules for emotion mapping. The literature [27] uses statistical features of skin electrical signals, ECG signals with body temperature and time-frequency features for global generalized emotion recognition. The literature [28] uses hierarchical support vector machines for reducing the bias of robot cognitive training binary classifiers. The literature [29] proposes an emotion model based on the Pruschik emotional color wheel to enable social robots to mimic human emotional changes and personality traits in entertainment and education to talk naturally with people. The literature [30] builds an affective cognitive model that implements emotion generation based on external event motivation and regulates the flow of information generated by the generated emotions through the competition under different drivers to determine the behavioral output.

In this paper, a reinforcement learning-based cognitive emotional interaction model for robots is proposed [31-32]. First, reinforcement learning is used to model the emotion generation process, and the one-dimensional emotion model theory is used as the emotion state space of the robot, which motivates the robot to improve efficiency in the process of emotional interaction; second, three emotional influencing factors of similarity, positivity and empathy are considered to quantify as the reward function for conducting emotional state assessment, and the optimal emotional strategy selection is derived based on the The optimal emotional strategy selection is derived based on the effectiveness function to realize the interaction motive of emotional support, emotional guidance and emotional empathy for the participants; thirdly, Lagrange factor is introduced in the process of environmental protection English articles translation by the robot, which makes the process of the highest value of machine translation probability transform into the process of obtaining the highest value of the auxiliary function at the random state. The retrieval speed of machine translation is improved, the efficiency of machine translation is enhanced, and high-precision translation results can be obtained more effectively. Finally, the Chinese-English parallel question-and-answer corpus commonly used in environmental protection articles is used as the experimental data set, and the optimal emotional state is combined with the optimal emotional state to update the robot's emotional state transfer probability, to realize the robot's state transfer in the translation process

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and ensure the continuity of the translation process. The experiments validate the model's effectiveness in terms of accuracy, MAP and MRR.

2. A COGNITIVE MODEL OF THE ROBOT WITH EMOTION AND MEMORY MECHANISM

2.1. COGNITIVE MODEL STRUCTURE

Different disciplines, such as brain science, cognitive neuroscience, and cognitive psychology, have researched brain structure and its emotional and cognitive principles. The results show that emotional and cognitive functional areas of the brain are mainly concentrated in the thalamus, limbic system, and cerebral cortex. The thalamus, as the sensory transmission center, is responsible for the transmission of external sensory information such as visual, auditory and olfactory information, as well as internal sensory information. The limbic system, as the emotional center, mainly includes the hippocampus, amygdala, and cingulate gyrus. The hippocampus is responsible for emotional memory and learning, the amygdala is responsible for emotion generation, regulation, and recognition, while the anterior lower part of the cingulate gyrus is related to emotional processing and the posterior upper part is related to cognitive functions. These structures are linked to the hypothalamus and the vegetative nervous system and are involved in regulating instinctive responses and emotional behavior; the cerebral cortex is mainly involved in human brain activities such as understanding events, making decisions about goals, and managing the timing of behavior.

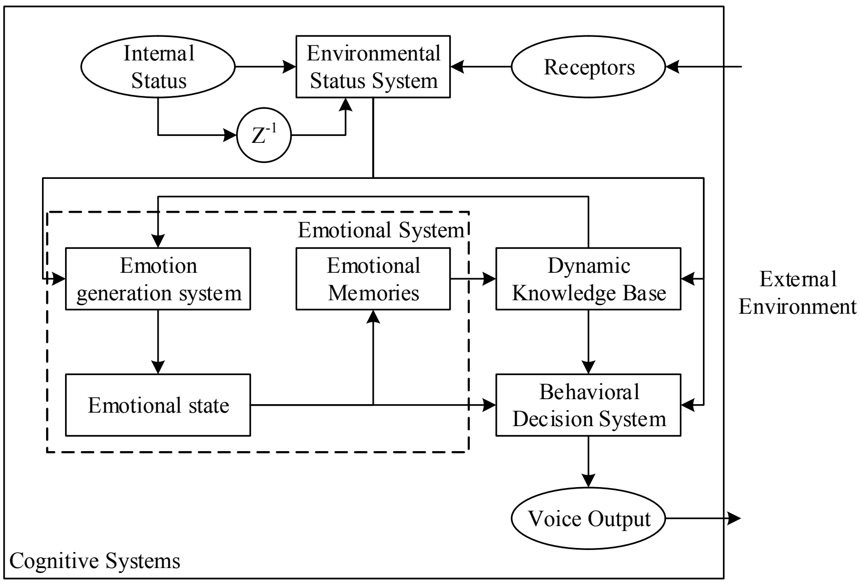

Figure 1. Cognitive model structure

Based on the above cross-disciplinary research foundation, this paper proposes a robot cognitive model, which contains seven parts: receptor, internal state, environmental state system, emotional system, behavioral decision system, dynamic

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knowledge base, and execution output, and the model structure is shown in Figure 1. The meanings of each part are as follows:

(1) Receptors: feel all kinds of information from the external environment, and represent the felt information as a triad:

$$PER\_ORG = \langle S, A, Ga \rangle \quad (1)$$

Where $S = \{S_i \mid i = 1,2,\cdots,n_s\}$ is the set of perceptible discrete states, $A = \{A_i \mid i = 1,2,\cdots,n_s\}$ is the set of optional action subsets corresponding to discrete states, $Ga = \{Ga_i \mid i = 1,2,\cdots,n_s\}$ is the set of maximum internal energy state replenishment corresponding to discrete states, and 4 is the number of perceptible discrete states.

(2) Internal state: the internal state information of the robot body, such as the internal energy robot and the durability of the robot. The internal state of the robot is the internal energy state $P(t)$, that is:

$$P = \{P(t) \mid t = 1,2,\cdots,n_t\} \quad (2)$$

Where P is the set of energy states inside the robot body, n_t is the robot task survival time, t=0 means the robot is at the task start moment; $t = n_t$ represents the robot body internal energy state is zero or the task completion moment.

