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ScienceDirect
Neurocomputing 70 (2007) 770–776
NEUROCOMPUTING
www.elsevier.com/locate/neucom

On-line adaptive control for inverted pendulum balancing based on feedback-error-learning

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Available online 14 October 2006

Abstract

A new on-line adaptive control scheme based on feedback-error-learning is proposed and applied to inverted pendulum balancing. The proposed adaptive controller for balancing consists of a conventional feedback controller (CFC) and a neural network feedforward controller (NNFC). In the NNFC, the feedback error signal is employed as input stimulator, instead of the usual reference signal. An on-line back-propagation (BP) algorithm with the self-adaptive learning rate is developed and employed in the NNFC to realize the combination of learning and controlling. Computer simulations on inverted pendulum balancing task demonstrate that the proposed adaptive controller could effectively reduce precision requirements of the CFC parameters, and guarantees good balance performance and acceptable robust performance.

Keywords: Feedback-error-learning model; On-line learning; Balance control

1. Introduction

Balance control is a fundamental motor behavior in stance and gait that allows an individual to maintain a position, adopt various voluntary movements, and react to external perturbations. Three levels of the central nervous system (CNS) take part in balance control. The spinal reflex is used in reactive situations triggered by external stimuli. At the sub-cortical and cortical level, the cerebellum and the cerebral cortex play an integral role in both motor control and motor learning [25]. An important feature of the CNS is its remarkable ability to adapt to changes both in the environment and inside the body. This ability indicates that the CNS learns and maintains internal models of the kinematics and dynamics of the environment and the body.

The concept of internal model was first introduced into the field of neurophysiology by Ito [9], who suggested that internal models existed for motor learning and control in the CNS. There are two varieties of internal model, i.e., forward model and inverse model. Both well suited to act as controllers because they can provide the motor command necessary to achieve some desired state transition. Acquiring an inverse internal model through motor learning is generally a difficult task, because the appropriate training signals, the motor command errors, are not directly available. Instead we received error signals in sensory coordinates, and these sensory errors need to be converted into motor errors before they can be used to train an inverse model. Based on forward and inverse models, Kawato proposed feedback-error-learning (FEL) model which comprised a fixed feedback controller that ensured the stability of the system and an adaptive feedforward controller that improved control performance [12]. The outputs of the feedback controller can be regarded as the motor errors that were used to train the inverse model. This approach was highly successful. Neurophysiological evidences [24] supported this learning mechanism within the cerebellum for the simple reflex eye movement called the ocular following response, implying that the cerebellum constructs an inverse model of the eye's dynamics. However, Although FEL method can be proven to work well in trajectory planning and controlling [26,11], there are only a few research based on FEL scheme to understand humanoid balance controlling tasks, even which is a fundamental issue for humanoid robots.

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doi:10.1016/j.neucom.2006.10.012

There is growing evidence that internal models of motor balance are stored in the cerebellum. Decades ago, Holmes pointed out that cerebellum was responsible for maintaining standing posture [7]. Based on historical medical cases, Glickstein concluded that there was no reported case histories exist in full recovery of a patient with an abnormally developed cerebellum [5]. Using PET [23], fMRI [10] methods, it is confirmed that the cerebellar vermis efferent system plays a central role in maintenance of standing posture. Meanwhile, plenty of experiments showed that the activity of certain classes of neurons of the motor cortex was closely related to a highly automatic motor activity [4,3]. From the view of anatomy, there are abundant afferent and efferent connections between cerebellum and cerebral cortex, therefore a motor learning scheme including both cerebellum and motor cortex is very reasonable.

In this paper, we focus on human postural control scheme during sudden exposure to off-balance conditions. Based on biological evidences which show that the anticipatory and feedback mechanisms are used in the cerebellar control of motor behaviors [25], we proposed a novel adaptive balancing controller based on the FEL scheme. In order to realize the anticipatory function, the feedback error signals are treated as parts of teacher signals for the neural network feedforward controller (NNFC). Any state estimation techniques, including Kalman filtering, Smith predictors, can be arranged as the signal preprocessor of the teacher signals. Furthermore, the neural network controller is trained using a new version of on-line BP learning algorithm. To ensure quick and stable convergence of network parameters, an adaptive learning-rate technique is introduced in the learning algorithm.

