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The Robot Cognitive Developmental Algorithm Based on Cerebellum-Basal Ganglia-Cerebral Cortex Circuits

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Abstract. Aiming at continuous two-wheeled robot behavior learning problem, we simulated the human psychological cognitive mechanism and sensory motor phenomena of brain nerve, and proposed a robot cognitive developmental algorithm based on cerebellum-basal ganglia-cerebral cortex circuits. Based on the theory of biological sensory motor system, the algorithm takes the learning automata as the frame. The mapping of the robot state to the behavior is realized in the cerebellum by supervised learning style. Then, we use evaluation module of probability selection based on intrinsic motivation principle for selecting the action of basal ganglia. Finally, the cerebral cortex receives the nerve signal and transfers to the basal nucleus and the cerebellum, forming the complete sensory motor feedback loop. The proposed algorithm was applied to the system of two-wheeled robot, and the experiments were carried out. Simulation experimental results show that robot in unknown environment, through independent learning development, gradually master motion balance control skill, reflecting the effectiveness and robustness of the algorithm. Compared with the classical learning automata algorithm, highlight the superiority of the algorithm.

Keywords: cognitive development, intrinsic motivation, learning automata, sensory motor system, two-wheeled robot

1 Introduction

Learning and memory are the essence of human intelligence behavior, and human's multiple skills are gradually formed and developed in the process of its nervous system and self-organization [1]. In order to study and simulate the neural activity and self adjustment mechanism of human, we endow it with the intelligent robot is the important research subject of artificial intelligence and control science. In 1996, J. Weng firstly proposed the idea of autonomous mental development in robot [2]. He believed that the agent should be based on the simulation of the human brain, within the control of the development process through the sensor and effector with the unknown environment to develop the mental ability [3]. Brooks et al. stressed the interaction between robots and teachers, environment, and gradually develop its intelligence [4], and through a combination of neuroscience research theory, then the calculation model was proposed for simulating human and animal cerebral cortex in the prefrontal cortex, hypothalamus, hippocampus and other regions to deal with complex problems in a complex environment, which related to the sensor motor system. The initial cognitive development was from the sensory motor system coordination mechanism of formation and development [5], At the same time, the sensory motor system was coordinated and improved in the process of intrinsic motivation formation and development. The neurological related literature shows that in the course of human and animal learning, the cerebral cortex, basal ganglia and cerebellum will work in its own unique way [6]. And in the relationship between human and animal movement related, the cerebellum and basal ganglia distributed on both sides of the

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movement signal transmission line between cerebral cortex and spinal cord, they were involved in the initiation and control of any action.

A lot of scholars have carried out the research in the early 80's of twentieth Century. In 1987, Houk and Gibson studied the role of the cerebellar cortex in the process of sensory motor signal processing [7]. In 2000, Moren et al. pointed at the MOWER dual process learning theory, a system of combining emotion and behavior selection was proposed [8]. In 2007, Wang based on the human brain emotional loop proposed a model with artificial emotion and applied to inverted pendulum system to make it successful learning balance control skill [9]. In 2010, Batto et al. from the perspective of evolution [10], took reinforcement learning as the theoretical frame, and adopted intrinsic motivation to drive the active learning, it greatly improved the agent learning efficiency. In 2013, Oudeyer from the exploration of the biological self consciousness [11], combined with intrinsic motivation thought, put forward the system state transfer error learning machine. It realized the active exploration of the unknown environment based on the intrinsic motivation model of the robot.

The biology literature shows that the mechanism of the correlation between the motive and the intrinsic target in the sensory motor system of human and animal, which was called Intrinsic motivation mechanism [12]. This mechanism is based on the sensory motor system, and it guided by the curiosity of the organism. Inspired by the above information, we combined the sensory motor system and the intrinsic motivation mechanism, simulated the cognitive behavior of the organism and took the learning automata as the basic frame, put forward a robot cognitive developmental algorithm based on cerebellum-basal ganglia-cerebral cortex circuits. By using this algorithm, the robot can gradually master the control skills of the motion balance by interacting with the unknown environment.

