J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 4275--4293

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Research on the interface design of an interactive system for concentration training of autistic children based on reinforcement learning

Bo Xia[1,✉], Shouyao Liu[1]

[1] *Department of Digital Media Art, College of Architecture and Arts, Taiyuan University of Technology, Jinzhong, Shanxi, 030600, China*

ABSTRACT
The study firstly introduces the reinforcement learning theory, and proposes a decision-making method based on reinforcement learning to build a robot for autistic children, centered on autonomous human-robot interaction, with the purpose of serving the task of concentration training for autistic children. Among them, the goal task in the current environment is formulated based on imitation learning in the high level, and the robot's action selection is realized based on interactive Q-learning in the low level. The decision making based on reinforcement learning to build a robot is applied to train the robot to interact with the training, and the simulation results verify the effectiveness and generalization of the designed algorithm in solving the concentration training path. Using the KANO model to analyze the needs of autistic children, based on which we design a multimodal human-computer interaction system for autistic children's concentration training, and carry out a personal concentration intervention containing academic tasks for an 8-year-old autistic child, to verify the effectiveness of the multimodal human-computer interaction system in intervening in the concentration behaviors of autistic children, and the results of the study show that: the children's concentration behaviors of the academic tasks in the intervention period are significantly improved compared with the baseline period compared with the baseline, and the mean value increased to 88.42%.

Keywords: reinforcement learning, KANO model, concentration training, interactive system

1. Introduction

Autism, also known as autism, is a pervasive developmental disorder whose symptoms are characterized by deficits in social communication, restricted interests and stereotyped behaviors [1]. There is a huge variation in the level of intelligence of individuals with autism, with some individuals

✉ Corresponding author.
E-mail address: lsy6101123@163.com (B. Xia).
Received 01 February 2024; Revised 20 April 2024; Accepted 10 November 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-242

suffering from severe intellectual impairment (low-functioning autism) and others having a higher level of intelligence (high-functioning autism), making each individual's case unique. Children with high-functioning autism usually present with difficulties in social interactions, communication disorders, repetitive behaviors and interests, and inflexible thinking styles can [2-4]. Children with low-functioning autism are usually unable to perform basic activities of daily living independently, have other behavioral abnormalities and emotional problems, such as stereotyped and repetitive behaviors, attention deficits, and hyperactivity [5-7]. The abilities and needs of children with autism vary and change over time.

Concentration deficits are one of the common symptoms in children with autism, and early intervention can greatly affect their language and behavior problems. In the early stages, the child's brain's nervous system is still developing rapidly. Therefore, intervention may be more likely to be successful. Early intervention can also help to develop social and language skills and reduce the stress they face in society. There are many effective training methods to help children with autism improve their concentration level, such as cognitive training, behavioral training, physical activities, etc. [8-10]. There are also a number of interactive systems specifically designed for their various aspects of rehabilitation training, but the existing interactive systems need to be optimized, including the rationality of interface design [11].

In this paper, we analyze the relationship between the system, the interaction object and the guardian oriented to the task of concentration training for children with autism, and establish a decision-making framework for the system in the process of autonomous human-robot interaction based on reinforcement learning. A mathematical description of the system's decision-making process was made, and the final goal of the robot's decision-making was clarified. Then a hierarchical decision-making method is designed to divide the whole decision-making process into two levels, and simulation experiments are conducted to verify the feasibility of its decision-making. On this basis, the KANO model is introduced, and the system interface design requirements applicable to autistic children are collected through questionnaires, so as to complete the interface design of the interactive system for concentration training by combining relevant technologies. Finally, the intervention of personal concentration training system containing academic tasks for year-old autistic children can explore the effectiveness of the system in intervening the concentration behavior of autistic children.

2. Overview

Today, there are few people with autism and the advancement of technology assists in intervening in their treatment. For example, adaptive multi-robot models significantly develop children’s attention and imitative behaviors [12]. In particular, attention training for individuals with autism has been a major focus of medical and academic attention. Some studies have shown the phenomenon that children with autism do not differ from other children in the speed of their focusing system, but show lower performance in fixation and accuracy in performing focus [13]. The literature [14] has designed a non-contact robotic intervention system that can be effective in helping children with autism to reduce joint attention deficits. Such early intervention systems tend to focus on such reinforcing desired behaviors as eye contact and reducing repetitive behaviors [15]. In contrast, a humanoid robot utilizing algorithms for reinforcement learning in the literature [16] can achieve repetitive displays of actions and experiences for children with autism and can assist therapists in treating patients. It can be seen that reinforcement learning training of concentration can be a continuous intervention treatment for children with autism. And the literature [17] used a virtual interaction system to improve communication and collaboration skills of children with autism with touch-based virtual play. Touch is the best way for children with autism to interact, and contact becomes a luxury when there are no accessible playmates. For this reason, literature [18] designed a touch-based interactive interface system that reinforced the interest of children with autism. However, there are few interactive systems for autistic children's concentration training, and their system interfaces are mostly based on interest attraction, and lack of fixation and executive training for some autistic children with low intelligence.

3. Reinforcement Learning Based Decision Making for Concentration Training for Autistic Children

3.1. Systematic decision-making for the educational and training tasks of children with autism

3.1.1. Reinforcement of learning mechanisms. Reinforcement learning (RL) is an important research area in machine learning. It differs from supervised or unsupervised learning in that reinforcement learning trains an intelligent body to select the correct action to maximize the cumulative reward in a specific environment or interaction problem [19]. Markov Decision Process (MDP), which is used to define the reinforcement learning problem introduced Convolutional Neural Networks (CNN) to extract features and fit the value function, further developed traditional Q learning algorithms and proposed Deep Q Networks (DQN) [20].

Q-learning is a reinforcement learning algorithm in which an intelligent body learns and performs optimal actions in a Markov domain. The intelligent body completes the learning process by interacting with the environment and accumulates feedback reward values in order to make decisions the next time it is in the same state.

The Markov decision process is shown in Figure 1:

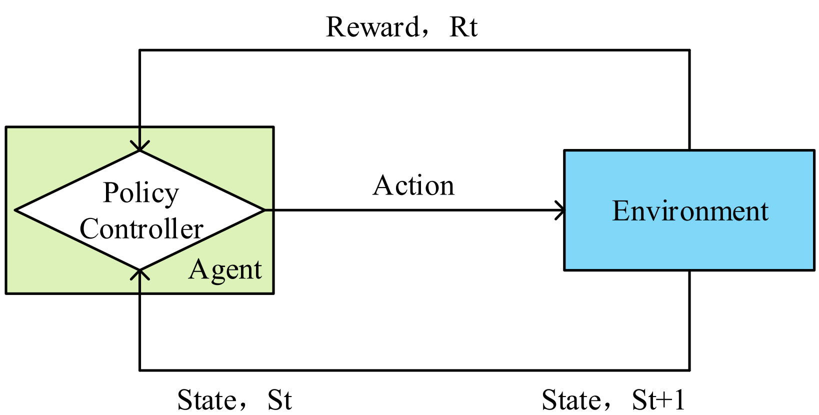

Fig. 1. Markov's decision-making process

The goal of Q-learning is to learn an optimal strategy Π, where the Agent performs action A in state S, i.e., $\Pi(s)=A$. The Agent starts performing action A_t and adopting subsequent strategies for reaching the final goal Π, from state S, with all the accumulated reward values during the period:

$$R^{\Pi}(s_t)=R_t+\lambda R_{t+1}+\lambda^2 R_{t+2}+\ldots=R_t+\lambda R^{\Pi}(s_{t+1})=\sum_{i=0}\lambda^i R_{t+i} \tag{1}$$