In Section 2, the balance control problem is presented and formulated. In Section 3, the new adaptive controller for balancing is derived based on FEL scheme, and then the on-line learning algorithm for the neural network is described. Next in Section 4, simulation results are presented to validate the proposed adaptive controller. Finally, conclusions are stated in Section 5.

2. Problem formulation

Lewis Nashner and his colleagues conducted investigations in the strategies that people use for the maintaining standing equilibrium [22,8]. In these experiments, Nashner studied how people maintained their balance while standing on a platform that was moved suddenly. Nashner's experiments demonstrated that, out of all the possible responses, compensation for the small disturbances in the moving-platform experiments involved movements of the hip and ankle. Indeed, there were two distinct compensatory patterns of muscular activation, which he referred to as hip and ankle strategies. All compensatory responses involved either pure hip movement, pure ankle movement, or combination of both. For the frontal stability of quiet stance, the body can be regarded as a stiff pendulum, and balance adjustments are mainly made in the ankle joint, with the person swaying like an inverted pendulum [22]. Moreover, in the dynamic walking model such as the ballistic walking model [18] and the passive walking model [17], the stance leg, which is left free to rotate as an inverted pendulum, is a key element of dynamic walking. Humans continue movement by transferring from one pendulum-like stance leg to the next.

Mechanically, the inverted pendulum balancing task involves a pendulum mounted on the top of a wheeled cart that travels along a track, as shown in Fig. 1. The cart and pendulum are constrained to move within the vertical plane. The state at time t is specified by four real-valued variables: the angle between the pendulum and vertical (θ), the angular velocity ($\dot{\theta}$), the horizontal position (x) and velocity of the cart ($\dot{x}$). The inverted pendulum system was simulated using the following equations of motion:

$$(M+m)\ddot{x} + ml\cos\theta\ddot{\theta} + d\dot{x} - ml\sin\theta(\dot{\theta})^2 = u, \tag{1}$$

$$(4\,\mathrm{ml}^2/3)\ddot{\theta} + ml\cos\theta\ddot{x} - mgl\sin\theta = 0, \tag{2}$$

where $g = 9.8\,\mathrm{m/s}^2$ is the acceleration due to gravity; M is the mass of the cart; m is the mass of the pendulum; l is the distance from the pivot to pendulum's center of mass; d is the friction of the cart; and u is the output of the controller.

The goal of the inverted pendulum balancing task is to balance upright the pendulum and put the cart back to the origin of the rail, that is, the reference signal is $r = [\theta_d, \dot{\theta}_d, x_d, \dot{x}_d]^{\mathrm{T}} = [0, 0, 0, 0]^{\mathrm{T}}$. The desired position of the cart can be set to any reasonable point on the rail, however, the rail origin is selected here as the desired position of the cart without losing generality. Since the desired values of the state variables are all zeros, the control problem can be regarded as a regulator design problem.

3. On-line adaptive controller for balancing

3.1. Feedback error learning

Supervised learning depends strongly on the availability of an external teacher. For a given set of inputs, neural network uses the error between the desired response from the teacher and the network's actual output to adjust the interconnection weights between each neuron. To address

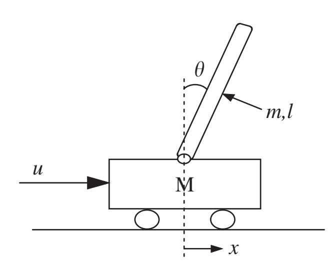

Fig. 1. The inverted pendulum system.

the problem of how to obtain the error signal for the neural network, Kawato proposed the FEL model which contains a NNFC and a conventional feedback controller (CFC), as shown in Fig. 2.

The aim of FEL scheme is to learn an inverse model that can generate motor commands given a series of desired states. A hard-wired and low-gain feedback controller is used to correct for errors between desired and estimated states. This generates a feedback motor command that is added to the feedforward motor command generated by the inverse model. If the feedback motor command goes to zero, then generally the state error will also be zero. Therefore, the feedback motor command as a measure of the error for the inverse model and is used as the error signal to modify it. By using a feedback controller, the system makes essential use of the error between the desired plant output and the actual plant output to guide the learning. This fact links the FEL approach to the indirect approach to motor learning that we discuss in the following section. In the indirect approach, the learning algorithm is based directly on the output error.