2 Cognitive Development Model and Algorithm Design

2.1 Sensory Motor System

Sensory motor system is a physiological organization, which is composed of sensory function and motor nerve function. Its basic function is to realize the mapping of perception to action. In the nervous system, the sensory nervous system is the biological neural structure to obtain information from the outside world, and the motor nervous system is the nervous system to control the movement and posture. It is composed of motor center and the peripheral nervous system. Its function is equivalent to the effector, and it can be directly exposed to the outside environment. As the goal of the movement is achieved by precise control, it requires the neural circuit to provide the external state of the integrated input signal to the motor nerve. The signal is provided by the cerebellum and the basal nucleus. To ensure proper implementation of any action is the goal of motion control.

Sensory motor nervous system is also a system with sensory motor control [13]. It contains the sensory function and motor skills, as shown in Fig. 1. Its components, in addition to the cerebellum, cerebral cortex, basal ganglia, also include sensory and motor organs. In each component, the cerebellum is the inverse controller of the sensory motor system, and it on the basis of the training signal sent by the inferior olive climbing fibers for different states selection related control action; The basal ganglia through reinforcement learning to adapt to obtain basic behavior in unknown environment [14], It is also an important medium for behavior selection of organisms. The dopamine signaling secreted by the substantia nigra pars is a very important role in the development of the guidelines, at the same time. Striosome is the evaluation mechanism of action oriented quality prediction; As a transit station of the system signal transmission, The thalamus is responsible for putting the sensory organs received from various external signal together and delivered to the cerebral cortex; In addition to the thalamus, the cerebral cortex receives signals from the basal ganglia and the cerebellum, combined with the input from other sensory states, and according to the relationship between fill left part, in order to achieve a more complex functions.

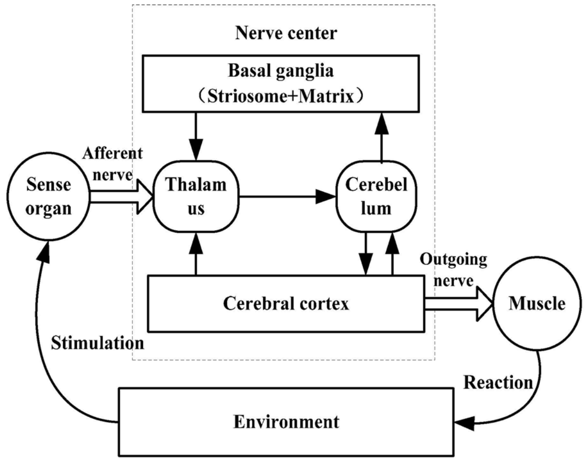


Fig. 1. Learning mechanism structure diagram of biological sensory motor system

2.2 Intrinsic Motivation Mechanism

Neurophysiology pointed out that [15], perception-action in the sensory motor system is constantly coordinated and improved in the process of the formation and development of the intrinsic motivation. Therefore, intrinsic motivation is the source of the coordination mechanism of sensory motor system. The human cognition is a process of transformation from unknown to understanding, and memory and learning is an important manifestation of intrinsic motivation. From "perception" to "action" is a process of cognitive development, and more precisely, It is a process of cognitive behavior development driven by intrinsic motivation mechanism.

Intrinsic motivation is a mechanism which guides curiosity driven exploration. It is also a very important mechanism for the development of human open cognition. It was originally studied in the category of psychology and later used in neuroscience. This motivation is influenced by many factors, such as survival, orientation, curiosity, emotion and belief, which is called the intrinsic motivation by psychologists, it is the most important mechanism of sensory motor and the cognitive development. Fig. 2 is the intrinsic motivation mechanism model. The sensor receives the perception of the external environment and transmits it to the cerebellum, the motion control command is given by the cerebellum which is in accordance with motor nervous system. effector will perform the action according to the command, and then cause environmental changes. The intrinsic motivation mechanism is no need for external environmental model. On this basis, the external state is transformed into an action, and a reward signal is received by the environment. The organism will transform the signal into evaluation index and generate orientation information, besides adjust the action on environment execution. Finally, the cognitive process of "perception-action-perception" is finished. In fact, the intrinsic motivation can improve and develop the movement control skills.