Eq. R_t is the reward value when the Agent moves from state S_t to state S_{t+1}, and λ is the reward factor, where $0\le\lambda\le1$ is predefined by the user. The closer λ is to 0, the more "short-sighted" the reward becomes, i.e., the reward is more focused on the immediate reward than on the future reward. The stated goal and objective of reinforcement learning can be thought of as maximizing the expected value of the cumulative sum of received scalar signals (rewards). This "expected return" is expressed in equation (1), where the goal of the agent is to find an optimal policy, and if there is an optimal policy $\Pi*$, there is always a policy that outperforms the others, which can be expressed as follows:

$$R*(s)\ge R^{\Pi'}(s),\Pi'\in\Pi \tag{2}$$

$$R^*(s_t) = \max_{\Pi} R^{\Pi}(s_t) \tag{3}$$

In (3) Eq. $R^*(s_i)$ denotes the optimal state value function, i.e., the highest reward can be obtained in state S_t.

$$\Pi(S_t) = \max_A [R(S_t, A) + \lambda R^*(S_{t+l}, A')] \tag{4}$$

Equation (4) represents the optimal state-action-value function, i.e., the highest reward can be obtained by obtaining the action A value in state S_t.

That is, a Q function is defined if the objective of Q learning is $R(S, A) + \lambda R'(S_{t+1}, A')$:

$$\begin{aligned} Q_{t+1}(S_t, A) &= (1-\alpha)Q_t(S_t, A) + \alpha(R(S_t, A) + \lambda R^*(S_{t+1}, A')) \\ &= (1-\alpha)Q_t(S_t, A) + \alpha(R(S_t, A) + \lambda \max_{\Pi} R^{\Pi}(S_{t+1}, A')) \end{aligned} \tag{5}$$

The Q-value represents the evaluation function when performing action A in state S_t, and α reflects the learning efficiency. The optimal strategy is obtained by substituting equation (4) into (5). Equation (5) represents the optimal strategy function to obtain the value of A that can obtain the highest reward in state S_t, which is a greedy strategy. As a result, the optimal policy for UAV routing can be found based on all the above formulas:

$$\Pi^*(S_t) = \max_A Q_{t+1}(S_t, A) \tag{6}$$

The Q evaluation function is obtained from Eqs. (5) and (6):

$$\begin{aligned} &Q_{t+1}(S_t, A) = (1-\alpha)Q_t(S_t, A) \\ &+\alpha(R(S_t, A) + \lambda \max Q_t(S_{t+1}, A')) \end{aligned} \tag{7}$$

Eq. (7) is the updated formula for offline Q learning, where $\alpha \in (0,1)$ is the learning rate, which indicates how much new information is learned. If the value of α is closer to 0 the learning process will be very slow, while a value of α closer to 1 will lead to fast learning. For better learning initially the learning rate should be close to 1 and over time the learning rate should gradually decrease. When action A is executed in state S_t it leads to S_{t+1}. Thus, according to all the above formulas in this paper, each node is designed as an intelligent body and each node maintains its own Q-table for updating the states, actions and rewards, the optimal strategy for UAV routing, i.e., the optimal path, can be found.

3.1.2. Reinforcement learning based decision making for concentration training. In the long run, achieving robot autonomy is a very necessary research direction in concentration training tasks for children with autism. However, it is unrealistic to realize full autonomy for robots under the limitations of the current technology. However, the realization of "supervised autonomous human-robot interaction" is a feasible intervention for the educational training of autistic children.

Based on the basic model of reinforcement learning system, the robot decision-making framework incorporating human feedback information is obtained by combining the idea of autonomous human-robot interaction under the intervention of the guardian, as shown in Fig. 2.

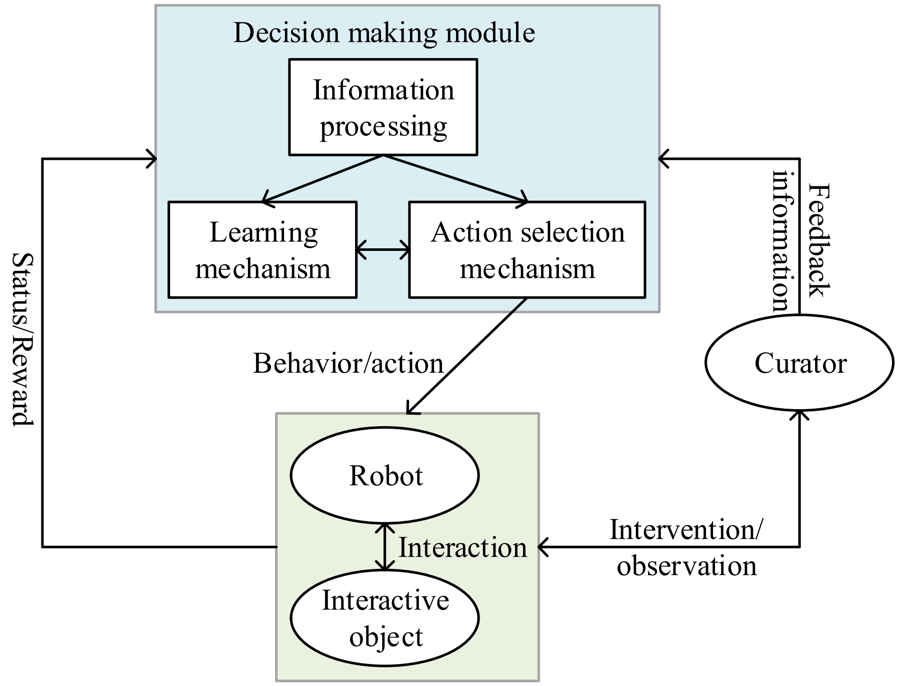

Fig. 2. Robot decision-making framework for children with autism in autism

3.2. Mathematical model for systematic decision making

Let T be the set of all tasks, S be the state space, and A be the action space of the robot. In practice, the robot is able to observe the environment and get the environmental observation result $o \in O$ related to state $s \in S$, where O denotes the observation space of the robot. Define the symbol Ψ to denote the task specification, which is used to describe the execution process of the task and the final goal to be achieved, and $\psi(t) \in \Psi$ to denote the semantic description for the task $t \in T$. Given a Boolean expression $g(s,t) \in \{0,1\}$ to describe the termination state of the robot when it executes a task $t \in T$ at state $s \in S$, and when $g(s,t)=1$ means that the task t execution is complete at state s. Furthermore, let $\pi : \Psi \to (O \to A)$ denote a decision making strategy of the robot, then the purpose of the robot to perform decision making can be described as follows: based on the task $\psi(t) \in \Psi$ to be accomplished, the robot observes the environment state $o \in O$ and outputs an action $a \in A$ under the strategy $\pi(a \mid o\psi(t))O \to i$ to realize $g(s^{'},t)$, where $s^{'} \in S$ denotes the environment state obtained by the robot through observation when performing the task t.