3.2. Control strategy for balancing

In the FEL scheme, the CFC is essential to guarantee global asymptotic stability of the whole system. After formulating FEL as an adaptive two-degree-of-freedom (TDOF) control, stability of FEL method was theoretically discussed by Miyamura and Kimura [19]. This stability proof was based on the following lemma.

Lemma 1. *Let $L(s)$ be a strongly positive real (SPR) transfer function and $\xi(t)$ be an arbitrary time-varying vector. Then, the solution $z(t)$ of the differential equation*

$$\frac{\mathrm{d}z(t)}{\mathrm{d}t} = -\xi(t)L(s)\xi(t)^{\mathrm{T}}z(t) \tag{3}$$

tends to a constant vector z_0 such that $\xi(t)z_0 \to 0$. If $\xi(t)$ satisfies the so-called persistent excitation (PE) condition [21]; the above z_0 is equal to 0.

Subsequently, Nakanishi and Schaal presented a Lyapunov analysis suggesting that the condition of SPR is a sufficient condition for asymptotic stability of the closed-loop dynamics. Moreover, they proposed that the relation between derivative control and proportional control ($K_{\mathrm{d}}^2 > K_{\mathrm{p}}$) is both a sufficient and necessary condition for asymptotic convergence of the error signal for a class of second-order SISO systems [20]. Since the certain transfer function consists of both the CFC and unknown parameters of the inverse model, their SPR condition accordingly requires the large gain of CFC to compensate for the unknown parameters of the inverse model, which is an unfavorable factor to design the CFC in advance.

On the other hand, since the control performance can be improved by feedforward controller, the feedback gain is not required to be large. In order to improve the performance of explicit force control task, Luo et al. modified the FEL scheme by adopting both the feedback errors and the outputs of the feedback controller to tune the feedforward control parameters so as to realize the inverse of the controlled object [14]. In the adaptive law proposed by Luo, in order to realize the convergence of the inverse model, it is necessary for the desired signal to satisfy PE condition during adaptation process. However, in the balance control task, the desired signal is constantly set as zero, thus the desired signal cannot serve as a qualified input for the feedforward controller. To assure both good control performance and accepted convergence stability, we designed an adaptive control strategy for balancing which acquires information in three ways: (1) from the input to the NNFC that specifies the current balancing performance, (2) from the output of the CFC that adjusts the NNFC as does in the original FEL and (3) from the feedback error signal that serves as an additional teacher signal. The framework of our adaptive controller for balancing is shown in Fig. 3.

In the adaptive controller for balancing, the error signal is defined as

$$e = [\theta_d - \theta, x_d - x]^{\mathrm{T}}. \tag{4}$$

The response of the CFC is formulated as

$$u_{\mathrm{fb}} = K_{\mathrm{d}}\dot{e} + K_{\mathrm{p}}e. \tag{5}$$

NNFC is expressed as

$$u_{\mathrm{ff}} = \Phi(e, w), \tag{6}$$

where w is the synaptic weight of NNFC.

Thus the total dynamic formulation is given as

$$u = u_{\mathrm{fb}} + u_{\mathrm{ff}} = K_{\mathrm{d}}\dot{e} + K_{\mathrm{p}}e + \Phi(e, w). \tag{7}$$

As the core of the adaptive controller, a three-layered neural network is adopted in the NNFC. Hecht-Nielsen

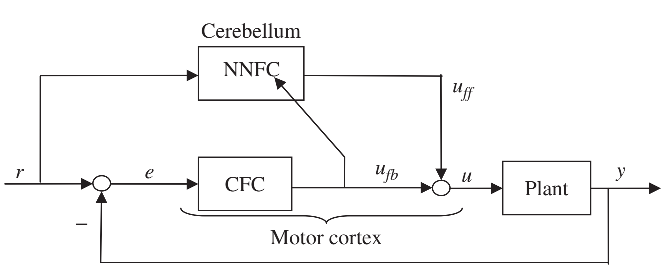

Fig. 2. The original FEL scheme.