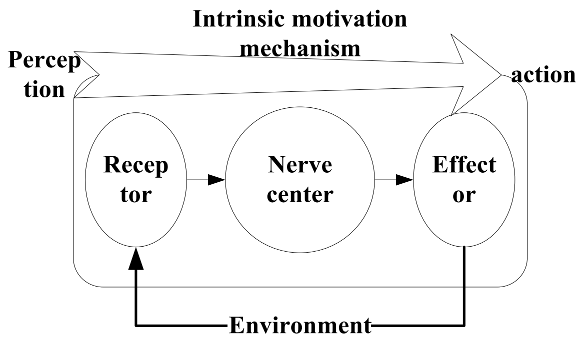


Fig. 2. The intrinsic motivation mechanism model

2.3 Cognitive Development Model and Algorithm Design

2.3.1 Cognitive Development Model

In this paper, we simulated the neural activity of the biological sensory motor system, which was based on the framework of the learning automata, combined with the intrinsic motivation mechanism to drive the characteristics of organism autonomous learning, and put forward a cognitive developmental algorithm based on cerebellar and basal ganglia cerebral cortical circuits. The control structure of the algorithm is shown in Fig. 3.

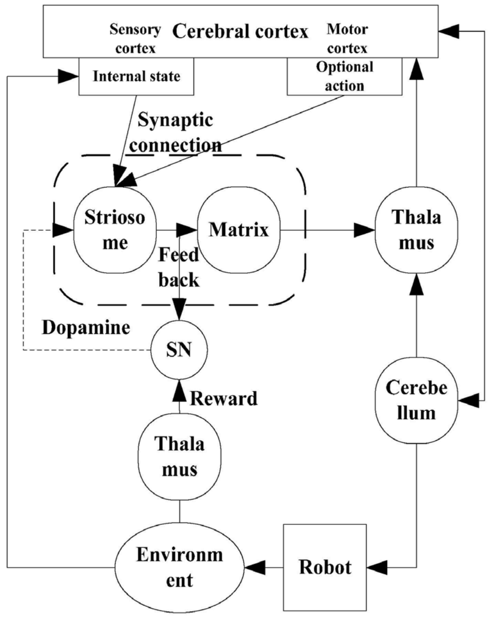


Fig. 3. The cognitive development algorithm control structure

Which, the solid lines are the signal transmission line, dotted line for synaptic modification. The basal ganglia in the dotted frame, which include the striatum and the matrix, are the main part of the evaluation of the orientation in the biological selection. The substantia nigra is mainly produce dopamine training signals. Thalamus to achieve the function of two parts: Generation of reward signals and information transmission. Cerebellum and basal ganglia, these two parts are important in the process of learning and controlling of motor nerve. The cognitive function of the basal ganglia is realized through the cortex, striatum, thalamus and cortex circuit. The thalamus plays the role of “relay station”, The sensory signals are transmitted to the cerebral cortex after the relay of the thalamus, The cerebral cortex transfer signal back to the thalamus and processing, at the same time, the thalamus is the limbic system of the brain, it can release the high consciousness, and it also plays an important role in cognition and emotion expression.

2.3.2 Cognitive Development Algorithm

The robot cognitive developmental algorithm based on cerebellum-basal ganglia-cerebral cortex circuits is referred to as cognitive development automata. The framework is shown in Fig. 4.