3.2.1. Hierarchical system-based decision making. The decision making model of the robot is composed of five key modules, namely the external environment coding module, the feedback information coding module, the core decision process module, the robot action decoding module, and the knowledge representation module.

The external environment encoding module is mainly used to map the observation information related to the environment to the robot's state space. Let the observation space be $O_c : o_c \in O_c$ and the state space of the robot be $S_c : s_c \in S_c$, then the external environment coding process can be expressed as:

$$O_c \to S_c : s_c = f_{OE}(o_c) \tag{8}$$

The feedback information encoding module is mainly used to convert the feedback information of the guardian into the external feedback signal of the robot. Let the feedback information of the guardian be $O_f : o_f \in O_f$ and the external feedback information be characterized as $H_f : h_f \in H_j$, then the feedback information encoding process can be expressed as follows:

$$O_f \to H_f : h_f = f_{OF}(o_f) \tag{9}$$

The core decision-making process is carried out at two levels, where the high-level role is task formulation and the low-level function is action selection. In the task formulation module, complex tasks are represented based on a hierarchical task network W. Let the robot's task space be T_s and the original task space be $T_p \subseteq T_s$ the robot needs to perform the winning task as $t_g \in T_p$ and π_h is the high-level strategy, then the task formulation process of the robot can be represented as:

$$\{S_c, H_f, W\} \to T_p : t_g = \pi_h(s_c, h_f, W) \tag{10}$$

The knowledge in the decision-making process is characterized using the form of a key-value database, where $d_k \in D_k$ and $d_v \in D_v$ denote the index key and data content of the database, respectively. In the decision-making process of the robot, the retrieval process of the database by the system can be represented as:

$$\begin{gathered} \{S_e, H_f\} \to D_k : d_k = f_{rel}(s_e, h_f) \\ D_k \to D_v : d_v = f_{d_k}(D_v) \end{gathered} \tag{11}$$

In addition, the database may be updated under the action of the robot decision system after the completion of a specific action output. Let the robot performs an action under the action of $d_v : (d_k \to d_v)$ and receives state feedbacks $s_e^{'} \in S_e$ and $h_f^{'} \in H_f$. When the update program for the database data is activated, the update process of the database may be represented as follows:

$$\{S_e, H_f\} \to D_k : d_v^{'} = f_{ju}(s_e^{'}, h_f^{'}), d_v = f_{ud_k}(d_v^{'}) \tag{12}$$

Among other things, the functions of the database update function f_{ud_k} include data modification, data addition, and data deletion.

3.2.2. System task formulation based on imitation learning. In the process of autonomous human-computer interaction, a hierarchical task network W is constructed to decompose a complex interaction task, which is a process of task abstraction based on a priori knowledge for complex tasks. Let the task space obtained after task decomposition be $M \sim (T, C)$, where T is the set of subtasks, C denotes the constraint relationship between subtasks, and $T_p \subseteq T$ denotes the original task set. On this basis, let the a priori data provided by the domain expert be:

$$\tilde{\pi} \sim \{\tau_1, \quad \tau_2, \quad \cdots, \quad \tau_m\} \tag{13}$$

where $\tau_i, i = 1, 2, \cdots, m$ represents a sequence of behaviors containing states and subtask execution paths obtained according to the expert policy $\tilde{\pi}$. Using s_j to represent the environment state observed at layer j, t_j to represent the subtask selected at layer j, $t_p \in T_p$ to represent the original task in the hierarchical task network, and β_{t_p} to represent the termination condition of the robot when executing the current original task, the behavior sequence obtained based on the a priori data can be represented as:

$$\tau_i = \left\{ s_1^i, t_1^i, s_2^i, t_2^i, \cdots, s_n^i, t_p^i, \beta_p^i \right\} i = 1, 2, \cdots, m \tag{14}$$

In the high-level task formulation process, the selection and execution of subtasks is a semi-Markov process. Let the high-level target task selection strategy be π_h, the environment state detected by the robot be S_e, and the termination condition during the current execution of the subtask be β, then the task formulation process of the robot can be described by a triad $\left(S_e, \pi_h(S_e), \beta\right)$.

Using $t_g = \pi_h(S_e) \in T_g = T_p$ to represent the subtasks obtained based on the high-level task formulation, and combining Eq. (14), the set of a priori data of the environment state and the original task is constructed:

$$\tilde{D}=\{(S^1,t_p^1,\beta_{t_p^1}),(S^2,t_p^2,\beta_{t_p^2}),(S^3,t_p^3,\beta_{t_p^3}),\cdots,(S^m,t_p^m,\beta_{t_p^m})\} \tag{15}$$

where $S^i=\{s_1^i,s_2^i,\cdots,s_n^{'}\}(i=1,2,\cdots,m)$ is the set of states required for each layer in the hierarchical task network.

The data set $\tilde{D}$ is further extended to obtain:

$$\tilde{D}_H=\{(S^1,\pi_h^1(S^1),\beta_{\pi_h^1(S^1)}),(S^2,\pi_h^2(S^2),\beta_{\pi_h^2(S^2)}),\cdots,(S^m,\pi_h^m(S^m),\beta_{\pi_h^m(S^m)})\} \tag{16}$$

where a collection of high-level task formulation strategies is formed from the target task selection strategies for each state:

$$\Pi_h=\left\{\pi_h^1,\quad \pi_h^2,\quad \cdots,\quad \pi_h^m\right\} \tag{17}$$

Based on this, the robot can perform task formulation in the initial stage of operation to get the target task to be accomplished in the current state:

$$t_g=\pi_h^i(S^i)=t_p^i \quad i=1,2,\cdots,m; S^i\subseteq S_e \tag{18}$$

3.2.3. System action selection incorporating external feedback information. In this section, a robot action selection strategy based on standard 2-Leaming and incorporating external feedback information will be investigated. In this process, the reward value in the standard 2-Leaming is used as the intrinsic reward of the learning system, and the external feedback information is processed and used as the external reward of the learning system, which together act on the robot's action selection process.

3.3. Simulation examples

The training performance of decision making for a robot built on reinforcement learning by performing 3 mutually independent simulations using different random seeds is shown in Figure 3. The solid curve is the average reward of the 3 experiments, and the shaded area depicts the minimum and maximum rewards for each round of the 3 trials. Each simulation was trained for 10,000 rounds each, with each round lasting no more than 110 environment steps and consuming approximately 24h of physical time.

As can be seen from the figure, all 3 randomized experiments end up with high rewards and the convergence results do not fluctuate much. The average reward convergence value is close to 100, and this reward value is sufficient for the robot to achieve the final search and rescue goal.