(3) Environmental state system: the robot's external environmental information and the body's internal state hub station, denoted as: $\langle PER\_ORG, P, G \rangle$. Where $G = \{G(t) \mid t = 1,2,\cdots,n_t\}$ is the set of internal energy state gains obtained by the robot from discrete states, and the internal energy state gains are defined as follows:

$$G(t) = \begin{cases} P(t) - P(t-1) & Ga(t) \neq 0 \\ G(t-1) & Ga(t) = 0 \end{cases} \quad (3)$$

Where $Ga(t)$ is the maximum internal state replenishment Ga_i corresponding to the discrete state at the time t.

(4) Emotional system: robot emotional state and emotional memory generation center, expressed as a triad:

$$EMO\_SYS = \langle E, R_{emo}, R_{men} \rangle \quad (4)$$

Where $E = \{E(t) \mid t = 1,2,\cdots,n_t\}$ is the set of emotional states generated by the emotion generation system; $R_{emo} = \{R_{emo}(t) \mid t = 1,2,\cdots,n_t\}$ is the set of inverse emotional rewards generated by the emotional memory; $R_{mem} = \{R_{mem}(T) \mid T = 1,2,\cdots,n_T\}$ is the set of periodic emotional rewards generated by the emotional memory, n_T is the robot task survival time internal energy state recharge cycle, $T = 1$ represents the first internal energy state recharge; $T = n_T$ represents the robot internal energy state before zero or the completion of the task maximum energy recharge cycle.

(5) Behavior decision system: Based on the output of the environment state system and the emotion system, we combine the dynamic knowledge base to realize the

robot's behavior decision. It is expressed as a binary group: $\langle \pi, a \rangle$, where $\pi = \left\{ \pi_j | j = 1,2,\cdots,n_j \right\}$ is the set of behavioral decisions, n_j is the number of behaviors of the translation robot, $a_m = \left\{ m = 1,2,\cdots,n_m \right\}$ is the set of translation word selection, and n_m is the number of actions of the translation robot. For the English translation task of environmental protection articles requiring "energy replenishment", the robot's behaviors are divided into the search, energy replenishment, and search actions for the selection of $\{north, south, east, west\}$ directions at each node of the article.

(6) Dynamic knowledge base: Knowledge base of English words for robotics and environment, with knowledge elements represented as five-tuples:

$$DYN\_KNO = \langle A', EL, D, STA\_EGW, STA\_PWO \rangle \tag{5}$$

$A' = \{A'_i | i = 1,2,\cdots,n_s\}$ is the set of discrete states corresponding to the best action of energy replenishment; $EL = \{EL(T) | T = 1,2,\cdots,n_T\}$ is the set of word search states; $D = \{D(T) | t = 1,2,\cdots,n_t\}$ is the set of environment search states; $STA\_EGW = \langle (Y, U), (Y', U') \rangle = \{(Y_k, U_k), (Y'_c, U'_c) | k = 1,2,\cdots,n_k, c = 1,2,\cdots,n_c\}$ is the set of state-English word memory, (Y, U) records the sequence of states encountered and English word selection during the cycle, n_k represents the total number of discrete states encountered during the cycle, (Y', U') records the last state encountered during the cycle and the sequence of English word selection for that state, n_c, $STA\_PWO = \{(Y''_z, B_z) | z = 1,2,\cdots,n_z\}$ is the state-energy memory set, which records the discrete states encountered during the cycle and the internal energy states required to return to the energy recharge point B_z,n_z is the number of discrete states encountered during the search cycle, STA_EGW and STA_PWO reflect the memory function of the robot cognitive model.

(7) Execution output: the robot article translation output actuator and the action actuator are represented as a binary group: $\langle V1, V2 \rangle$. Where $V1 = \{V1_m | m = 1,2,\cdots,n_m\}$ is the first article translation output set; $V2 = \{V2_m | m = 1,2,\cdots,n_m\}$ is the correction article translation output set.

2.2. EMOTION GENERATION SYSTEM

To study robots with emotional mechanisms, first of all, artificial emotions have to be generated, which requires modeling emotions. In this paper, based on the theory of the one-dimensional emotion model, an emotion interaction model is designed for the emotion generation system, which can generate six emotions: happy, surprised, disgusted, angry, fearful and sad, in the following form:

$$E(t) = \frac{G(t)}{k_1}[\arctan(P(t) - k_2) + \frac{P(t) - B(t)}{k_3}] \cdot e^{-D(t)} \tag{6}$$

$$E(t) = G(t) \cdot e^{\frac{2P(t) - B(t) - k_4}{k_5} - D(t)} - k_6 \tag{7}$$

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Where $B(t)$ is the internal energy state value B_z required to return to the energy recharge point corresponding to the discrete state at the time t. The emotional intensity $|E(t)|$ is positively related to the internal state gain $G(t)$ obtained by the robot. When $G(t) > 0$, (6) produces four emotions: happy, surprised, sad, and fearful, with positive happy emotion at $E(t) > 0$ and fearful emotion at $k_7 < E(t) < 0$. When $G(t) < 0$, (7) produces angry emotion at $k_6 < E(t) < k_5$ and disgustful emotion at $k_7 < E(t) < k_6$. $k1 \sim k7$ is the emotion model parameters.

2.3. INCENTIVE MECHANISM

In everyday life, rewards are usually sparse. The performer often needs to go through a series of attempts during a task until the task is completed to obtain a reward, and no reward is manifested during the process. However, the human brain possesses a reflective mechanism that can establish a relevant connection between the temporal situation and the target thing and obtain a reward based on the memory mechanism. Therefore, in this paper, while considering affective cognition, we combine memory cognition, based on the framework of reinforcement learning theory, to integrate intra-emotional reward with memory. A reward mechanism is proposed, which consists of environmental reward, reversed affective reward and periodic affective reward. Among them, the reversed affective reward and the periodic affective reward are internal rewards.

