A Growing Cognitive Model of Motor Balance Skill: Architecture, Algorithm and Application[1]

Yumei Zhang, Guoyu Zuo , Daoxiong Gong and Xiaogang Ruan[2]

Institute of Information and Control, Beijing
University of Technology, Beijing , China 100022

{ammie,gyzuo}@emails.bjut.edu.cn ,
{gongdx, adrxg@bjut.edu.cn}

Abstract

A growing cognitive model of motor balance skill (CMMBS), which simulates the manners of human beings and animals in motor balance skill learning, is presented. CMMBS, whose architecture is similar to the reflex arc of the biologic nerve, adopts a growing algorithm from reference to Growing Cell Structures in order to perform the pattern classification in the nerve center. This growing mechanism is able to be evolved through the continuous growing of the new neuron. Reinforcement Hebbian Synaptic Modification is used as the self-learning method in CMMBS to make the neurons in difference fields to respond to the different stimulus in the best way. The inverted pendulum is chosen as the control object and CMMBS is used to achieve the self-skill-learning. The experimental results are shown that CMMBS can interact autonomously with the environment and develop the motor balance skill by the growing manners of neural system itself.

Keyword: cognitive model, growing cell structures, Hebbian learning, inverted pendulum

1. Introduction

Many skills of the biology are acquired gradually as the individual grows up, which is called as cognitive skill acquisition. It is an important part of studies for motor learning to simulate the cognitive manners of human beings and animals. The goal in this paper is to develop a computational model of the cognitive skill learning for motor balance control.
Most existing models of skill learning are presented in lots of papers with focus on track programming of the Robotic Agent.

The Vector Integration to Endpoint (VITE) model (Bullock & Grossberg, 1988) [1] successfully explains psychophysical and neurobiological data about how synchronous multi-joint to reach trajectories. Later, VITEWRITE (Bullock, Grossberg, and Mannes, 1993) [2] used a synergy-overlap strategy to generate curved movements from individual, target-driven strokes. And then

[1] This work is supported by the National Natural Science Foundation of China (60375017, 60304012) and Doctor Research Startup Foundation of BJUT (52002011200401.
[2] Xiaogang Ruan: the corresponding author.

AVITEWRITE (Grossberg and Paine, 2000) [3]), which is the combination of VITE and VITEWRITE, describes how the complex sequences of movements involved in handwriting can be learned through the imitation of previously drawn curves.

A development approach called AA-learning (Automated, Animal-Like Learning) is proposed by Weng (1998) [4] and is motivated by automatic human mental development. Meanwhile, a robotic project called SAIL (short for Self-organizing, Autonomous, Incremental Learner) is implemented. The goal of the SAIL project (2000) [5] is to automate the process of mental development for robots. Studies above are only focus on highly intellectual tasks. In fact, skills vary in complexity and degree of cognitive involvement and they range from simple motor movements and other routine tasks in everyday activities to high-level intellectual skills. Therefore, it is also important to study "lower"-level cognitive skills, which have not received sufficient research attention in cognitive modeling.

A skill learning model CLARION is presented by Ron Sun, etc (1998~2001) [6]. A bottom-up approach toward low-level skill learning is adopted, where procedural knowledge develops first and declarative knowledge develops later. But such robotic agent cognitive models hardly deal with the motor balance skill acquisition. Indeed, with the development of the studies for biped walking robot, the skill learning for motor balance control is attached importance gradually.

There are lots of methods proposed so far on biped walking robot. For example, a Genetic Algorithm gait synthesis method is proposed by Capi (2001) [7], which can select an appropriate gait with the reduction of the consumed energy and Zhang (2002) [8] uses wavelet neural networks to make a gait planning controller of biped robot, etc. However, this kind of works is not related to cognitive acquisition closely.