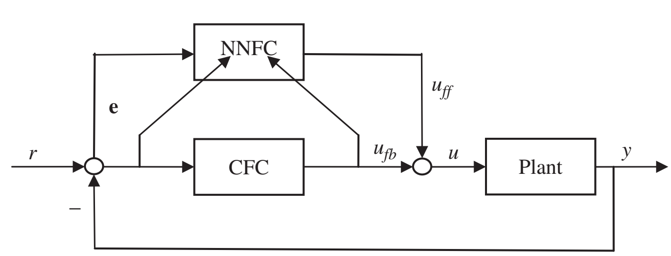

Fig. 3. The adaptive controller for balancing.

has proved that a three-layered feedforward neural network (i.e., only one hidden layer) can produce surfaces for discriminating any nonlinearly separable classes [6]. The input layer is simply a distribution of signals to all input weights of the first hidden layer. The hidden layer acts as a feature extractor, and should, thus contain enough neurons to extract the salient features of the data. The optimal number of hidden units (neurons) in this layer is difficult to determine, but typically it should be chosen between the number of input nodes (4) and output units (1). In this paper, the number of hidden units is set to 4, and the transfer function of hidden units is selected as sigmoid function.

The NNFC is updated so as to realize the inverse model of controlled plant after learning. The parameter update law is

$$\frac{\mathrm{d}w}{\mathrm{d}t} = -\eta\left(\frac{\partial \Phi}{\partial w}\right)^{\mathrm{T}}(\mu u_{\mathrm{fb}} + (1-\mu)k^{\mathrm{T}}e), \tag{8}$$

where η is the learning rate of neural network and $0<\eta<1$, $0<\mu<1$, $k^{\mathrm{T}}\geqslant 0$.

Therefore, the aim of the training algorithm is to adjust the network weights through the minimization of learning error:

$$E = \tfrac{1}{2}(\mu u_{\mathrm{fb}} + (1-\mu)k^{\mathrm{T}}e)^{\mathrm{T}}(\mu u_{\mathrm{fb}} + (1-\mu)k^{\mathrm{T}}e). \tag{9}$$

3.3. *Training algorithm*

A broad class of batch-type first-order algorithms, which are considered much simpler to implement than second-order methods, uses the correction term $\varphi^k = -\nabla E(w^k)$. The term $\nabla E(w^k)$ defines the gradient vector of the MLP and is obtained by means of back-propagation (BP) of the error through the layers of the network. The most popular algorithm of this class, called batch back-propagation applies the steepest descent method with a constant, heuristically chosen, learning rate that usually takes values in the interval (0, 1) [13]. Values in this interval are considered small enough to ensure the convergence of the BP training algorithm and consequently the success of learning [2]. However, it is well known that this practice tends to be inefficient [2,13] and the use of adaptive learning rate strategies is suggested in order to accelerate the learning process.

On-line training in neural networks is related to updating the network parameters after the presentation of each training example, which may be sampled with or without repetition. On-line training may be the appropriate choice for learning a task either because of the very large (or even redundant) training set, or because of the slowly time-varying nature of the task. Although batch training seems faster for small-size training sets and networks, on-line training is probably more efficient for large training sets and networks [1]. It helps to escape local minima and provides a more natural approach to learning in nonstationary environments. On-line methods seem to be more robust than batch methods as errors, omissions or redundant data in the training set can be corrected or ejected during the training phase. Additionally, training data can often be generated easily and in great quantities when the system is in operation, whereas they are usually scarce and precious before. Lastly, on-line training is necessary in order to learn and track time varying functions and continuously adapt in a changing environment.

Since the essential point of FEL method is that the neural network's control process corresponds with tuning progression of its weights, on-line BP learning rather than batch learning should be adopted in this work. Magoulas et al. proposed a new version of on-line BP [15,16], which adapts the learning rate parameters based on the stochastic gradient descent. It can be considered as a meta-learning algorithm. In this paper, we aim to accelerate the training process. In order to achieve this aim, we maintain the acceptable robust performance and enhance the algorithm by applying momentum term to weights updating. Also, we had defined the upper bound of the learning rate. The proposed on-line training algorithm is given in Step 0–Step 6:

Step 0: Initialize the parameters: $w_0, \eta_0, \alpha, \gamma, \rho$ and $\eta_{\max}$.

Step 1: Repeat for each new input training pattern x^k.

Step 2: Calculate propagate backwards $E(w^k)$ and gradient component $\nabla E(w^k)$.