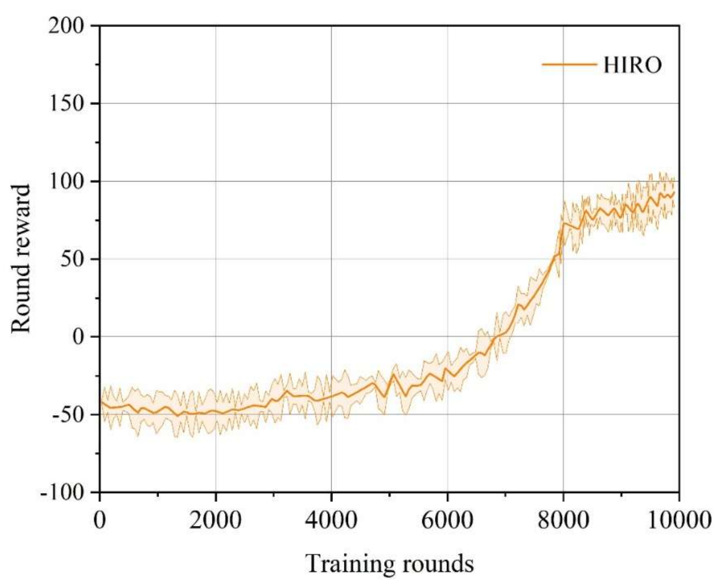

Fig. 3. Learning curve based on strengthening learning to establish a robot

Fig. 4 shows the success rate of decision making in the training process of the robot built based on reinforcement learning, where the success rate is defined as:

$$success = \begin{cases} 1 & \text{if } \| s_t - g_{center} \|_2 < 0.6 \\ 0 & else \end{cases} \tag{19}$$

That is, when the distance between the robot's position in the state vector and the final target point to be rescued is less than 0.6m, it can be regarded that the robot has opened a path to the target point to be rescued and successfully completed a search and rescue mission, otherwise the mission fails.

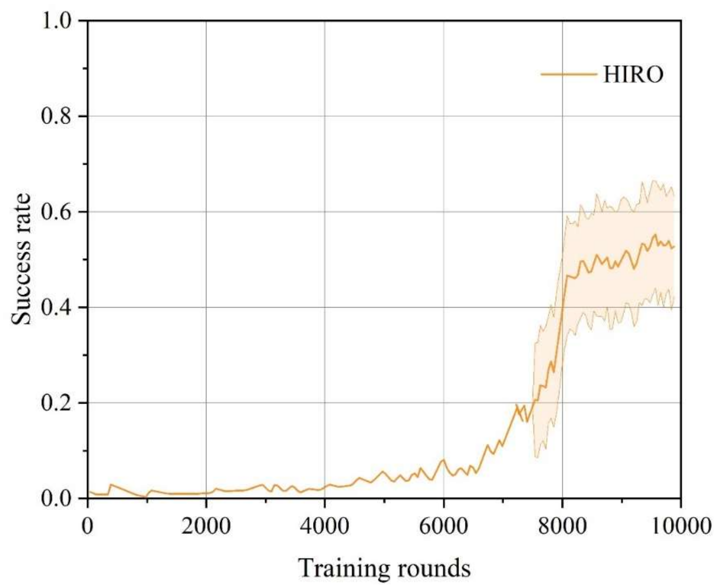

Fig. 4. Learning success rate

Figures 5 and 6 show the successful training results of the robot's search and rescue task as a series of snapshots, with the two sets of plots representing the two different search and rescue paths learned.

Figure 5 shows that the robot successfully finds path C (i.e., pushes open the door) and eventually reaches the area to be rescued. Figure 6 shows that the robot successfully finds path A (i.e., pushes open the wooden box) and finally reaches the area to be rescued. It is demonstrated that the designed decision making based on reinforcement learning to build the robot is possible to learn multiple strategies to solve the task, so that the robot has the ability to complete the search and rescue task in complex interactive scenes through multiple paths. The fact that path A did not become the final path learned from the training is due to the fact that these rounds experiencing path A during the entire training process accounted for too small a proportion of all 1000 rounds, which was not enough to provide sufficient success for the learning of the intelligent body.

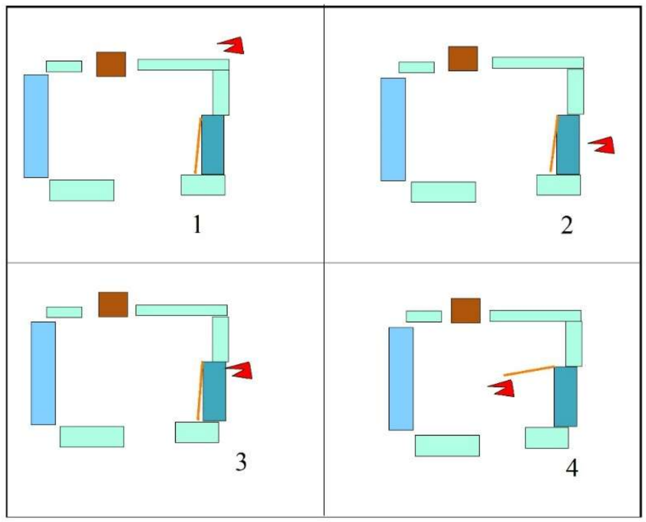

Fig 5. A test of success for path C

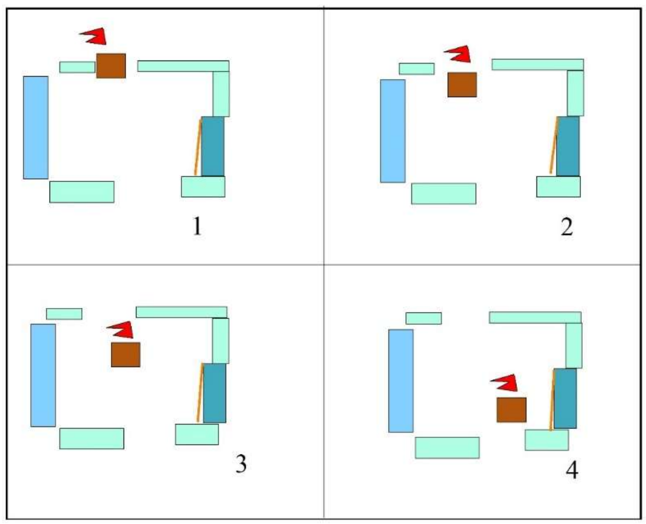

Fig. 6. A successful result of a training of path A

In addition, through the above training and testing it was also found that the robot never successfully searched for path B and path D (pushing through the blue wall and passing through the lowest gap, respectively), the main reason for this is that these two paths have to pass through locations far away from the center point of the area to be rescued (e.g., the upper-left corner and the lower-right corner of the closed area), and in terms of the environmental reward formula, the robot would be more inclined to greedily search for the paths that are nearer to the final goal point.

After 10,000 rounds of training, the testtest results obtained to establish the robot's decision making based on reinforcement learning are shown in Fig. 7:

From the figure, it can be found that to learn the path B robot needs to do more exploration while interacting more with the environment rather than utilizing the more easily learned experience of pushing a wooden box. Thus the optimal policy that is eventually learned is longer and more complex compared to the ones in Figures 5 and 6. From Figs. 5, 6, and 7, it can be seen that decision making based on reinforcement learning to build robots can achieve the learning of optimal strategies with different levels of difficulty.