So in this paper a growing cognitive model of motor balance skill (CMMBS), which simulates the manners of human beings and animals in motor balance skill learning, is presented. CMMBS, whose architecture is similar to the reflex arc of the biologic nerve, adopts a growing algorithm from reference to Growing Cell Structures in order to perform the pattern classification in the nerve center. This growing mechanism is able to be evolved through the continuous growing of the new neuron. Reinforcement Hebbian Synaptic Modification is used as the self-learning method in CMMBS to make the neurons in difference fields to respond to the different stimulus in the best way. The inverted pendulum, which is an abstract physical model of the Motor Balance, is chosen as the control object and CMMBS is used to achieve the self-organization and self-skill-learning. The experimental results are shown that CMMBS can interact autonomously with the environment and develop the motor balance skill by the growing manners of neural system itself.

2. CMMBS

Fig.1 is a schematic diagram of the architecture of CMMBS. We may define the CMMBS Model which has the architecture of reflex arc as a dualistic set: $CMMBS = \{RC, CA\}$.

- *RC*: the reflex arc architecture of the neural network , which is defined as $RC = \langle IF, WF, OF, R_{IW}, R_{WO} \rangle$, where *IF* is the input field, corresponding to afferent nerve; *WF* is the work field, corresponding to nerve center; *OF* is the output field, corresponding to efferent nerve; R_{IW} is the connection relationship between *IF* and *WF*; R_{WO} is the connection relationship between *WF* and *OF*.

- *CA*: the cognitive algorithm, which is defined as *CA*=<*EA, GA, RA*>, where *EA*, the evaluator, evaluates the effect of stimulus and response and generates the value of r_G and r_H; *GA* is the growing algorithm; *RA* is the reinforcement Hebbian Synaptic modification algorithm.

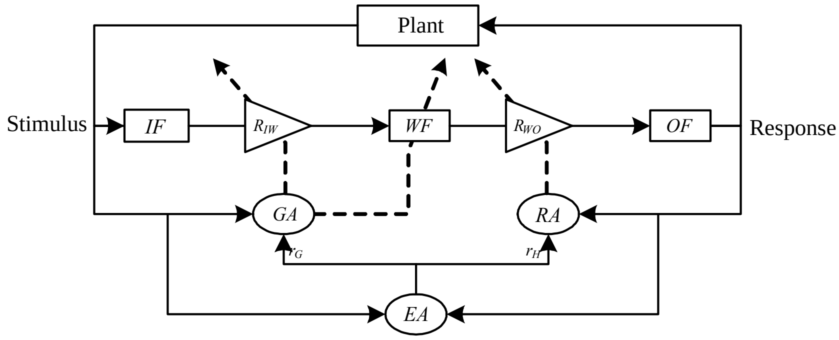


Fig. 1. Schematic diagram of the architecture of CMMBS.

Its fundamental principles can be described as follows: *IF* transmits the external environment stimulus to *WF* through the connection R_{IW} ; *WF*, combined with competitive and growing neural network, helps the input pattern to find its correct response region by the competitive and self-organizing rules; *OF* sends the right response to the external object; *EA*, generates the evaluation results of r_G and r_H, who are the evaluation signal of growth and the reinforcement signal of Hebb learning respectively, according to the effect of the plant's balance movements; *GA*, the growing algorithm, adapts the elements of R_{IW} through the rules of self-organizing feature mapping and according to r_G and the network information *GA* can control size and architecture of the network in *WF* through its growing algorithm to make the neural network grow spontaneously for the purpose of improving the ability of pattern recognition to the input simulations; *RA* adjusts the elements of R_{WO} self-organizing according to r_H to make each region approach the optimized response value.

2.1. Architecture

The whole neural network architecture of CMMBS is shown in Fig.2. The external stimulus vector $P=(p_1,p_2,\cdots,p_{n_I})$ enters the network from *IF*. And the topology of the nerve center consists solely of k-dimensional simplices. In view of calculation quantity problem, $k=2$ has been chosen here, that is, the nerve center is always combined with a number of triangular with one neuron in every corner.