Definition 1. The robot cognitive developmental algorithm based on cerebellum-basal ganglia-cerebral cortex circuits can use a eight element array to represent:

$$CBCLA = \{SC, MC, Cb_A, f, r(t), BG_{strio}, BG_{matrix}, SN_{DPA}\}$$

(1) $SC = \left[s_1, s_2, \ldots s_j\right]$ is expressed as a finite set of internal states, corresponding to the sensory cortex in the cerebral cortex, s_j is expressed in terms of the j state, and the j is the number of internal states.

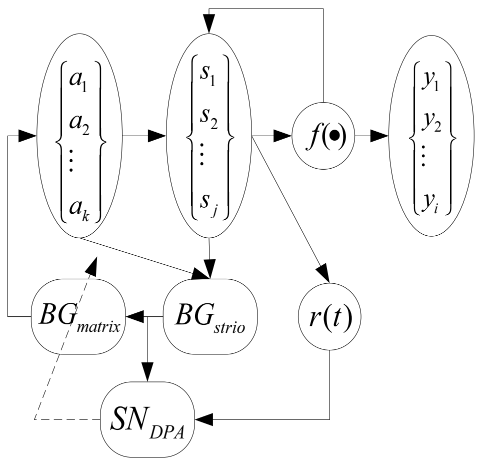


Fig. 4. Cognitive development automata framework

(2) $MC=[y_1,y_2,...y_i]$ is represented as a collection of the system output, corresponding to the motor cortex in the cerebral cortex, y_i represents the i output, and the i represents the number of outputs.

(3) $Cb_A=[a_1,a_2,...a_k]$ is expressed as a collection of internal operating behavior, corresponding to the cerebellar region, a_k represents the k internal action, and the k is the number of internal action.

(4) $f: s(t)\times a(t)\rightarrow s(t+1)$ is the state transfer equation. What's more, The state $s(t+1)$ is determined by the state $s(t)$ and the internal action $a(t)$, generally by the environment or model to decide.

(5) $r(t)=r(s(t),a(t))$ is a reward signal, which takes internal action $a(t)$ to make the state transfer from $s(t)$ to $s(t+1)$, corresponding to the thalamus.

(6) The input signal in the cerebral cortex contains two parts, namely, sensory cortex and motor cortex, as the input of the striatum. Thus

$$CC=\{SC,MC\} \quad \textbf{(1)}$$

The striatum is mainly the evaluation mechanism to predict the orientation of the organism movement. It is also the evaluation mechanism of the intrinsic motivation mechanism orientation is good or bad. Definition evaluation functions are as follows:

$$BG_{strio}(t)=r(t+1)+\gamma r(t+2)+\gamma^2 r(t+3)+... \quad \textbf{(2)}$$

which $\gamma\in[0,1]$ is the discount factor. Because of the existence of the intrinsic motivation mechanism, the evaluation function (BG_{strio}) of the system gradually approaches to 0, thus ensuring that the system is finally in a stable state, we define η as the orientation core of the intrinsic motivation mechanism, The main function is to guide the cognitive direction of organisms. Generally define the range of orientation core is $[\eta_{\min},\eta_{\max}]$, That is between the best orientation function value and the worst orientation function value. Then the intrinsic motivation orientation function in the striatum is defined as the formula (3).

$$\eta(t)=\frac{1-e^{-\lambda BG_{strio}(t)}}{1+e^{-\lambda BG_{strio}(t)}} \quad \textbf{(3)}$$

which λ is the parameters of orientation function.

Definition 2. The difference of the orientation function of two adjacent moments is $\theta(t)=\eta(t)-\eta(t-1)$, to determine the orientation degree of the system. If $\theta(t)>0$, the orientation value of the moment t is greater than the orientation value of moment $t-1$. On the contrary, if $\theta(t)<0$, the orientation value of the moment t is smaller than the orientation value of moment $t-1$.