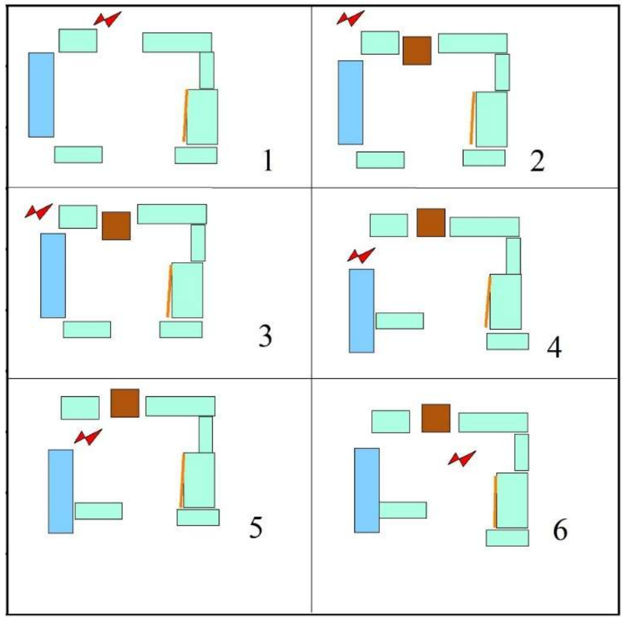

Fig. 7. Test results(Corresponding path B)

4. Interactive system interface design based on KANO modeling

4.1. Introduction of the KANO model

4.1.1. KANO modeling theory. The KANO model divides the quality attributes of products and services into five categories: "must-have", "desirable", "charismatic", "undifferentiated", and "inverse" [21]. A schematic diagram of the KANO model is shown in Figure 8. The horizontal axis indicates the degree of possession of the functional characteristics of the product; The vertical axis indicates the level of satisfaction of the respondent. The origin represents the industry average.

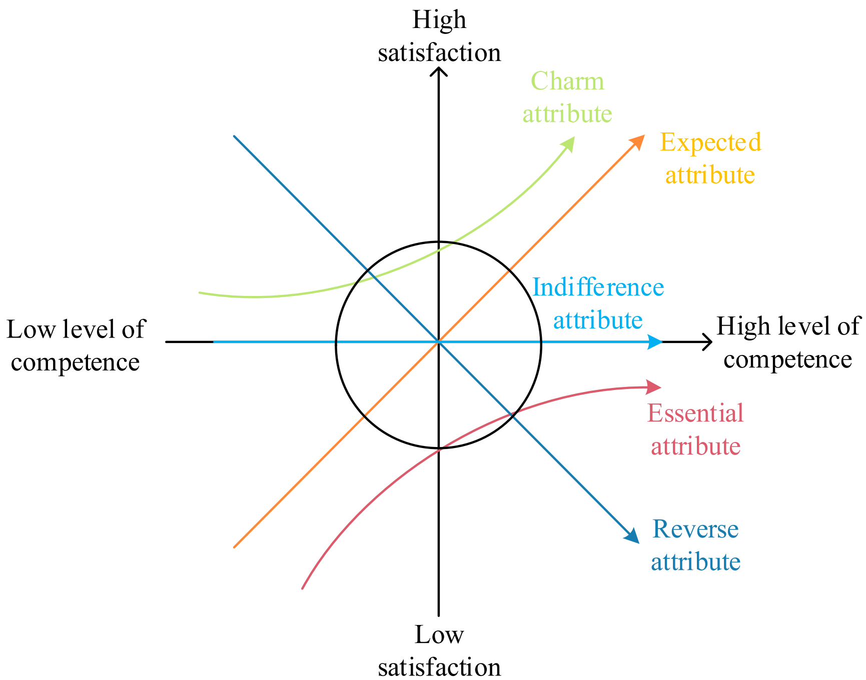

Fig. 8. Kano model diagram

4.1.2. Methodology for the application of the KANO model. The customer satisfaction coefficient indicates the extent to which service or design features and functions are likely to increase respondent satisfaction or decrease respondent dissatisfaction, as shown in the following formula:

Respondent Satisfaction Coefficient:

$$SI = (A+O)/(A+O+M+I) \tag{20}$$

Respondent dissatisfaction coefficient:

$$DSI = (O+M)/(-1)*(A+O+M+I) \tag{21}$$

In this case, if the quality of the design content is not up to the mark, a negative sign is placed in the formula to emphasize its negative impact on respondent satisfaction. The interval of satisfaction is [-1,1], for a positive value of satisfaction of [0,1], if the value is close to 1, the impact on satisfaction is greater; conversely, the satisfaction is smaller, and the closer the positive coefficient is to the value 0 means that the impact is unimportant, and the value of zero means that this feature does not cause dissatisfaction. However, in the case of negative satisfaction for [-1,0], the closer the coefficient of a functional characteristic is to -1, the higher the impact of negative satisfaction (i.e., dissatisfaction) on the respondent, which means that the lack of fulfillment of this characteristic raises the level of dissatisfaction of the respondent.

4.2. Demand Analysis of Concentration Training for Autistic Children

4.2.1. Acquisition of Concentration Training Needs for Autistic Children. Research on autistic children through observation, user interviews and questionnaires, this research mainly focuses on autistic children's ability to concentrate, the autistic children's ability to concentrate on training needs to obtain, and combined with the results of the interviews will be the initial extraction of the needs, mainly from the two directions of the universal design and learning needs.

4.2.2. Classification of Concentration Training Needs for Autistic Children:
1) Kano questionnaire results (see Table 1). The results of the questionnaire were classified according to the Kano model, in which "Q" represents an invalid answer to the question. The functional attribute "A" of the Kano model represents the charisma attribute function, "O" represents the desired attribute function, "M" represents the essential attribute function, "R" represents the reverse demand function, and "I" represents the non-difference attribute function.

Table 1. Questionnaire data results table

Serial number	Function name	Q	A	O	M	R	I	Total
1	Search course	0	14	26	26	0	25	100
2	Programme broadcast	0	43	13	0	0	35	100
3	Recommended course	0	17	36	14	0	24	100
4	Course playback	2	18	33	16	2	20	100
5	Course data	0	13	28	23	0	27	100
6	Course introduction	0	28	22	8	0	33	100
7	Curriculum communication	0	28	33	8	0	22	100
8	Course sharing	0	18	18	32	0	33	100
9	Small class	0	23	23	16	0	29	100
10	Thumb up support	0	8	26	28	0	29	100
11	Cue	2	18	33	16	2	20	100
12	Topic	0	4	34	28	0	25	100
13	Reciprocal flow	0	6	28	30	0	27	100

14	Icon design	0	28	12	28	0	23	100
15	literation	0	3	40	28	0	20	100
16	Focused vision	0	1	35	31	0	24	100
17	Quick feedback	0	8	30	14	0	29	100
18	Navigation clarity	0	4	35	17	0	35	100
19	First guide	0	25	18	11	0	37	100

2)Satisfaction calculation. Each extracted functional item is calculated according to the user satisfaction and user dissatisfaction index calculation formula to determine the satisfaction and dissatisfaction index values for each functional attribute, and then the functional attributes are determined according to the four-quadrant functional attribution as shown in Fig. 9, and the functional attributes are attributed as shown in Table 2.