Step 3: Terminate the training process once the upper limit to the error function $E(w^k)$ is met.

Step 4: Update the weights: set $w^{k+1} = w^k - (\alpha \Delta w^k + \eta^k \nabla E(w^k))$.

Step 5: Update the learning rate for the next pattern following the formula below.

$$\eta^{k+1} = \eta^k + \gamma\langle \nabla E(w^{k-1}), \nabla E(w^k)\rangle + (1-\gamma)\langle \nabla E(w^{k-2}), \nabla E(w^{k-1})\rangle. \tag{10}$$

Step 6: If $\eta^{k+1}>\eta_{\max}$ then $'\eta^{k+1} = \rho\eta^{k+1}$; If $\eta^{k+1}<0$ then $'\eta^{k+1} = 0$ where η is the learning rate $(0<\eta<1)$, $\eta_{\max}$ is the upper bound of learning rate, α is the momentum term $(0\leqslant\alpha<1)$, γ is the meta-stepsize $(0\leqslant\gamma<1)$, ρ is a fixed factor for learning robustness $(0<\rho<1)$, and $\langle\cdot,\cdot\rangle$ represents the usual inner product in R^n.

In this algorithm, the momentum term is set for smoothing out the oscillations in the trajectory. The upper bound of the learning rate is fixed to ensure learning process remain stable. However, during the course of training, either with or without adaptive step sizes, one may come to a region of weight space for which the current step size parameters are so large that it cause the learning process to become unstable. To prevent this situation from too large to stable, reduce the learning rate by multiplying a fixed factor is a simple but practical method. In the next section, we present to you simulation experiments which indicate that this variant algorithm of on-line BP provides fast and stable learning for the adaptive control system.

4. Simulation results analysis

In order to verify the effectiveness of the adaptive controller for balancing in this paper, we carried out a series of simulations. Admittedly, if we carefully select the parameters of CFC like the strategy proposed in [20], the stability of the FEL controller maybe guaranteed. In this paper, we select the parameters of the CFC as $K_p = [20, 5]$, $K_d = [2, 2]$ to show that the proposed control model is more suited to motor balancing tasks than the original FEL controller. The training procedure of NNFC starts from an arbitrary initial model that specifies the action to be taken at every possible state.

4.1. Balancing performance

The control performance of original FEL is depicted in Fig. 4, which illustrates that the selected feedback gains cannot ensure the convergence of FEL. In contrast, the response of the proposed controller is given in Fig. 5, which demonstrates that the convergence of both the angle and the position error is guaranteed by the proposed controller.

From the simulation results above, we discover that the reference signal alone fails to stimulate the neural system as it attempts to keep balance. It should be pointed out that, when the feedback error alone is adopted as a teacher signal for the NNFC in this work, the convergence of learning is also unwarranted. These results suggest that more information should be adopted to accomplish the desired balancing task. When we take advantage of the available information, the balancing task can be accomplished even if the parameters of CFC are unfavorable.

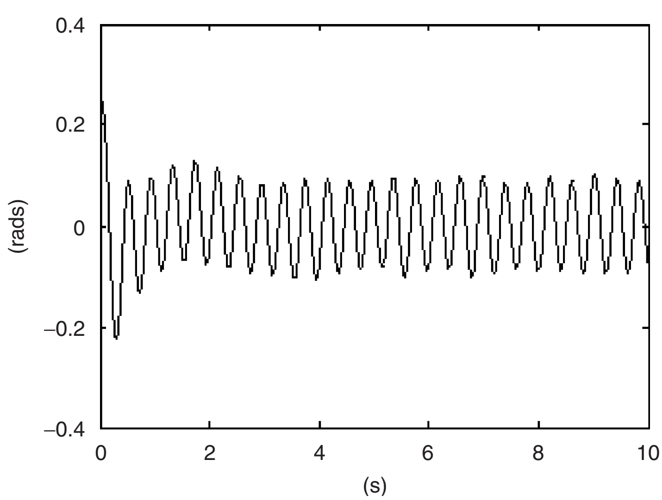

Fig. 4. Pole angle response of the original FEL controller.