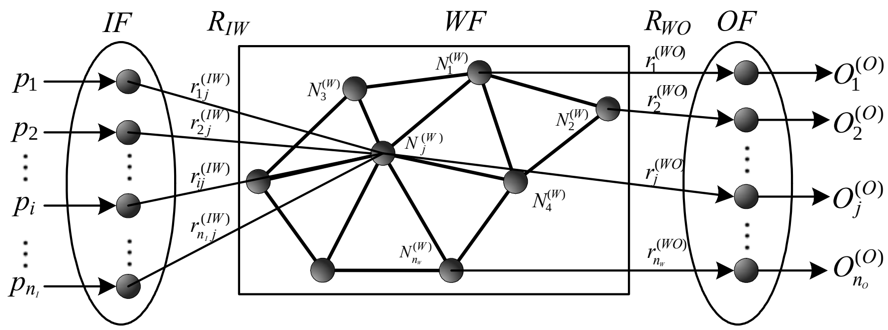


Fig. 2. The whole neural network of CMMBS. The external stimulus vector $P=(p_1,p_2,\cdots,p_{n_I})$ enters the network from *IF*. The topology of the nerve center consists solely of triangles with one neuron in every corner.

$I_j^{(W)}$ and $O_j^{(W)}$ are defined as the input and output value of $N_j^{(W)}$, the neuron in *WF*:

$$\begin{cases} I_j^{(W)} = \sum_{i=1}^{n_I} (p_i - r_{ij}^{(IW)})^2 \\ O_j^{(W)} = \begin{cases} 1, & I_j^{(W)} = \min\{I_i^{(W)} \,|\, (i = 1, 2, \cdots, n_W)\} \\ 0, & others \end{cases} \end{cases} j = 1, 2, \cdots n_W \quad (1)$$

$I_j^{(O)}$ and $O_j^{(O)}$ are the input and output value of $N_j^{(O)}$, the neuron in *OF*:

$$\begin{cases} I_j^{(O)} = O_j^{(W)} r_j^{(WO)} \\ O_j^{(O)} = f(I_j^{(O)}) = e^{(-I_j^{(O)})2} \end{cases} \quad (2)$$

where $f(\bullet)$ is the activation function and the radial-basis function is proposed here.

2.2. Growing algorithm

Growing Cell Structures (GCS), which is proposed as a new self-organizing network model by Fritzke in 1992 [9], is used as growing mechanism of the nerve center. GCS has a superiority of automatically determining a problem specific network structure. The Growing algorithm can be described as follows:

Step1 t=1, initialize $WF=\{N_i^{(W} \mid i=1,2,\cdots,n_W\}$ contain 3 neurons, with reference vectors $R_{IW}=(r_{ij}^{(IW)})_{n_I \times n_W}$ ($r_{ij}^{(IW)} \in [0,1]$) chosen randomly (see Fig.3 (a)). A local counter variable τ_j=0 (j=1, 2,$\cdots$, n_W) is defined for every neuron to counter the times each neuron has been best-matching unit.

Step2 For a stimulation vector $P(t)$, locate the best matching unit $N_s^{(W)}$ as

$$\left\| r_{\bullet s}^{(IW)}(t) - P(t) \right\| = \min_{j=1,\cdots,n_W} \left\| r_{\bullet j}^{(IW)}(t) - P(t) \right\| \quad (3)$$

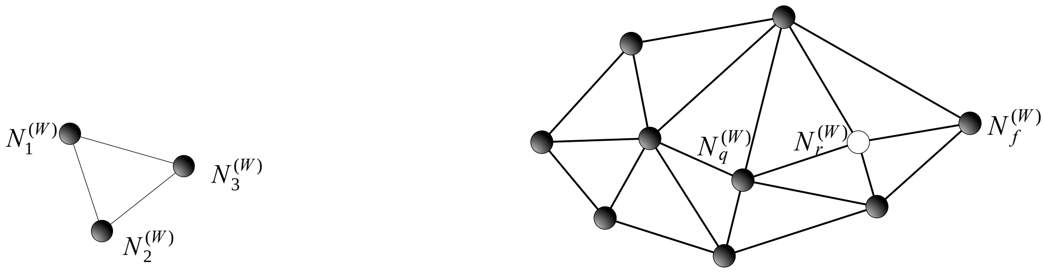
where $\|\bullet\|$ denotes the Euclidean vector norm and denote the n_I -dimensional synaptic vector of $N_j^{(W)}$ is denoted as $r_{\bullet j}^{(IW)} = (r_{1j}^{(IW)}, r_{2j}^{(IW)}, \cdots, r_{n_I j}^{(IW)})$.