Table 2. Functional attribute belonging table

Serial number	Function name	SII	DDI	T value	Kano belong
1	First guide	0.41	0.26	0.4	Indifference attribute
2	Quick feedback	0.36	0.41	0.41	Indifference attribute
3	Small class	0.44	0.36	0.43	Charm attribute
4	Course introduction	0.48	0.27	0.47	Charm attribute
5	Course sharing	0.34	0.47	0.47	Essential properties
6	Icon design	0.48	0.37	0.47	Charm attribute
7	Course data	0.39	0.48	0.48	Essential properties
8	Search course	0.38	0.49	0.49	Essential properties
9	Course playback	0.5	0.47	0.49	Expected attribute
10	topic	0.36	0.49	0.49	Essential properties
11	Navigation clarity	0.37	0.49	0.49	Essential attribute
12	Recommended course	0.51	0.47	0.5	Expected attribute
13	Cue	0.51	0.47	0.5	Expected attribute
14	Thumb up support	0.32	0.51	0.51	Essential properties
15	Programme broadcast	0.54	0.1	0.53	Charm attribute
16	Reciprocal flow	0.32	0.55	0.55	Essential attribute
17	Curriculum communication	0.59	0.28	0.58	Charm attribute
18	Focused vision	0.34	0.63	0.63	Essential attribute
19	literation	0.41	0.65	0.65	Essential attribute

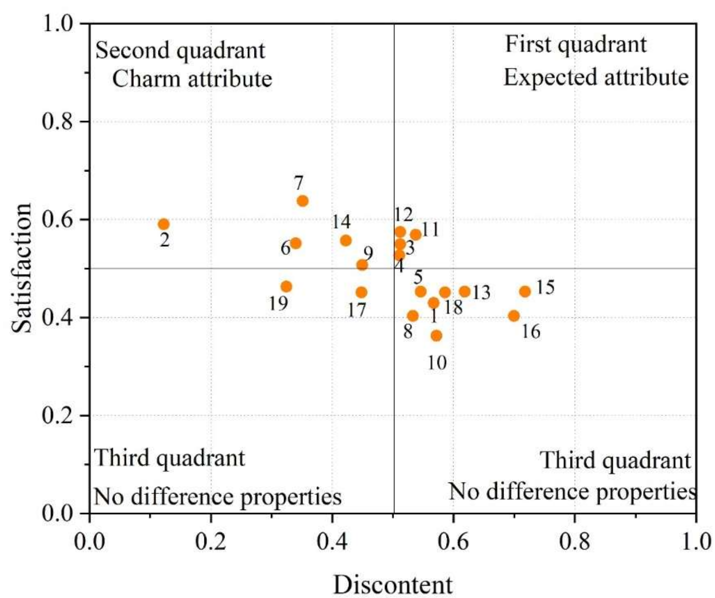

Fig. 9. Functional attribution of the four quadrants

4.3. Interface Design of Interactive System for Concentration Training for Autistic Children

4.3.1. System design. The multimodal human-computer interaction system for autistic children's concentration training is shown in Figure 10, which consists of training content, multimodal interaction and other parts based on the design principles of the concentration training system for autistic children. Children with autism are able to carry out the process of concentration training for children with autism through the multimodal human-computer interaction model that combines audio-visual feedback and vibration feedback for oral training, pronunciation training, and assessment of speech comprehension ability.

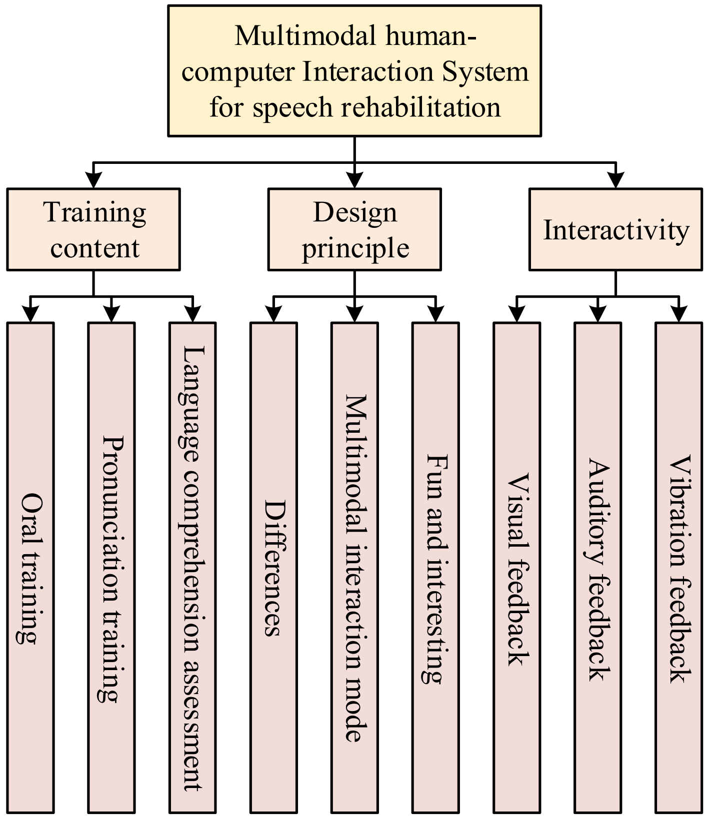

Fig. 10. Multi-modal machine interaction system framework

4.3.2. System implementation. Multimodal human-computer interaction is mainly divided into three modules: multimodal interaction information input, multimodal interaction information fusion and processing, and multimodal interaction information feedback. The multimodal interaction information is collected and input by the data acquisition device, and then the information input module of each channel mainly receives the sensory information (audio information, video information, vibration information) from the human being, etc. With the help of the multimodal interaction information fusion and processing module, it can form the "sensory" perception and cognition, and through the feedback module (audio feedback, video feedback, haptic feedback), it can provide the information to the human-computer interaction. With the help of multimodal interaction information fusion and processing module, "sense" and cognition are formed, and through the multimodal interaction information feedback module (audio feedback, video feedback and haptic feedback), the information is fed back, so as to construct a multimodal human-computer interaction system.

The basic idea of this paper is a multimodal human-computer interaction system for speech rehabilitation, which mainly relies on the visual, auditory and tactile senses as the inputs of human-computer interaction information, and adopts the video data information acquisition device, the audio data information acquisition device and the vibration data information acquisition device respectively to collect the facial information and voice information of the speaker in multimodal human-computer interaction.

5. Empirical analysis of the effect of concentration training for children with autism

5.1. Study design

5.1.1. Study subjects. The subject of this study was Little B (a pseudonym), a male, 8 years old, who was diagnosed with autism in the hospital when he was 6 years old. Little A was enrolled in a regular kindergarten and is now in the 2nd grade, receiving group study programs and individual training programs at school. Little A's basic abilities are as follows: motor ability can meet the needs of daily life; weak hand manipulation ability; visual, auditory, gustatory, vestibular, and proprioceptive senses can meet the needs of daily life; visual and olfactory responses are good, and vestibular senses belong to the high-threshold performance; he has difficulty in adapting to the environment in daily life, and has a low level of alertness, and is prone to behaviors such as distraction or moving around; he possesses the concept of conservation of objects, and is able to Find hidden objects; can match colors; know a small number of unique characters, such as mouth, hand, and person.