(7) In the learning process of the basal ganglia, the matrix, the main function of the matrix in the striatum is action selection. One of the most important features in the learning process driven by the intrinsic motivation mechanism is that the action is executed according to the probability. We use the

Boltzmann probability rule to implement the behavior selection of the matrix [16], In order to achieve the probability selection mechanism of learning automata. First we define:

$$A = Boltz_T\left\{E(s,a_j), j = 1,2,....m\right\}$$
$$\Leftrightarrow p(a = a_j) = \frac{e^{\frac{E(s,a_j)}{T}}}{\sum_{j=1}^{m} e^{\frac{E(s,a_j)}{T}}} \quad \textbf{(4)}$$

According to the definition of formula (4), we can express the action selection probability output of the matrix in the striatum by using the formula (5).

$$BG_{matrix}(s,a) = \frac{e^{\frac{\mathrm{BG}_{strio}(\mathrm{SC}(t),a_j)}{T}}}{\sum_{j=1}^{m} e^{\frac{\mathrm{BG}_{strio}(\mathrm{SC}(t),a_j)}{T}}} \quad \textbf{(5)}$$

which, T is the temperature parameter, indicating the random degree of action selecting. The bigger the T value is, the greater the degree of action selection is. On the contrary, the smaller the T value is, the smaller the degree of action selection is. When T gradually tends to 0, the probability of action selection corresponding to $BG_{strio}(SC(t),a_j)$ gradually tends to 1. The T value in the system is gradually reduced with the time. It indicates that in the course of the study, the knowledge of the system is gradually increasing, and the system is gradually evolving from a unstable system into a stable system.

(8) Dopamine released from the substantia nigra pars compacta can be used as the action evaluation guidance signal, for improving caused by action on the future of the biggest reward behavior expression, in order to obtain more precise action. In $t+1$ time, the evaluation function is determined by the striatum.

$$BG_{strio}(t+1) = r(t+2) + \gamma r(t+3) + \gamma^2 r(t+4) + ... \quad \textbf{(6)}$$

The formula (2) and the formula (6) can be derived from the formula (7).

$$BG_{strio}(t) = r(t+1) + \gamma BG_{strio}(t+1) \quad \textbf{(7)}$$

It indicates in the t time, Evaluation function $BG_{strio}(t)$ can be expressed by the evaluation function $BG_{strio}(t+1)$ of the moment $t+1$. However, because of the influence of the error in the initial prediction, the value of evaluation $BG_{strio}(t+1)$ is not equal to the actual value. Such reward information, which transmission from the thalamus and striatum, needs to be processed in the substantia nigra pars, and the release of dopamine can modulate the evaluation value. It can be expressed by formula (8).

$$SN_{DPA} = r(t+1) + \gamma BG_{strio}(t+1) - BG_{strio}(t) \quad \textbf{(8)}$$

2.4 The Proof of Convergence Algorithm

Definition 3. The evaluation function $BG_{strio}(t)$ of the striatum output is set to $\boldsymbol{J}(t)$ to facilitate the proof. That is to say, using formula (9):

$$BG_{strio}(t) = \boldsymbol{J}(t) \quad \textbf{(9)}$$

Theorem 1. In Markov environment using the Iterative algorithm: $\hat{\boldsymbol{J}}_n(t) = r(t) + \gamma \max \hat{\boldsymbol{J}}_{n-1}(t+1)$, If for any state action pair (s,a), both the absolute value of the instant reward $|r(s,a)|$ and the initial value of the iterative initial value $\hat{\boldsymbol{J}}_0(s,a)$ have a boundary. $0 \le \gamma < 1$, n is the iteration number. When n approaches infinity, If every state action pair (s,a) are not limiting the number of dispatch, Then the $\hat{\boldsymbol{J}}_n(s,a)$ will eventually tend to the optimal value $\boldsymbol{J}^*(s,a)$ with probability 1.