Step3 Increase matching for $N_s^{(W)}$ and its direct topological neighbors:

$$\begin{cases} r_{\bullet s}^{(IW)}(t+1) = r_{\bullet s}^{(IW)}(t) + \varepsilon_s (P(t) - r_{\bullet s}^{(IW)}(t)) \\ r_{\bullet j}^{(IW)}(t+1) = r_{\bullet j}^{(IW)}(t) + \varepsilon_n (P(t) - r_{\bullet j}^{(IW)}(t)), \quad \forall j \in NB_s \end{cases} \quad (4)$$

where ε_s and ε_n are constant adaptation parameters for the best matching unit and the neighboring neurons, respectively. And then increase the signal counter of $N_s^{(W)}$ by $\tau_s(t+1) = \tau_s(t)+1$.

Step4 If $r_G = -1$, go to Step5, else Step6.



(a) Initial Situation (b) After insertion

Fig. 3. Topology of the Network in *WF*. Fig (a) shows the initial situation of the 3 neurons in *WF*, whose topology is a triangle. Fig (b) shows the situation after a new neuron $N_r^{(W)}$ is inserted between $N_q^{(W)}$ and $N_f^{(W)}$

Step5 Insertion of a new neuron (shown in Fig.3 (b)). Determine $N_q^{(W)}$ by

$$h_q \geq h_j, (j = 1, 2, \cdots, n_W),\ h_j = \tau_j / \sum_{i=1}^{n_W} \tau_i \tag{5}$$

where h_j the relative signal frequency of $N_j^{(W)}$. Determine among the neighbors of $N_q^{(W)}$ the unit $N_f^{(W)}$ with the largest distance in input space, then insert a new neuron $N_r^{(W)}$ between $N_q^{(W)}$ and $N_f^{(W)}$. Initialize the synaptic vector $r_{\bullet r}^{(IW)}$:

$$r_{\bullet r}^{(IW)}(t+1) = (r_{\bullet q}^{(IW)}(t) + r_{\bullet f}^{(IW)}(t))/2 \tag{6}$$

Compute the changes of counters τ_j ($j \in NB_r$) and initialize τ_r:

$$\begin{aligned} \tau_j(t+1) &= \left(1 - \frac{\left|F_j^{(old)}\right| - \left|F_j^{(new)}\right|}{\left|F_j^{(old)}\right|}\right)\tau_j(t), \\ \tau_r(t+1) &= \sum_{j \in NB_r} \frac{\left|F_j^{(old)}\right| - \left|F_j^{(new)}\right|}{\left|F_j^{(old)}\right|}\tau_j(t) \end{aligned} \tag{7}$$

where $|F_j|$ is the n_I-dimensional volume of F_j.

Step6 The output of the best matching unit, $O_S^{(W)}=1$, and other outputs are all zero. $O_S^{(W)}$ is sent to output field to generate the response, and then the algorithm of *RA* will be used to train the connection vector R_{WO}.

Step7 $t=t+1$. The network will receive a new stimulation vector. Go back to Step2.

2.3. Reinforcement Hebbian Learning

An reinforcement Hebb learning algorithm, which is the combination of the theory of Hebbian Learning [10] and Anti-Hebbian Learning(derived from Law of Repulsion presented by Barlow in 1990 [11]), is used here as the self-organizing training approach for the connection R_{WO} in *OF*.