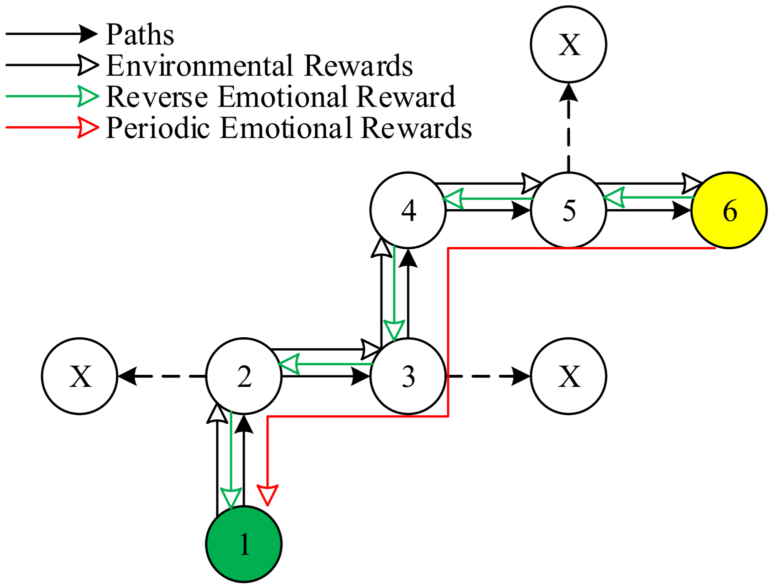

Figure 2. Schematic diagram of the robot cognitive reward mechanism

Figure 2 shows the process of obtaining a search reward for an article to be translated by the article English translation robot (schematic diagram). The robot consumes internal energy during the search process, and translates the word a_m selection according to the optional action subset $A_i \in \{north, south, east, west\}$ of nodes, assuming that node 1 is the energy replenishment point and node X indicates the unsearched point. As shown in Figure 2, the robot search trajectory is:

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$1 \to 2 \to 3 \to 4 \to 5 \to 6$, if it reaches node 6, the robot must go back to node 1 to replenish the internal energy state to maintain the next search, the return trajectory is: $6 \to 5 \to 4 \to 3 \to 2 \to 1$, the robot from the energy replenishment point to search and then back to the energy replenishment point. At this point, the article English translation robot completes a cycle of the search for the article to be translated. The reward mechanism in this process generates rewards $R = \langle R_{env}, R_{emo}, R_{mem} \rangle$, and each reward is shown in Table 1:

Table 1. Schematic diagram of the robot cognitive reward mechanism

Reward type	Reward collection
R_{env}	$R_{env1\to2}, R_{env2\to3}, R_{env3\to4}, R_{env4\to5}, R_{env5\to6}$
	$R_{env6\to5}, R_{env5\to4}, R_{env4\to3}, R_{env3\to2}, R_{env2\to1}$
R_{emo}	$R_{emo1\leftarrow2}, R_{emo2\leftarrow3}, R_{emo3\leftarrow4}, R_{emo4\leftarrow5}, R_{emo5\leftarrow6}$
R_{mem}	$R_{mem6\to5\to4\to3\to2\to1}$

Where, $1 \to 2$ process to node $R_{env1\to2}$, 2 is the external environment reward for node 1 to obtain action toward node 2; $R_{emo1\leftarrow2}$ is the reward for node 2 to obtain action toward node 1, i.e., the reverse emotional reward. $6 \to 5 \to 4 \to 3 \to 2 \to 1$ the process to node 1, $R_{mem6\to5\to4\to3\to2\to1}$ is the reward for node 6, node 5, node 4, node 3, and node 2 to obtain the tendency to node 1 action step by step, i.e., the periodic affective reward.

The environment bonus is set according to (8). The energy replenishment point is the node where the robot replenishes internal energy during the article translation process; the dead-end node is the node where only the "return" action can be selected when there is a single word that cannot be searched; the trap point is the node where the robot loses additional internal energy at this node; and the normal node is the node with internal state gain $Ga(t) = 0$ and is not a dead-end node. The Q value is updated by (9), s is the current state, a is the current action state of the selected English word, α is the learning rate, and $max\ Q(s', a')$ is the maximum gain of the next state after the current state selected action.

$$R_{env}(t) = \begin{cases} 100 & \text{Energy recharge point} \\ 0 & \text{General Node} \\ -5 & \text{Dead end nodes} \\ -100 & \text{Trap point} \end{cases} \tag{8}$$

$$Q(s,a) = (1-\alpha)Q(s,a) + \alpha[R_{env} + \max Q(s',a')] \tag{9}$$

The reverse sentiment reward is set as in equation (10), and the Q value is updated as in equation (11), with a'' the reverse direction at the time of entering this node state.

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$$\mathrm{R}_{emo}(t) = \begin{cases} E(t) & \mathrm{E(t)>0} \\ \dfrac{1}{|E(t)|} & \mathrm{E(t)>0} \end{cases} \tag{10}$$

$$Q(s,a'') = \mathrm{R}_{emo} \tag{11}$$

The cycle sentiment reward is set according to equation (12), where $E(T)$ is the sentiment state generated at the moment of completion of the Tth cycle, and the Q value is updated according to equation (13); this reward is obtained only when the cycle is completed.

$$R_{mem}(T) = \begin{cases} E(T) & \mathrm{T>0} \\ 0 & \mathrm{T=0} \end{cases} \tag{12}$$

$$Q(s,a) = (1-\alpha)Q(s,a) + \alpha[R_{mem} + \max Q(s',a')] \tag{13}$$

3. GAME MODEL BASED ON COGNITIVE-EMOTIONAL INTERACTION MODEL OF ROBOT

3.1. GAME MODEL

Modeling the emotion generation process of the participant and the robot during human-robot interaction, the emotional cognitive interaction model tries to get the optimal emotional response of the robot based on the previous historical emotion and the current interaction input emotion of the participant, which leads to a more natural and harmonious human-robot interaction, i.e., the optimal E_{RH}^{k+1} is obtained by knowing $E_{HR}^{l}(1 \leq l \leq k)$, as shown in Figure 3 (R denotes the robot and H denotes the participant object).