Prove. Consider the evaluation function of any state action pair and the optimal value of the absolute value of the difference is:

$$
\begin{aligned}
\left|\hat{\boldsymbol{J}}_n(s_t,a_t)-\boldsymbol{J}^*(s_t,a_t)\right| &= \left|\begin{matrix}[r(s,a)+\gamma\max\limits_{a'}\hat{\boldsymbol{J}}_{n-1}(s',a')]- \\ [r(s,a)+\gamma\max\limits_{a'}\boldsymbol{J}^*(s',a')]\end{matrix}\right| \\
&= \gamma\left|\max_{a'}\hat{\boldsymbol{J}}_{n-1}(s',a')-\max_{a'}\boldsymbol{J}^*(s',a')\right| \\
&\le \gamma\max_{a'}\left|\hat{\boldsymbol{J}}_{n-1}(s',a')-\boldsymbol{J}^*(s',a')\right| \\
&\le \gamma\max_{\tilde{s},a'}\left|\hat{\boldsymbol{J}}_{n-1}(\tilde{s},a')-\boldsymbol{J}^*(\tilde{s},a')\right|
\end{aligned}
\quad \textbf{(10)}
$$

Which, the state and action after the transfer is s' and a'. The two transfer state is s'', $\tilde{s}$ is arbitrary state. The maximum estimation error of the evaluation function after the Nth iteration is located:

$$\Delta\boldsymbol{J}_n = \max_{s,a}\left|\hat{\boldsymbol{J}}_n(s,a)-\boldsymbol{J}^*(s,a)\right| \quad \textbf{(11)}$$

then:

$$\Delta\boldsymbol{J}_n \le \gamma\Delta\boldsymbol{J}_{n-1} \le \gamma^n\Delta\boldsymbol{J}_0 \quad \textbf{(12)}$$

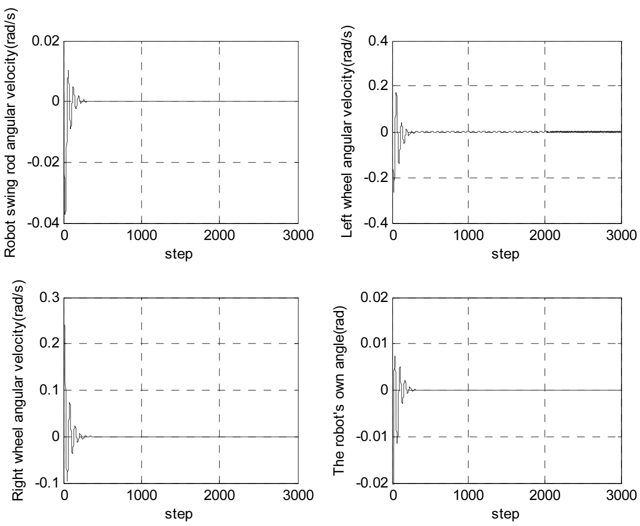
Because $\hat{\boldsymbol{J}}_0(s,a)$ is bounded, $\Delta\boldsymbol{J}_0$ is bounded. Each (s,a) will be dispatch, when n approaches infinity, $\Delta\boldsymbol{J}_0$ approaches 0. So the evaluation function $BG_{strio}(t)=\boldsymbol{J}(t)$ for the robot cognitive developmental algorithm based on cerebellum-basal ganglia-cerebral cortex circuits in $n\to\infty$ case is convergent, then the system is in a stable equilibrium state.