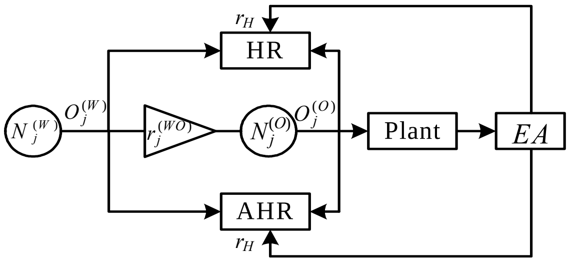


Fig. 4. Training scheme diagram of the neuron $N_j^{(W)}$,which is supposed to be the best matching unit is, then $O_j^{(W)}$=1 and $r_j^{(WO)}$ needs to be adjusted.

$N_j^{(W)}$ is supposed to be the best matching unit is, then $O_j^{(W)}$=1 and $r_j^{(WO)}$ needs to be adjusted. The training scheme of the neuron $N_j^{(W)}$ is shown in Fig.4. The output neuron is a single input and single output nonlinear model. The reinforcement Hebbian learning is defined as follows:

$$r_j^{(WO)}(t+1) = r_j^{(WO)}(t) + \eta(t) \cdot r_H \cdot O_j^{(W)}(t) \cdot O_j^{(O)}(t) \qquad \textbf{(8)}$$

where $\eta(t)$ is a learning-rate parameter. In Fig.4, *EA* generates the critic value r_H according to the "stimulation-response" effect of the object. When r_H >0, that means the response can make the system in a better manner, then the self-organizing mechanism chooses Hebbian Learning to make the synapse strength, $r_j^{(WO)}$, increased. Whereas, when r_H <0, that means the response makes the system in a worse manner, then the self-organizing mechanism chooses Anti-Hebbian Learning to weaken the synapse strength.
Through this self-organizing way, the synaptic weight $r_j^{(WO)}$ can approach the right response of each region.

3. Skill Learning for Motor Balance Based on CMMBS

How does CMMBS take place during the cognitive skill acquisition for motor balance? The inverted pendulum, an abstract physical model of the Motor Balance, is chosen for the experiment here. Inverted pendulum balancing is the task of keeping a pendulum, hinged to a cart and free to fall in a plane, in a roughly vertical orientation by moving the cart horizontally in the plane while keeping the cart within some maximum distance of its starting position. u is controlling force applied to the cart's center of mass; θ and $\dot{\theta}$ are angle and angular velocity of the pendulum, respectively; x and $\dot{x}$ is the horizontal position and velocity of the cart relative to the track. The control object is making the angle move within ±10° and making horizontal position of the car move within ±2*m*.

Fig.5 shows the controlling schematic diagram based on CMMBS. The input vector of the CMMBS is combined with four state variables, $P=(\theta,\dot{\theta},x,\dot{x})$, and the output produces the control signal u. Each trail starts with an initial state of $P_0=(5^{\circ},0,0,0)$, and then the neuron-controller begins to "grow" with three neurons in the nerve center according to the evaluations from *EA*.

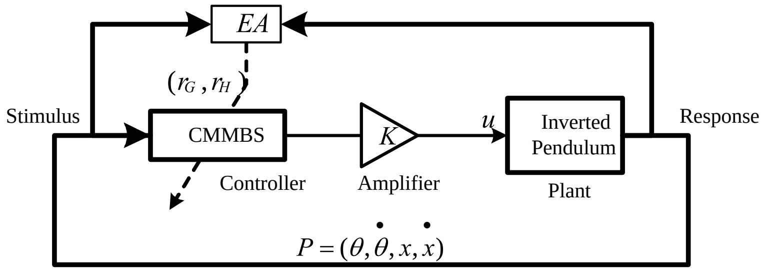


Fig. 5. The controlling schematic diagram based on CMMBS

For the inverted pendulum system, r_H and r_G are defined as:

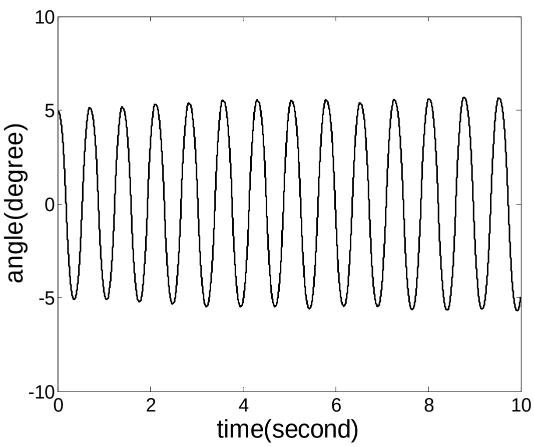
$$r_H = \begin{cases} 0.15, & \dfrac{d|\theta|}{dt} < 0 \ \ and \ \ |\theta| < 10^\circ \ \ and \ \ |x| < 2m \\ -0.2, & \dfrac{d|\theta|}{dt} > 0 \ \ and \ \ |\theta| < 10^\circ \ \ and \ \ |x| < 2m \\ -1.0, & |\theta| \geq 10^\circ \ \ and \ \ |x| \geq 2m \end{cases} \tag{9}$$

$$r_G = \begin{cases} -1, & trial > Maxtrial \\ -1, & e_\theta > Maxe_\theta \\ 0, & others \end{cases} \tag{10}$$

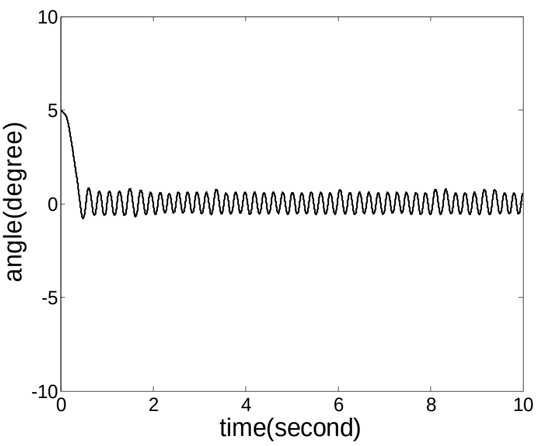
where $r_H = -1$ means that a failure signal occurs, and one trail ends for that. *trial*=*trial*+1. A new trail begins from the original state again. If the failure signal doesn't occur within 100 seconds, this trial is successful. In formula (8), *Maxtrial* is the permitted maximal trail time; $Maxe_\theta$ as the permitted maximal angle error of steady-state. When the number of fail times exceeds *Maxtrial* or the performance of pendulum angle controlling doesn't reach the criteria, the nerve center neural network needs to grow, that is to insert new neuron in *WF*.

4. Simulation Results

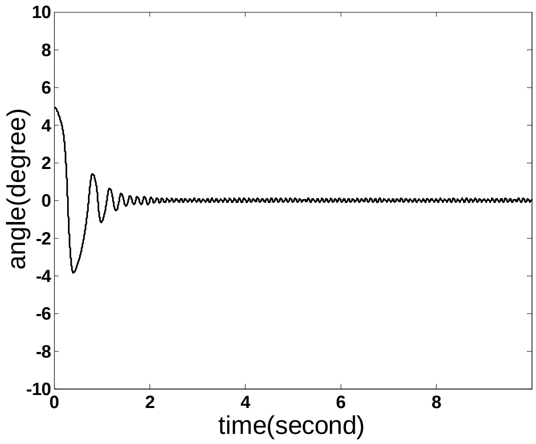
The experiment result curves shown in Fig.6 show that the pendulum will not be controlled until the number of neuron in *WF* is nine. But from Fig.6 (a), the angle curve is oscillating with high magnitude. When there are 20 neurons in *WF*, the angle control effect has been improved (see Fig.6 (b)). At last we choose 27 neurons as the final result. As shown in Fig.6 (c), the angle signal has been well control with a good performance, whose error of steady-state is less than ±0.2°.



(a) 9 neurons



(b) 20 neurons



(c) 27 neurons

Fig. 6. Fig (a) shows that the angle curve is oscillating with high magnitude. Then when there are 20 neurons in *WF*, as shown in Fig (b), the angle control effect has been improved. At last we choose 27 neurons as the final result. As shown in Fig (c), the angle signal has been well control with a good performance, whose error of steady-state is less than ±0.2°.