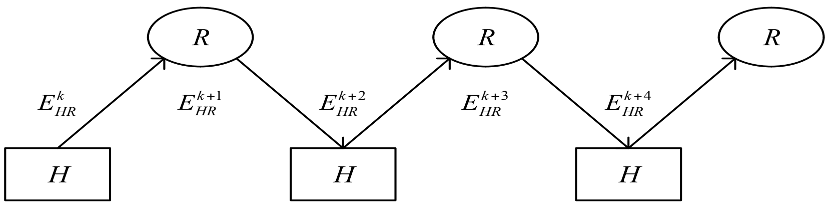

Figure 3. Human-machine interaction process

To facilitate theoretical analysis, as mentioned above, this paper unifies and normalizes the emotional strategies of the participating object and the robot in the human-robot interaction process into six basic emotions. After the robot is stimulated by the external emotion of the participant E_{HR}^{k}, it then selects the optimal emotion strategy from the six basic emotions. In the process of making the optimal emotion selection, the robot needs to perform the emotion trend prediction for each emotion selection. The prediction of the emotion E_{HR}^{k+2} that will be generated by the participant in $k+2$ interactions and the emotion that may be replied to by the participant in $k+3$ sessions E_{HR}^{k+3}. The emotion strategy selection process of the robot is shown in Figure 4.

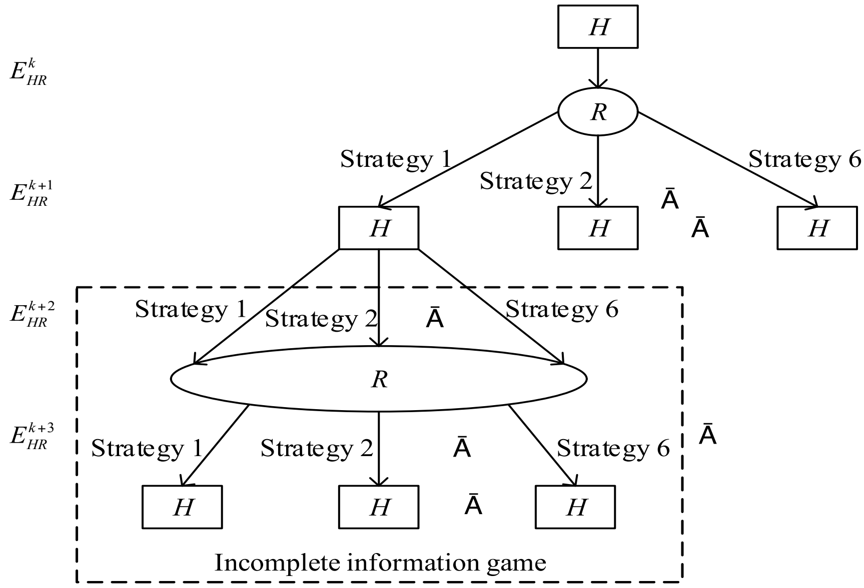

Figure 4. The emotional strategy selection process of the robot

The game model should be judged by 3 elements: the participant, the strategy combination, and the game gain. The participant and the robot constitute the two objects of the game model, and both parties make different strategy choices around subjective satisfaction, and different combinations of these strategies will produce different game outcomes. Considering the human-robot interaction, both the participant and the robot start from their subjective satisfaction, which is a non-cooperative game. In human-robot interaction, emotions are bidirectional, i.e., the subjective satisfaction of the participant is influenced by the robot's reply emotions, and the subjective satisfaction of the robot is also influenced by the participant's reply emotions, and the robot does not know what kind of emotional response it will get from the participant for $k+1$ sessions, which is an incomplete information game. Therefore, this paper uses an embedding game based on the robot cognitive-emotional interaction model to model the emotion generation process of the participant and the robot.

3.2. DEFINITION OF UTILITY FUNCTIONS

The utility is the subjective satisfaction obtained by the interacting parties during human-computer interaction without loss of generality. Consider the definition of the participant's utility function: $UH(E_{RH}^{k}, E_{RH}^{k+1}, E_{HR}^{k+2}, E_{HR}^{k+3})$ denotes k session participant interactions with an input sentiment of E_{RH}^{k}. Assuming that the sentiment value of the $k+1$ session robot response is E_{RH}^{k+1}, predict the value of subjective satisfaction obtained by the participant if the sentiment value of the $k+2$ session participant is E_{HR}^{k+2} and the sentiment value of the $k+3$ session robot is E_{HR}^{k+3}.

In this paper, we define the utility function of a participant based on whether the robot can adjust its self-friendliness according to the change in participant friendliness

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and define the utility function of a participant based on whether the value of emotional empathy between the participant and the robot keeps increasing. $UH(E_{RH}^{k}, E_{RH}^{k+1}, E_{HR}^{k+2}, E_{HR}^{k+3})$ is defined as:

$$UH(E_{RH}^{k}, E_{RH}^{k+1}, E_{HR}^{k+2}, E_{HR}^{k+3}) = 10 \cdot \left\{0.5 \frac{F_{\min}}{F_{\max}} + 0.5(R_2 - R_1)\right\} \tag{14}$$

where F_{min}/F_{max} denotes the ratio of the amplitude of change in participant and robot friendliness, and F_{min}/F_{max} tends to 1 when the amplitude of change between participants and robots is essentially the same, and vice versa, tends to 0; for F_{min} and F_{max} are defined as:

$$\left.\begin{aligned} F_{\min} &= \min(F(k+2) - F(k), F(k+3) - F(k+1)) \\ F_{\max} &= \max(F(k+2) - F(k), F(k+3) - F(k+1)) \end{aligned}\right\} \tag{15}$$

R_1, R_2 denote the empathy values between k session participant emotions and $k+1$ session bot emotions, and $k+2$ session participant emotions and $k+3$ session bot emotions, respectively. The multiplication term 10 is to ensure that the values are taken in the range [0,10].

$$\left.\begin{aligned} R_1 &= R(E_{RH}^{k}, E_{RH}^{k+1}) \\ R_2 &= R(E_{HR}^{k+2}, E_{HR}^{k+3}) \end{aligned}\right\} \tag{16}$$