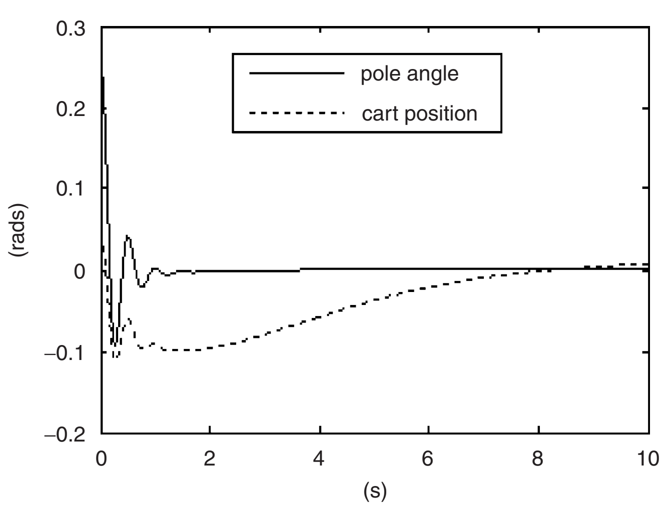

Fig. 5. Response of the proposed adaptive controller for balancing.

4.2. Robustness of adaptive controller

To further demonstrate the effectiveness of the adaptive controller for balancing, we tested the proposed adaptive controller by adding impulse noise disturbance to the output of adaptive controller u and adding stochastic white noise disturbance to the sensor measurement x.

The normal range of u is between -10 and 10. The impulse noise is added as $u = u + 50$, and the corresponding system response is shown in Fig. 6. The stochastic white noise is added as $x = x + v$, where v is the stochastic white noise in which amplitude is set to 0.05, and the corresponding system response is shown in Fig. 7.

From Fig. 6, we learnt that the adaptive controller have a tolerance of casual trajectory error. From Fig. 7, we learnt that the adaptive controller can function adequately despite significant noise in sensor measurements. These results further reflect that the adaptive controller could drive the system toward an implicit equilibrium position and velocity.

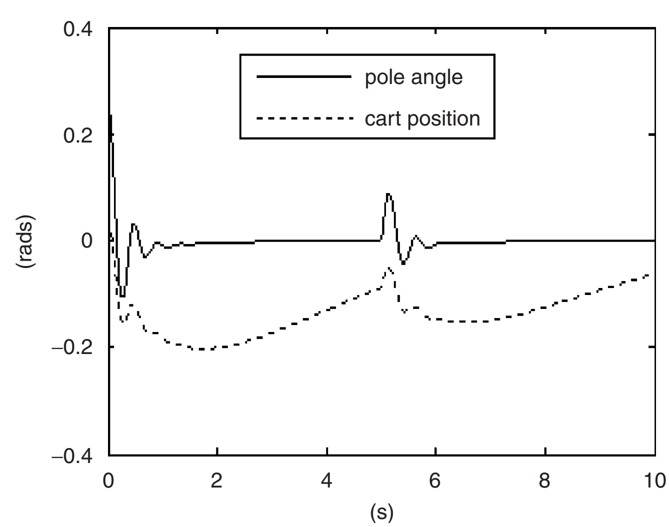

Fig. 6. The response of the adaptive controller for balancing with impulse noise.

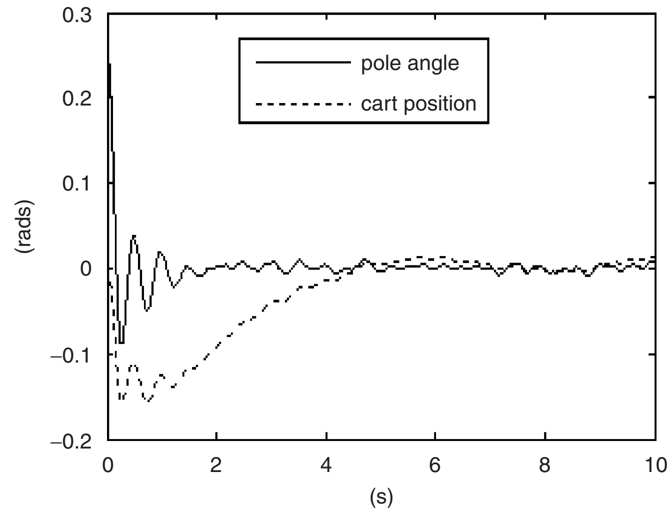

Fig. 7. The response of the adaptive controller for balancing with white noise.