5 Conclusions and Future Research

This work has shown that the skill learning method based on CMMBS has achieved the balance skill of controlling the inverted pendulum in the process of trial, fail, learning and growing. The cognitive model has been well developed with an appropriate size and structure spontaneously.

The work in this paper is an attempt of the skill cognitive in the field of balance control of the robot agent. But the evaluation unit is too simple and the parameters are still constant by man-made method. Further investigations are being made to build a better evaluation mechanism, which is maybe the evaluation network, to induct the neural network of CMMBS to gain an optimum scale and architecture.

References

[1] D. Bullock, and S. Grossberg, "the VITE model: a neural command circuit for generating arm and articulator trajectories", *Dynamic patterns in complex systems*, Singapore: World Scientific, 1988.

[2] D. Bullock, and S. Grossberg, "A neural network model for cursive script production", *Biological Cybernetics*, 70, 15-28, 1993.

[3] S. Grossberg, and R. W. Paine, "A neural model of cortico-cerebellar interactions during attentive imitation and predictive learning of sequential handwriting movements", *Neural Networks*, 13, 999-1046, 2000.

[4] J. Weng, "The Developmental Approach to artificial intelligence: Concepts, developmental algorithms and experimental results", *Proceedings of the NSF Design and Manufacturing Grantees Conference*, 1998.

[5] J. Weng, W. S. Hwang, Y. Zhang, C. Yang, and R. Smith, "Developmental Humanoids: Humanoids that Develop Skills Automatically", In *Proceedings the first IEEE-RAS International Conference on Humanoid Robots*, Cambridge MA, September 7-8, 2000.

[6] R. Sun, E. Merrill, and T. Peterson, "From implicit skills to explicit knowledge: a bottom-up model of skill learning", *Cognitive Science*, 25, 203-244, 2001.

[7] G. Capi et al, "Application of genetic algorithms for biped robot gait synthesis optimization during walking and going up-stairs", *Advanced Robotics*, 15, 675-694, 2001.

[8] K. Zhang, W. Y. Qiang, and P. C. Fu, “Gait planning controller of biped robot using wavelet neural networks”, *Journal of Astronautics*, 23, 1000-1328,2002.
[9] B. Fritzke, “Growing cell structures -- a self-organizing network in k dimensions”, *Artificial Neural Networks II*, North-Holland, Amsterdam, 1992, 1051-- 1056.
[10] D. O.Hebb. “The Organization of Behavior”, *New York*: John Wiley & Sons,1949
[11] H. B. Barlow, “A theory about the functional role and synaptic mechanism of visual after-effects”. In Blakemore, C., editor, Vision: Coding and Efficiency, 363--375. *New York*: Cambridge University Press, 1990.

Yumei Zhang is a guaduated student of Institute of Artificial Intelligent and Robotics (IAIR), Beijing Universiy of Technology (BJUT), Beijing, China. And she has received her M.E degree from pattern recognition and intelligent systems from BJUT in July, 2005. Her research interests include cognitive science, machine learning, and intelligent control.

Guoyu Zuo is an Assistant Professor of Institute of Artificial Intelligent and Robotics (IAIR), BJUT, Beijing, China. He received the Ph.D. degree from pattern recognition and intelligent systems from Beijing Universiy of Technology (BJUT), China, in 2005. His research interests include information and signal processing, and intelligent control.

Daoxiong Gong is an Assistant Professor of IAIR, BJUT. He received the Ph.D degree in pattern recognition and intelligent system from the Beijing University of Technology , Beijing, China, in 2004. He His research interests include evolutionary computing, artificial intelligence, and bioinformatics.

Xiaogang Ruan is the Professor and Director of Institute of Artificial Intelligent and Robotics, BJUT. He received Ph.D. degrees in computer science and Ph.D degree from Zhejiang University, Hangzhou, China, in 1989 and 1992, respectively. His research interests include evolutionary computing, artificial intelligence, and bioinformatics.received his. His research interests include information and signal processing, intelligent control, and bioinformatics.