The definition of the robot utility function $UH(E_{RH}^{k}, E_{RH}^{k+1}, E_{HR}^{k+2}, E_{HR}^{k+3})$ takes into account, on the one hand, the change in the participant's friendliness, and if the participant's friendliness increases, then the robot's utility value increases; on the other hand, the robot's utility value decreases. On the other hand, the robot's emotional resonance with the participant is considered based on the "principle of increase and decrease in interpersonal attraction", which is similar to the definition of the participant's utility function. Thus, the utility function of the robot is defined as:

$$UH(E_{RH}^{k}, E_{RH}^{k+1}, E_{HR}^{k+2}, E_{HR}^{k+3}) = 10 \cdot \{0.5[F(k+3) - F(k+1)] + 0.5(R_2 - R_1)\} \tag{17}$$

3.3. OPTIMAL EMOTIONAL STRATEGY SELECTION

Based on the definition of the utility function, the optimal emotional choice strategy of the robot is obtained for the emotional interaction input of the participant with the help of the game model:

(1) The emotional stimuli of k session participants, each emotional strategy of $k+1$ session robots, 6 emotional strategies of $k+2$ session participants, and 6 emotional strategies of $k+3$ session robots form a game matrix, and since $k+1$ session robots share 6 emotional strategies, there are 6 game matrices in total;

(2) Assume that the emotional choice strategy of the robot for $k+1$ sessions is s. Predict the emotional choice strategies of the participants and the robot by finding a

pure strategy Nash equilibrium for the game matrix formed by $k+2,\ k+3$ sessions, i.e.:

$$\left.\begin{array}{l} UH(E_{RH}^{k},E_{RH}^{k+1}(s),E_{HR}^{k+2}(\cdot),E_{HR}^{k+3}(\cdot)) \\ \geq UH(E_{RH}^{k},E_{RH}^{k+1}(s),E_{HR}^{k+2}(i),E_{HR}^{k+3}(\cdot)), \\ \exists E_{HR}^{k+2}(\cdot),E_{HR}^{k+3}(\cdot)\in E_{l},\forall E_{HR}^{k+2}(i)\in E_{l} \\ UH(E_{RH}^{k},E_{RH}^{k+1}(s),E_{HR}^{k+2}(\cdot),E_{HR}^{k+3}(\cdot)) \\ \geq UH(E_{RH}^{k},E_{RH}^{k+1}(s),E_{HR}^{k+2}(\cdot),E_{HR}^{k+3}(j)), \\ \exists E_{HR}^{k+2}(\cdot),E_{HR}^{k+3}(\cdot)\in E_{l},\forall E_{HR}^{k+2}(j)\in E_{l} \end{array}\right\} \tag{18}$$

(3) Solving for the optimal affective choice strategy s using the cis-induction method.

$$UH(E_{RH}^{k},E_{RH}^{k+1}(s),E_{HR}^{k+2}(\cdot),E_{HR}^{k+3}(\cdot))\geq UH(E_{RH}^{k},E_{RH}^{k+1}(s),E_{HR}^{k+2}(i),E_{HR}^{k+3}(\cdot)),\exists s(\cdot)\in E_{l} \tag{19}$$

The solution of the static embedded game Nash equilibrium is mainly for the prediction of the next session sentiment trend from the subjective satisfaction of participants and robot self, and the sub-game perfect equilibrium of the embedded game is mainly for obtaining the optimal sentiment selection strategy of the sub-session robot from maximizing the subjective satisfaction of the robot by using the parsimonious induction method to simplify the Nash equilibrium.

3.4. CONSTRUCTION OF A COGNITIVE-EMOTIONAL INTERACTION MODEL FOR ROBOTS

The game model is used to model the emotion generation process of the participant and the robot during human-robot interaction, and the optimal emotional response of the robot is obtained based on the previous historical emotions and the interaction input emotions of the participant. The model construction process is as follows:

Step 1 Input: $k-1$ post-session friendliness update values $F(k-1)$ and the probability of transferring the sentiment state of the robot $P_r(k-1)$, k sessions of participant interaction input sentiment E_{RH}^{k};

Step 2 Output: the sentiment value of the robot at $k+1$ sessions E_{RH}^{k+1};

Repeat:

Step 3 Participant input interaction emotion E_{RH}^{k};

Step 4 Calculate the utility values of the participant and robot under each sentiment strategy choice for $k+1$ the sessions robot, predicted $k+2$ sessions participant for each sentiment strategy choice, and $k+3$ sessions robot for each sentiment strategy according to Eqs. (14)-(17);

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Step 5 Solve the emotional choice strategy s of the cognitive model according to Eqs. (18)-(19);

Step 6 The probability of transferring the emotional state of the robot is updated by the optimal emotional strategy s; the human-robot interaction friendliness is updated such that $k = k + 2$;

Step 7 Until the participant stops entering interactive emotions;

Step 8 End of the HCI session.

During each round of human-computer interaction, the cognitive interaction model is mainly a matrix operation with a time complexity of constant order O(1) in the process of participant interaction input emotion evaluation and robot optimal emotion strategy selection. Assuming that the number of human-computer interaction rounds is n, the time complexity of the model is O(n), which ensures that the response time of the model during human-computer interaction is acceptable.

4. ENGLISH TRANSLATION MODEL BASED ON ROBOT COGNITIVE-EMOTIONAL INTERACTION

Setting any Chinese matrix f and an English sentence e, the probability of e being machine translated into f is $P(e|f)$. The problem of machine translation of f into e can be viewed as the process of solving equation (20):

$$\hat{e} = arg\ max\ P(e|f) \tag{20}$$

If the lengths of the English string e, as well as the Chinese string, are $f = f_1^m = f_1 f_2 \cdots f_m$ and m, respectively, then we have 1. The alignment can describe the positions of the words within the Chinese sentence corresponding to the words in the English sentence by the presence of the position information of each value, then we have $a = a_1^m = a_1 a_2 \cdots a_m$. Where the value interval of each value is [0,1], then we have :

$$P(f,A|e) = p(m|e)\prod_{j=1}^{m} p(\alpha_j | a_1^{j-1}, f_1^{j-1}, m, e) \cdot p(fj | a_1^j, f_1^{j-1}, m, e) \tag{21}$$

In this process, we generate Chinese sentences and alignment process based on English sentences, obtain Chinese sentence length based on English sentences, obtain the link position of the first Chinese word string, and then obtain the first word of Chinese sentences based on English sentences, Chinese sentence length and the position of the English sentence related to the first Chinese word, and loop the process to obtain the overall Chinese sentences.