5.1.2. Research tools:
1)Dependent Variables. The dependent variables in this study were Little B's focused behavior in completing academic tasks and the duration of completing academic tasks. Focused behavior refers to children engaging in activities related to classroom instruction. Inattentive behavior is defined as the inability to focus on a fixed direction or target, such as the child's inability to look at a single object and to pay attention to the target for only a short time, thus often failing to complete the task. Based on the above definitions, preliminary observations of Little B, and interviews with parents and teachers, this study determined that Little B's attentive behaviors for completing academic tasks were as follows: writing according to the task, making corrections (rewriting with a pen, erasing with an eraser), looking at the worksheet, and seeking help from the teacher. The duration of completing an academic task is the total time spent by Little B in the process of completing an academic task.
2)Experimental tools. First, the observation recording form of focused behavior. Based on the definition of Jr. B's attentive behavior in completing academic tasks, an observation recording form was created for use by the researcher and recorder. The form used the partial time-distance recording method to record Little B's attentive behavior in 10-second increments. If Little B exhibits any of the focusing behaviors within 10 seconds, the interval is recorded as "√"; if none of the focusing behaviors occurs within 10 seconds, the interval is recorded as "×". The record ends when Little B completes the worksheet.

Second, the time-keeping tool. Due to the need to record the duration of Little B's completion of the academic task, this study used a cell phone timer as a time recording tool. Timing started when Little B got the academic task and stopped when the academic task was completed.

Third, Personal Work System Intervention Effectiveness Interview Form. The self-administered Personal Work System Intervention Effectiveness Interview Form was used for the collection of social validity to investigate the perceptions and suggestions of stakeholders, including teachers and parents, on the content and intervention effectiveness of this study.

5.1.3. Research procedures. This study utilized a cross-situational multi-probe design in a single-subject experiment, and the entire study consisted of two phases: a baseline period and an intervention period.

First, the baseline period. Little B was given an academic task every day, and Little B's completion was recorded using the Concentration Behavior Observation Record Sheet and a timer. No intervention or training was given to Little B during the completion of the academic task. Meanwhile, if Little B did not show attentive behavior for 1 minute (6 10-second intervals), the researcher was required to use physical or spoken words or gestures to assist. If the focused behavior appeared after the assistance, the assistance was stopped. On the contrary, the assistance was continued.

Second, the intervention period. Ten interventions were conducted in the individual training room and 10 interventions in the classroom. Little B was asked to complete four tasks in a “top-to-bottom” personal work sequence. The academic task was placed in the personal work system as the first task to be completed, and the remaining three tasks were the number mosaic, bead threading, and animal mosaic. The tasks are fixed except for the academic tasks which are changed randomly. Only the completion of the academic task (i.e., the first task) of Little B was recorded, and the other 3 tasks were not recorded. During the completion of the academic tasks, if Little B did not show attentive behavior for 1 minute (6 10-second intervals), physical or spoken words or gestures were used to assist. If the focused behavior appeared after the assistance, the assistance was stopped; conversely, the assistance was continued.

5.2. Empirical analysis

5.2.1. Academic Task Concentration. The trend of the two subjects' performance in academic task concentration in the baseline period, the intervention period, and the maintenance period is shown in Figure 11. Visual analysis showed that, overall, Little B's academic task concentration achieved a more significant improvement in both the intervention period and showed some maintenance effects.

For Little B, his academic task concentration in the six training units at baseline ranged from 53.61% to 66%, with a mean concentration value of 58.47%, indicating that Little B was able to fully focus on the academic task he was performing for about 58% of the 1-minute time period in each 30-minute training unit at baseline, and that his performance was relatively smooth in the baseline period, and therefore the intervention was started in the seventh training unit from the beginning. Intervention was initiated from the seventh training unit onwards. After Little B learned to self-monitor his attention during homework, his academic task focus increased significantly, and after 17 training units, he successfully reached the pre-determined goal of 97% or higher in three consecutive training units. During the 17 training units of the intervention period, Little B's academic task focus ranged from 78.57% to 95.08%, with a mean value of 88.42%, which was an increase of 30.42% compared with the baseline period, and had remained relatively more stable. However, two weeks later during the maintenance period, Jr. B's performance dropped, and without the use of the self-multimodal HCI system, Jr. B's academic task focus mean dropped to 73.84%, which is 14.58% lower compared to the intervention period but still higher than the baseline period of 15.84%.

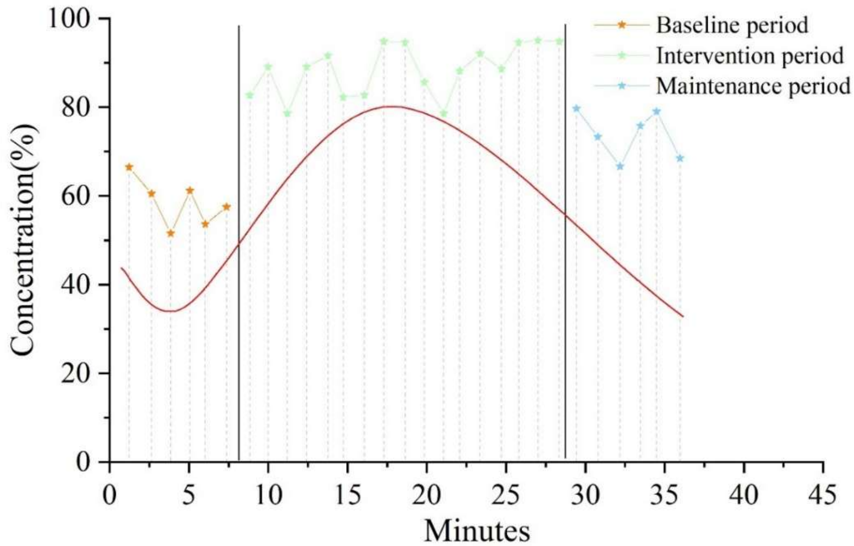

Fig. 11. Academic tasks focus on changing trends

5.2.2. Correctness of academic tasks. The trends in academic task correctness scores during the baseline, intervention, and maintenance periods are shown in Figure 12. For Little B, the average score of academic task correctness in the baseline period was 62.9%, and the difference between the highest and lowest scores was 24 points, which was relatively smooth. After entering the intervention period, with a significant increase in his concentration level, Jr. A's average academic task correctness reached 81.1% points, ranging from 63-98 points, which was an 18.2% increase from the baseline period. During the maintenance period, Jr. A's academic task correctness ranged from 57-88 points, with an average of 73.3 points, which was between the baseline period and the intervention period, but not significantly different. Jr. B's academic task correctness improved more than concentration in the intervention period, but also produced some maintenance effects, and Jr. B's performance in the maintenance period was better than in the baseline period in all cases.