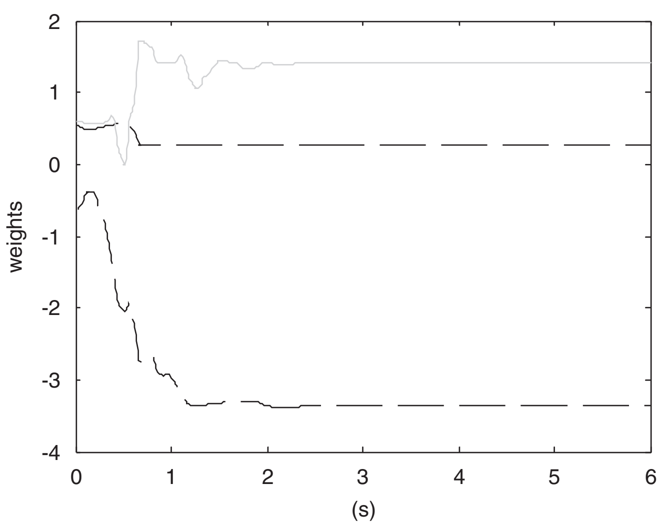

Fig. 8. The time evolution of weights during NNFC learning term.

4.3. Adaptation of learning rate

In order to verify the usefulness of the on-line BP algorithm proposed in this paper, the time evolution process of part of the weights of NNFC and the learning rate is reported as below. The time evolution of weight values during NNFC learning term is shown in Fig. 8. The time evolution of the learning rate during NNFC learning term is depicted in Fig. 9.

As the results above showed, the proposed algorithm assures the convergence of neural network in less than 5 s. These results also suggest that the procedure described in this paper is rather effective in making the training robust. Correspondingly, such fast and robust adaptations led to the asymptotic convergence of the error for the NNFC.

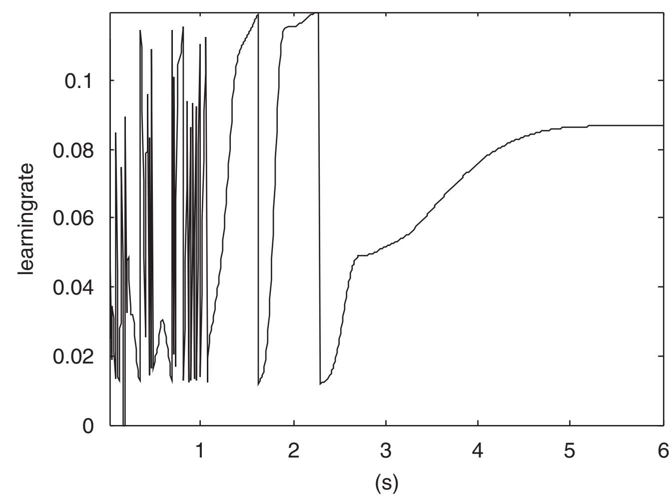

Fig. 9. The time evolution of the learning rate during NNFC learning term.

5. Conclusion

This paper proposed an adaptive controller for balancing based on feedback-error-learning scheme. In the proposed controller, the nonlinearity of the controlled object can be compensated by the neural network that stimulated by previous feedback error signals. To realize the combination of learning and controlling, an on-line BP algorithm with the self-adaptive learning rate was developed and used as training algorithm for NNFC. This scheme may, to a certain extent, account for what cerebellum did in keeping body in balance. In the computer simulation of inverted pendulum balancing, the proposed adaptive controller and relevant training algorithms worked well, while the original FEL failed to converge.

Acknowledgment

This work is supported by National Natural Science Foundation of China (60375017), BaoSteel Group (50274003), and Doctor Research Startup Foundation of Beijing University of Technology (52002011200401). The authors would like to thank Professor Huang Deshuang for his valuable comments to this paper.

References

[1] L.B. Almeida, T. Langlois, J.D. Amaral, A. Plankhov, Parameter adaptation in Stochastic Optimization, in: D. Saad (Ed.), On-line Learning in Neural Networks, Cambridge University Press, Cambridge, 1998, pp. 111–134.

[2] R. Battiti, First- and second-order methods for learning: between steepest descent and Newton's method, Neural Comput. 4 (1992) 141–166.