The English translation model based on robot cognitive-emotional interaction can be implemented to simplify equation (21) and then give the model the ability of emotional interaction, which makes the text more colorful in translation and can keep the semantic and emotional color of the original text. The prerequisites set at the same time are:

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(1) If $p(m|e)$ does not correlate with the target language e and the source language length m.

(2) If $p(\alpha_j|\alpha_1^{j-1}, f_1^{j-1}, m, e)$ is related to the target language e length l, then we have:

$$p(\alpha_j | a_1^{j-1}, f_1^{j-1}, m, e) = \frac{1}{l+1} \tag{22}$$

(3) If $p(\alpha_j|\alpha_1^{j-1}, f_1^{j-1}, m, e)$ is related to f_j and f_{al}, then there exists $\varepsilon = P(m|e)$, $t(f_j|e_{al}) = p(f_j|a_1^j, f_1^{j-1}, m, e)$. $t(f_j|e_{al})$ is the probability given e_{al} and f_j.

After incorporating the Lagrangian factors λ_1, the process of obtaining the highest value of machine translation probability is transformed into the process of obtaining the highest value of the auxiliary function at the random state, then the English machine translation model based on the robot cognitive-emotional interaction model is as follows:

$$h(p,\lambda) = \frac{s}{(l+1)^m} \sum_{al=0}^{l} L \sum_{al=0}^{l} \prod_{j=1}^{m} t(f_\theta | \alpha_\theta) - \sum_{\theta} \lambda_\theta (\sum_{l} t(f|e) - 1) \tag{23}$$

The above English machine translation model is transformed into a reverse machine translation model to accomplish accurate machine translation of the English language using the statistical machine method of maximum entropy. The transformation within the model ensures that the machine translation efficiency of the machine translation model is improved by obtaining improved parameter values through the great likelihood prediction method as follows:

$$\hat{\theta} = \arg\max_{\theta} \prod_{s=1}^{S} p_\theta(f_s|e_s) \tag{24}$$

$$\hat{\gamma} = \arg\max_{\gamma} \prod_{s=1}^{S} p_\gamma(e_s) \tag{25}$$

and then obtain the formula:

$$\hat{e}_1^l = \arg\max_{e_1^l} \{p_{\hat{\gamma}}(e_1^l) \cdot P_{\hat{\theta}}(f_1^j | e_1^l)\} \tag{26}$$

After incorporating the new property, $P_{\hat{\theta}}(e_1^j|f_1^l)$ replaces $P_{\hat{\theta}}(f_1^j|e_1^l)$ and the framework of the obtained extended statistical machine translation is:

$$\hat{e}_1^l = \arg\max_{e_1^l} \{p_{\hat{\gamma}}(e_1^l) \cdot P_{\hat{\theta}}(e_1^j | f_1^l)\} \tag{27}$$

Equation (27) enables the implementation of more efficient retrieval and the acquisition of high-quality English machine translation results.

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5. EXPERIMENTAL DESIGN AND ANALYSIS OF RESULTS

5.1. EXPERIMENTAL DESIGN

To facilitate the performance analysis and comparison experiments of the robot-based cognitive-emotional interaction model proposed for the text, an English text translation robot based on the robot-based cognitive-emotional interaction model of this paper is built using the open-source chatbot ChatterBot. First, the English translation model is used to match English translation answers of environmental protection articles with the translation robot logic adapter, and the top answers with higher confidence are returned as the candidate answer set; then, the sentiment strategy is evaluated using the model of this paper, and the optimal sentiment strategy is selected. Finally, the candidate answers are optimally ranked based on the response sentiment of this paper's model, and the answer with the highest ranking level is selected as the robot response output. In addition, since the number of emotional states to be explored increases exponentially with the number of interaction rounds, the maximum number of interaction rounds T=8 (rounds) for two bits of intelligence and the number of candidate emotional states selected in each round n=8 (kinds) are set in this model for emotional state evaluation.

The experimental data uses the sample dataset from the NLPCC2017 shared task Emotional Conversation Generation, which contains a total of 11207 Chinese-English parallel question-and-answer corpus of articles about environmental protection. 6000 question and answer pairs are randomly divided as the validation set, 5000 question and answer pairs as the test set, and the remaining question and answer pairs are used as the training corpus for the chatbot to translate from English to Chinese.

The experiment focuses on the translation and affective accuracy of the English translation of environmental protection articles, as well as the actual effect of human-computer interaction sessions, so the following cognitive models are selected for comparison experiments:

(1) A single robot cognitive model, Chatterbot, outputs responses based on the high confidence level of each answer in the candidate answer set. Since it does not have cognitive-emotional computing capability, it is only used for model validation comparison experiments;

(2) Emotional Chat Machine ECM, which can produce appropriate responses in terms of content-related grammar and emotional coherence;

(3) Adversarial network SentiGAN model, capable of generating generic, diverse and high-quality sentiment texts;

(4) Two-way asynchronous sentiment session generation method E-SCBA, which can generate text with a logical and emotional degree;

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(5) An emotional interaction model based on the guided cognitive reassessment strategy GCRs can reduce the robot's dependence on external emotional stimuli and, to some extent, prompt positive emotional expressions.