3 Experimental Simulation and Results Analysis

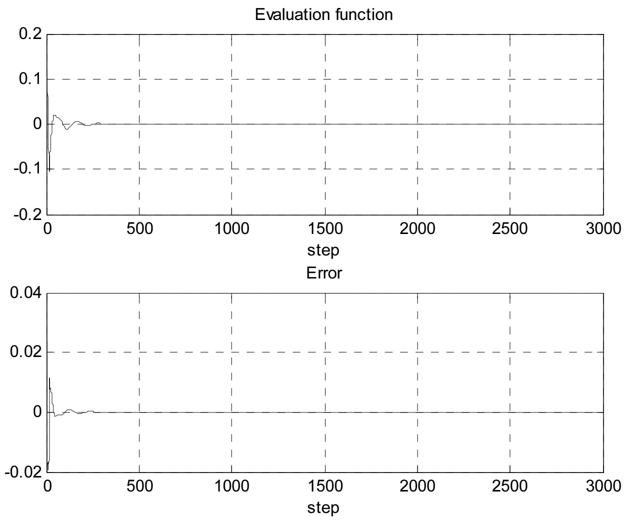
In the case of non-complete two-wheeled self-balancing robot, it is an unstable system. In order to realize all kinds of motion, First of all, to ensure that the robot can maintain its own balance, So the attitude balance of two-wheeled robot is the primary condition for the motion control. In order to verify the validity, robustness and superiority of the proposed robot cognitive developmental algorithm based on cerebellum-basal ganglia-cerebral cortex circuits (CBCLA) in this paper. In the unknown environment, Taking two-wheeled robot as the experimental object, We have studied how the robot learns the motor skills by autonomous learning.

In the experiment, the robot has four outputs and meets the corresponding conditions. That is, the left and right angular velocity of θ_l and θ_r are less than 3.489rad/s, Body's own inclination $\alpha<0.1744$ rad, and the robot swing rod angular velocity $\beta<3.489$ rad/s. Discount factor $\gamma=0.9$, Sampling time is 0.01s, In each experiment, when the robot's attempt to exceed 1000 times or an attempt to balance number more than 20000 steps, then stop the robot's learning and start another experiment, If the robot has been able to maintain its balance after 20000 steps in one attempt, it is considered that the robot has learned to balance control skills. Every time after the failure of the experiment, the initial state and the each weight reset to a random value within a certain range, and then re-learning.

(1) Balance control experiment: robot in the unknown environment without interference, using the CBCLA algorithm proposed in this paper, after continuous learning, After the 42 test and in 43rd test completed the experiment, about to go through 220 steps, namely the robot used 2.2s to learn the balance control skill. Performance of its fast learner autonomy and the effectiveness of the algorithm. The simulation results in the first 3000 steps, the response curve of each state and the evaluation function and the error simulation curve as shown in Fig. 5.



(a) response output curve of each state



(b) Evaluation function and error simulation curve

Fig. 5. Balance control experiment simulation results

(2) Anti interference experiment: In the actual operation of the system, the input and output signals are more or less affected by the external noise, or the detection device is not accurate, will make the state of a certain error. Then in order to simulate the actual environment, when the robot has learned to maintain the balance of control after the 9800 step, a pulse signal with amplitude of 25 is added to each input state, If the robot can withstand the interference of the pulse signal and maintain the balance, it is considered that the experiment is successful and the CBCLA algorithm proposed in this paper has a certain robustness. Fig. 6 shows the output response of each state after the addition of the pulse signal. It can be seen that after 200 steps (that is 2S), the robot can reach the equilibrium position.

(3) Algorithm contrast experiment: Since the algorithm of this paper introduced intrinsic motivation mechanism to drive the robot's autonomous learning, it can reduce the error of the system and improve the convergence speed of the algorithm. we respectively used classical learning automata (LA) algorithm and CBCLA algorithm for the balance control experiments on two-wheeled robot, and analyzed the results of the experiments. In the experiment, the parameters of the two algorithms are the same. Fig. 7 shows that the comparison between the two algorithms of evaluation function and the error curve in the first 2000 steps. Through Fig. 7(a), we can see that the CBCLA algorithm in the 220 steps (that is 2.2s) to