[3] I.N. Beloozerova, M.G. Sirota, H.A. Swadlow, G.N. Orlovsky, L.B. Popova, T.G. Deliagina, Activity of different classes of neurons of the motor cortex during postural corrections, J. Neurosci. 23 (2003) 7844–7853.

[4] J.C. Eliassen, T. Souza, J.N. Sanes, Human brain activation accompanying explicitly directed movement sequence learning, Exp. Brain Res. 141 (2001) 269–280.
[5] M. Glickstein, Cerebellar agenesis, Brain 117 (1994) 1209–1212.
[6] R. Hecht-Nielsen, Theory of the backprogation neural network, Proceedings of IJCNN '89, June 1989, pp. 593–605.
[7] G. Holmes, The Croonian Lectures on the clinical symptoms of cerebellar disease, and their interpretation, Lancet 1 (1922) 1177–1237.
[8] F.B. Horak, L.M. Nashner, Central programming of postural movements: adaptations to altered support-surface configurations, J. Neurophysiol. 55 (6) (1986) 1369–1381.
[9] M. Ito, Neurophysiological aspects of the cerebellar motor control system, Int. J. Neurol. 7 (1970) 162–176.
[10] K. Jahn, A. Deutschlander, T. Stephan, M. Strupp, M. Wiesmann, T. Brandt, Brain activation patterns during imagined stance and locomotion in functional magnetic resonance imaging, Neruoimage 22 (2004) 1722–1731.
[11] M. Kawato, Internal models for motor control and trajectory planning, Curr. Opinion Neurobiol. 9 (1999) 718–727.
[12] M. Kawato, H. Gomi, A computational model of four regions of the cerebellum based on feedback error learning, Biol. Cybern. 69 (1992) 95–103.
[13] C.G. Looney, Pattern Recognition using Neural Networks, Oxford University Press, Oxford, UK, 1997.
[14] Z.W. Luo, S. Fujii, Y. Saitoh, E. Muramatsu, K. Watanabe, Feedback-error learning for explicit force control of a robot manipulator interacting with unknown dynamic environment, Proceedings of the IEEE International Conference on Robotics and Biomimetics 2004, August 2004, pp. 262–267.
[15] G.D. Magoulas, V.P. Plagianakos, M.N. Vrahatis, Adaptive stepsize algorithms for on-line training of neural networks, Nonlinear Anal. 47 (2001) 3425–3430.
[16] G.D. Magoulas, V.P. Plagianakos, M.N. Vrahatis, Neural network-based colonoscopic diagnosis using on-line learning and differential evolution, Appl. Soft Comput. 4 (2004) 369–379.
[17] T. McGeer, Passive dynamic walking, Int. J. Robotics Res. 9 (2) (1990) 68–82.
[18] T.A. McMahon, Muscles, Reflexes, and Locomotion, Princeton University Press, Princeton, NJ, 1984.
[19] A. Miyamura, H. Kimura, Stability of feedback error learning scheme, Syst. Control Lett. 45 (2002) 303–316.
[20] J. Nakanishi, S. Schall, Feedback error learning and nonlinear adaptive control, Neural Networks 17 (2004) 1453–1465.
[21] K.S. Narendra, L.S. Valavani, Stable Adaptive Systems, Prentice-Hall International Editions, Englewood Cliffs, NJ, 1989.
[22] L.M. Nashner, G. McCollum, The organization of human postural movements: a formal basis and experimental synthesis, Behav. Brain Sci. 8 (1985) 135–172.
[23] Y. Ouchi, H. Okada, E. Yoshikawa, S. Nobezawa, M. Futatsubashi, Brain activation during maintenance of standing postures in humans, Brain 122 (1999) 329–338.
[24] M. Shidara, K. Kawano, H. Gomi, M. Kawato, Inverse-dynamics encoding of eye movement by Purkinje cells in the cerebellum, Nature 365 (1993) 50–52.
[25] J.F. Stein, M. Glickstein, Role of the cerebellum in visual guidance of movement, Physiol. Rev. 74 (1992) 967–1017.
[26] D.M. Wolpert, R.C. Miall, M. Kawato, Internal models in the cerebellum, Trends Cognitive Sci. 2 (1998) 338–347.

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