5.2. EMOTIONAL ACCURACY ANALYSIS

To avoid the ambiguity of the robot's emotional expression that makes it difficult for the participants to recognize the response emotion state, the response emotion state should have a certain degree of accuracy in the expression of the expected emotion category. To visually evaluate the accuracy of the robot's emotion generation state under the action of each model, the accuracy of the target emotion category of the response emotion is calculated:

$$Acc(E_{RH}^{k+1}) = P_{k+1}(i) - \frac{1}{5}\sum_{j\neq i} P_{k+1}(j) i, j = 1,2,\cdots,6 \tag{28}$$

The results are shown in Table 2. As can be seen from Table 2, the models in this paper are better than other models in terms of sentiment accuracy, which is mainly because the confidence of the input response sentiment state to each basic sentiment state transfer probability is used as the update factor when the robot sentiment state transfer probability is updated. This is mainly because the confidence of the input response emotional state to each basic emotional state transfer probability is used as the update factor in this paper, which effectively increases the influence of the input response expected emotional category on the robot's emotional state transfer probability.

Table 2. Statistical table of sentiment accuracy for different models

Cognitive models	Accuracy
ECM	0.785
GCRs	0.821
E-SCBA	0.802
SentiGAN	0.856
This article	0.895

5.3. RETRIEVING TRANSLATION VALIDITY

To facilitate the verification of the effectiveness of model answer retrieval translation, two information retrieval evaluation indexes, MRR and MAP, were used to calculate the sorting accuracy of each model candidate answer, 60 sentences were randomly selected from the test set for the experiment, and the average of the sorting accuracy was taken as the final result of the experiment, and the results are shown in Figure 5.

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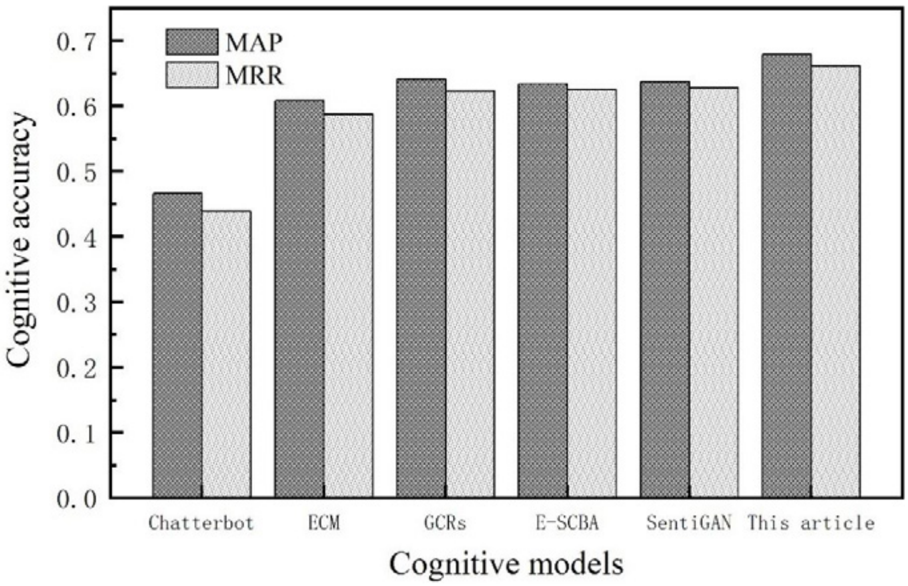

Figure 5. Different models retrieve translation accuracy statistics

Figure 5 shows the statistical results of the average accuracy of retrieving translation ranking for different cognitive model answers (m=6), and it can be seen from the table that this paper's model achieves relatively satisfactory results compared with other models. This is because the model in this paper ensures more effective retrieval by combining quantitative evaluation of contextual affective states and quantitative analysis of factors influencing human-like affective states when ranking candidate answers, and transforming the translation model into a reverse machine translation model by incorporating Lagrangian factors in the English translation model, to obtain high-quality English translation results. Reinforcement learning is used to establish the correlations between contextual long-term affective states to achieve a comprehensive and optimal assessment of the following state response with better cognitive affective ability.

5.4. VALIDATION OF INTERACTION TRANSLATION

To effectively evaluate the effectiveness of interactive sessions, 20 volunteers were invited to participate in multiple human-computer interaction translation tests under different models in this paper. At the same time, to increase the objective comparability among the models, each model was subjected to 30 rounds of multi-round human-computer interaction conversation experiments. Thirty English sentences were randomly selected from the test set and used as the initial input for each model to conduct interactive sessions. The average number of conversations and the average interaction time for each model are shown in Table 3.

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Table 3. Conversation translation rounds and interaction time statistics table

Cognitive models	N(rounds)	T(s)
Chatterbot	7	67.51
ECM	10	98.54
GCRs	15	137.51
E-SCBA	12	119.47
SentiGAN	10	107.63
This article	18	152.92

As shown in Table 3, this model outperforms other models in terms of the average number of conversation rounds and the average interaction time, which indicates that the translation robot under the effect of this model can better express the meanings expressed in English, can better communicate with people in English, and can effectively extend the human-robot interaction session time. This is because the response emotions obtained from the model in this paper are more diverse, positive and accurate by considering human-like emotion generation in the continuous space of multiple emotion states and combining with the robot's emotion state update, which effectively guides the participants to participate in human-robot interaction.

5.5. MODEL SATISFACTION ASSESSMENT

To evaluate the model satisfaction effectively, this paper conducts questionnaire experiments in two aspects: single-round sentence translation and dialogue subjective satisfaction, and multi-round sentence translation and conversation subjective satisfaction. The evaluation indexes of subjective satisfaction with single-round sentence translation and conversation are rationality, diversity, and empathy. The experiment process is as follows: 100 question-and-answer phrases are randomly selected from the test set for the test, 500 question-and-answer pairs are used in total, and 200 volunteers are invited to conduct the questionnaire survey online and offline through multiple channels. The evaluation indexes of subjective satisfaction of multi-round sessions were fluency, positivity, interestingness and participation. The experimental process is as follows: based on the evaluation indexes, a multi-round session satisfaction survey is conducted for 20 HCI volunteers in the validation of interactive sessions. At the same time, all indicators were evaluated using a three-point scale (0,1,2): 0 indicates a low degree, 1 indicates an average degree, and 2 indicates a high degree. The final statistical results were averaged, and the higher the score the higher the model satisfaction. The results of the model's single-round sentence translation and dialogue subjective satisfaction survey are shown in Figure 6, and the results of the multi-round sentence translation and dialogue subjective satisfaction survey are shown in Figure 7.