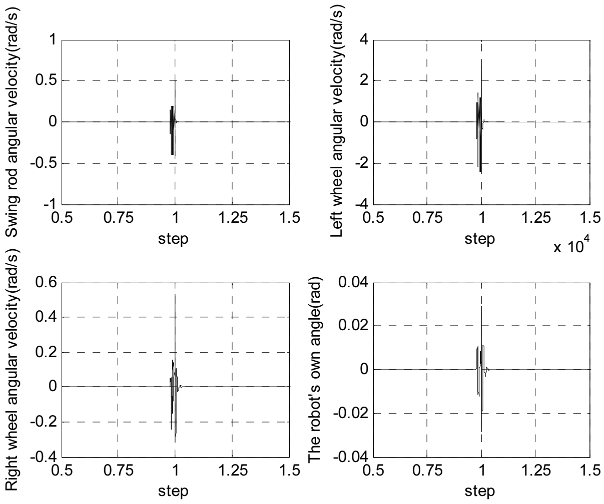
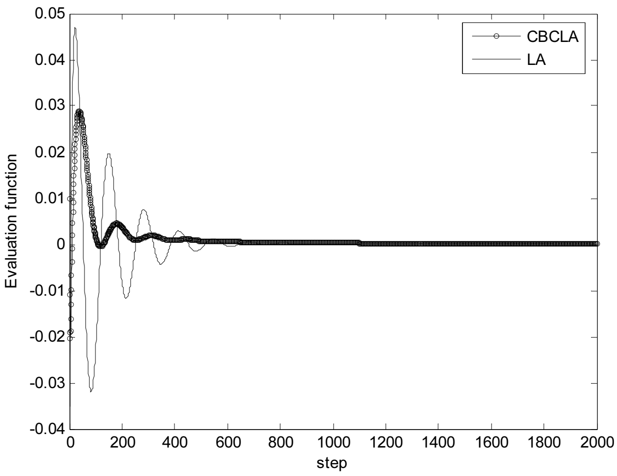
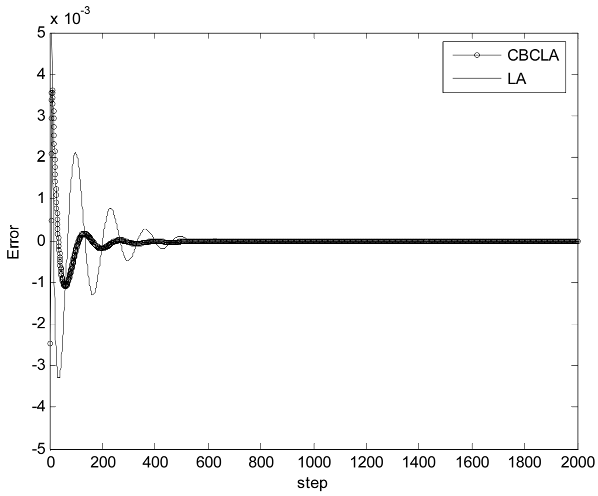


Fig. 6. Anti interference experiment simulation results



(a) The evaluation function comparison of two algorithms



(b) The error comparison of two algorithms

Fig. 7. Comparison between the CBCLA algorithm and the classical LA algorithm of evaluation function and the error curve

complete the balance control skills learning, and the classic LA algorithm in about 600 steps (6S) to complete the study. It is proved that the convergence rate of CBCLA algorithm is better than that of classical LA algorithm. Fig. 7(b) indicates that the error margin of the CBCLA algorithm is better than the classical LA algorithm, what's more, the CBCLA algorithm is more conducive to the stability of the system.

4 Conclusion

In this paper, aiming at the problem of aiming at the problem of robot continuous behavior learning, we simulated the structure of human or animal nervous system and the evolution law of neural information, according to the related knowledge of the sensory motor system, and combined the characteristics of the interaction between the cerebellum, basal ganglia, cerebral cortex and other nerve organs, then introduced the intrinsic motivation mechanism in psychology to drive robot autonomous learning, finally put forward the robot cognitive developmental algorithm based on cerebellum-basal ganglia-cerebral cortex circuits. Through the simulation experiment proves that the algorithm can successfully make robot learn to balance control skill and has certain robustness. In addition, the algorithm also shows a good self-organizing, adaptive and self-learning ability. finally through comparing with the traditional algorithm, embodies the superiority of the algorithm in this paper.

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