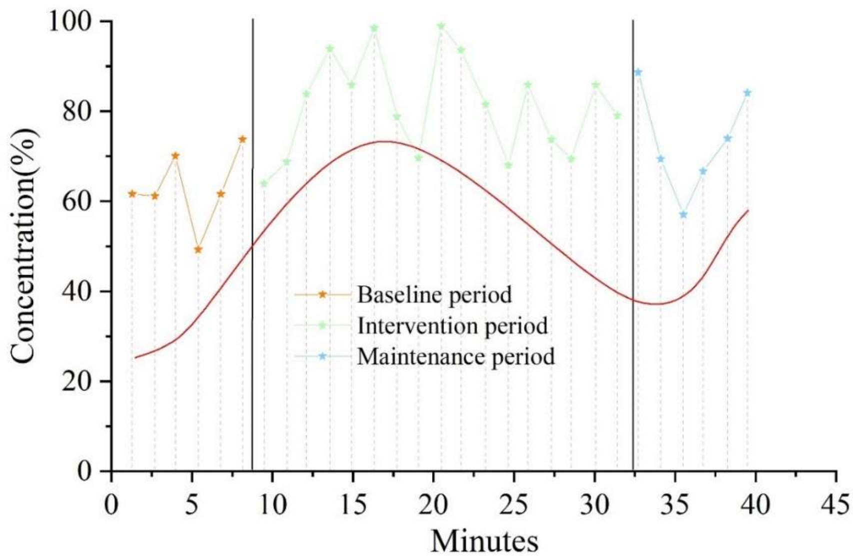

Fig. 12. The trend chart of the accuracy of academic tasks

6. Conclusion

The study first analyzes the relationship between the robot, the interaction object and the guardian for the interaction task of concentration training for children with autism, and establishes a framework for the robot's decision-making in the process of autonomous human-robot interaction based on reinforcement learning, and divides the whole decision-making process into two levels for simulation, and the results show that the robot learns to get training paths with different realization difficulties in the process of interaction with the robot. The KANO model is used as the theoretical basis to analyze the training needs of autistic children. On this basis, a multimodal human-computer interaction system for autistic children's concentration training was designed, and the results of experimental evaluation of the system showed that the system could effectively improve the concentration behavior of Little B in completing the writing task, and the concentration behavior of Little B in the academic task in the intervention period was significantly improved compared with the baseline period, with an average value of 88.42%, which is an improvement of 30.42% compared with the baseline period.

References

[1] Lord, C., Brugha, T. S., Charman, T., Cusack, J., Dumas, G., Frazier, T., ... & Veenstra-VanderWeele, J. (2020). Autism spectrum disorder. Nature reviews. Disease Primers, 6(1), 5-5.

[2] McIntyre, N. S., Solari, E. J., & Gonzales, J. E. (2017). The Scope and Nature of Reading Comprehension

Impairments in School-Aged Children. Journal of autism and developmental disorders, 47, 9.

[3] Craig, F., Lorenzo, A., Lucarelli, E., Russo, L., Fanizza, I., & Trabacca, A. (2018). Motor competency and social communication skills in preschool children with autism spectrum disorder. Autism Research: Official Journal of the International Society for Autism Research, 11(6), 893-902.

[4] Fujino, J., Tei, S., Itahashi, T., Aoki, Y., Ohta, H., Kubota, M., ... & Takahashi, H. (2019). Need for closure and cognitive flexibility in individuals with autism spectrum disorder: A preliminary study. Psychiatry Research.

[5] Cohen, S., Fulcher, B. D., Rajaratnam, S. M. W., Conduit, R., Sullivan, J. P., St Hilaire, M. A., ... & Lockley, S. W. (2017). Sleep patterns predictive of daytime challenging behavior in individuals with low-functioning autism. Autism Research: Official Journal of the International Society for Autism Research, 11(2), 391-403.

[6] Kirby, A. V., Boyd, B. A., Williams, K. L., Faldowski, R. A., & Baranek, G. T. (2017). Sensory and repetitive behaviors among children with autism spectrum disorder at home. Autism.

[7] Muskens, J. B., Velders, F. P., & Staal, W. G. (2017). Medical comorbidities in children and adolescents with autism spectrum disorders and attention deficit hyperactivity disorders: a systematic review. European Child & Adolescent Psychiatry, 26(9), 1093.

[8] Pasqualotto, A., Mazzoni, N., Bentenuto, A., Mulè, A., Benso, F., & Venuti, P. (2021). Effects of Cognitive Training Programs on Executive Function in Children and Adolescents with Autism Spectrum Disorder: A Systematic Review. Brain Sciences (2076-3425), 11(10).

[9] Postorino, V., Sharp, W. G., McCracken, C. E., Bearss, K., Burrell, T. L., Evans, A. N., & Scahill, L. (2017). A Systematic Review and Meta-analysis of Parent Training for Disruptive Behavior in Children with Autism Spectrum Disorder. Clinical Child and Family Psychology Review, 20(4), 391-402.

[10] Healy, S., Nacario, A., Braithwaite, R. E., & Hopper, C. (2018). The effect of physical activity interventions on youth with autism spectrum disorder: A meta-analysis. Autism Research: Official Journal of the International Society for Autism Research, 11(6), 818-833.

[11] Nojavanasghari, B., Hughes, C. E., & Morency, L. P. (2017, May). Exceptionally social: Design of an avatar-mediated interactive system for promoting social skills in children with autism. In Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems (pp. 1932-1939).

[12] Ali, S., Mehmood, F., Dancey, D., Ayaz, Y., Khan, M. J., Naseer, N., ... & Nawaz, R. (2019). An Adaptive Multi-Robot Therapy for Improving Joint Attention and Imitation of ASD Children. IEEE Access, 7, 81808-81825.

[13] Ridderinkhof, A., de Bruin, E. I., van den Driesschen, S., & Bögels, S. M. (2020). Attention in Children With Autism Spectrum Disorder and the Effects of a Mindfulness-Based Program. Journal of Attention Disorders, 24(5), 681.

[14] Zheng, Z., Zhao, H., Swanson, A. R., Weitlauf, A. S., Warren, Z. E., & Sarkar, N. (2018). Design, Development, and Evaluation of a Noninvasive Autonomous Robot-mediated Joint Attention Intervention System for Young Children with ASD. IEEE transactions on human-machine systems, 48(2), 125.

[15] Schuetze, M., Rohr, C. S., Dewey, D., McCrimmon, A., & Bray, S. (2017). Reinforcement learning in autism spectrum disorder. Frontiers in Psychology.

[16] Salhi, I., Qbadou, M., Gouraguine, S., Mansouri, K., Lytridis, C., & Kaburlasos, V. (2022). Towards Robot-Assisted Therapy for Children With Autism—The Ontological Knowledge Models and Reinforcement Learning-Based Algorithms. Frontiers in Robotics and AI, 9.

[17] Zhao, H., Swanson, A. R., Weitlauf, A. S., Warren, Z. E., & Sarkar, N. (2018). Hand-in-Hand: A Communication-Enhancement Collaborative Virtual Reality System for Promoting Social Interaction in

Children with Autism Spectrum Disorders. IEEE transactions on human-machine systems, 48(2), 136.

[18] Tashnim, A., Nowshin, S., Akter, F., & Das, A. K. (2017, October). Interactive interface design for learning numeracy and calculation for children with autism. In 2017 9th international conference on information technology and electrical engineering (ICITEE) (pp. 1-6). IEEE.

[19] Tao Sheng,Yun Xiong,Haofen Wang,Yao Zhang,Siqi Wang & Weinan Zhang. (2024). Deep reinforcement learning for community architectural layout generation. Knowledge and Information Systems(prepublish),1-28.

[20] Cyrille Vessaire,Pierre Carpentier,Jean Philippe Chancelier,Michel De Lara & Alejandro Rodríguez Martínez. (2024). Complexity Bounds for Deterministic Partially Observed Markov Decision Processes. Annals of Operations Research(prepublish),1-38.

[21] Sitan He,Yutong Zhang,Mingshuo Tian,Ruijie Li & Ke Chen. (2024). A Study on the Product Demand of New Energy Vehicles Based on the Kano Model. Journal of Service Science and Management(05),464-477.