As seen in Figure 6, the model in this paper is significantly better than other models in terms of dialogue rationality, diversity and empathy, especially in terms of diversity

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of emotional expressions, which is because this paper makes full use of multiple emotional states in the emotional space when making emotional decisions, and the results show that the model in this paper can effectively improve the satisfaction of the robot's single-round dialogue response in many ways.

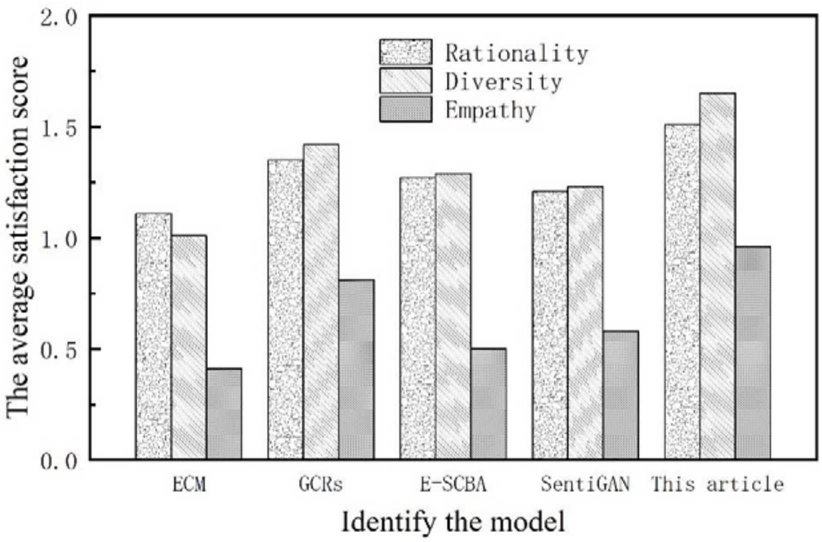

Figure 6. Statistical chart of single-round subjective evaluation data

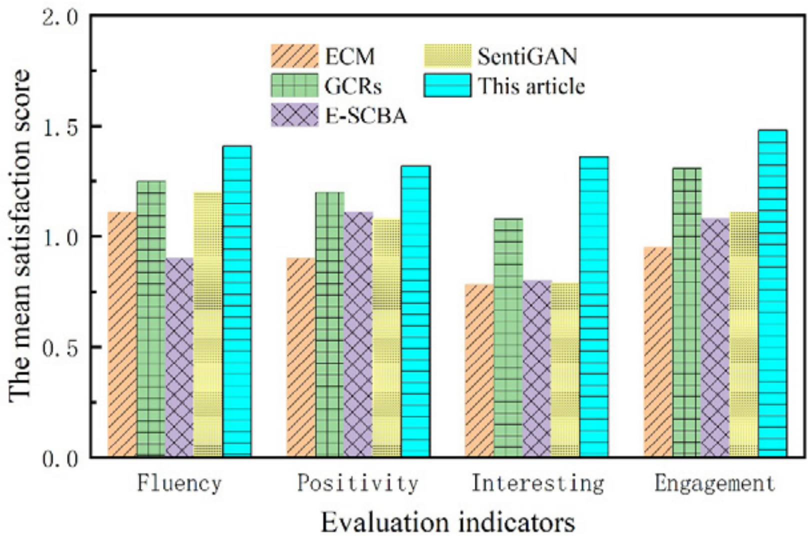

Figure 7. Statistical chart of subjective evaluation data for multiple rounds

As can be seen from Figure 7, the model in this paper has effectively improved the overall fluency and positivity of the robot's emotional utterance translation expression, the interestingness of human-robot interaction, and the participant's involvement compared with other models, indicating that the contextual long-term dependency relationship and the factors influencing emotion generation established in this paper are reasonable and effective in the construction of the emotional interaction model, which can further increase the participant's willingness to interact with human-robot and build a natural and harmonious human-robot interaction relationship.

6. CONCLUSION

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Robot cognitive-based affective interaction computing is to give computers the ability to observe, understand and generate various emotional states similar to human beings, so that they can interact naturally and intimately, vividly and interestingly like human beings. In this paper, we propose a reinforcement learning-based emotional interaction model for robot cognition. First, we use reinforcement learning to model the emotion generation process, and use the one-dimensional emotion model theory as the emotion state space of the robot, with small granularity of emotion division and delicate expression, which motivates the robot to improve efficiency in the process of emotional interaction; second, we consider quantifying the three emotional influencing factors of similarity, positivity and empathy as the reward function for conducting reward function for emotional state assessment, and derive the optimal emotional strategy selection based on the utility function to realize the interaction motive of emotional support, emotional guidance and emotional empathy for the participants; thirdly, in the process of environmental protection English articles translation by the robot, the Lagrange factor is introduced, which makes the process of machine translation probability maximum transformed into the process of obtaining the highest value of the auxiliary function at the random state. The retrieval speed of machine translation is improved, the efficiency of machine translation is enhanced, and high-precision translation results can be obtained more effectively. Finally, the Chinese-English parallel question and answer corpus commonly used in environmental protection articles is used as the experimental data set, and the optimal emotional state is combined with the optimal emotional state to update the robot's emotional state transfer probability, to realize the robot's state transfer in the translation process and ensure the continuity of the translation process. The experiments verified the validity of the model in terms of accuracy, MAP and MRR, and also proved that the robot cognitive-emotional interaction model can competently translate environmental protection English articles as a whole with faster translation efficiency and more accurate retrieval translation quality. Due to the complexity of the human emotion generation process and the diversity of factors influencing the probability of emotion state transfer, the model in this paper only considers some of the influencing factors in the process of emotion generation and translation of English articles. Therefore, future work needs to consider all the factors influencing the process of human emotion generation and translation of English texts to further optimize human-like emotion state generation, so that the robot cognitive-emotional interaction model can help people in all aspects of daily life in a real sense.

DATA AVAILABILITY

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

https://doi.org/10.17993/3ctic.2023.121.222-246

CONFLICTS OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this paper.

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