Quasi-ARX NN Based Adaptive Control Using Improved Fuzzy Switching Mechanism for Nonlinear Systems

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Abstract: In this paper, an improved fuzzy switching mechanism based on Quasi-ARX neural network (NN) is presented for the adaptive control of nonlinear system. The proposed improved fuzzy switching adaptive control is composed of a quasi-ARX NN based prediction model and an improved fuzzy switching mechanism using two new adaptive control laws. The obtained quasi-ARX NN model is divided into two parts: linear part and nonlinear part. The linear part is used to ensure the nonlinear control stability, and the nonlinear part is utilized to improve the control accuracy. The linear controller is obtained based on the linear part, while the nonlinear controller is given based on the quasi-ARX NN model. As the control result of nonlinear predictor is better than the linear predictor in most of time, the adaptive control with a simple switching mechanism has many useless switching during the processing. So the improved fuzzy switching mechanism is proposed to replace the original switching mechanism, it can improve the performance by reducing the useless switching while guarantee stability of the system control. The simulations show efficiency of the proposed control method satisfies in stability, accuracy, and robustness.

Keywords: adaptive switching control, an improved fuzzy switching mechanism, Quasi-ARX NN prediction model.

1 INTRODUCTION

Adaptive control of complex nonlinear dynamical systems has attracted much attention and developed significantly during the last few decades. Many adaptive control methods have been proposed, and the corresponding stability and convergence have been proved [1-4].

However, the stabilizing adaptive control of dynamical systems is a difficult problem because the plants are always nonlinear in practical dynamical systems. Hence, the performance of linear control models can not satisfy the requirement. For this reason, some nonlinear prediction models have been developed for nonlinear systems to overcome the difficulty in design of predictor and controller for nonlinear systems. Until now neural networks have been used to identify and control nonlinear dynamical systems because of its ability to approximate the arbitrary mapping to any desired accuracy [5-6].

However, from the view of a user, there are two major problems on those neural network models. The first, one is that their parameters do not have useful interpretations. The second, they do not have a friendly interface for controller design and system analysis. To solve these problems, in the previous work a quasi-linear black box modeling scheme has been proposed based on well-developed linear system theory and could be extended to nonlinear systems. The models consisting of two parts: a macro model part and a kernel part [7-8].

The macro-part is a user-friendly interface constructed by using the specific knowledge and the characteristics of network structure; the efforts of this part are to introduce some properties favorable to certain applications, such as controller design. In this paper, ARX model structure is chosen as macro model part because of various useful linearity properties. This macro structure makes the proposed controller can be obtained and used easily.

Moreover, the kernel part is an ordinary neural network, which is used to parameterize the coefficients of macro model and different from a nonlinear ARX model based directly on neural networks. Because of the nonlinear characteristics, the quasi-ARX neural network can be used to identify and to control nonlinear systems accurately. In the control system, the prediction model and controller share are the same parameters as in linear cases.

However, there are two problems for this nonlinear model: the controller design and the stability of corresponding control system. The controller bases on these nonlinear models are more difficult to be obtained than based on the linear models. Stability and accuracy of the control for nonlinear systems are difficult to be ensured in one method or one nonlinear model.

Nevertheless, there are some aspects needed to be improved in the control method, since the 0/1 hard switching method is not very smooth. By the hard switching law , the linear and nonlinear predictors are alternately used, while from the 1/0 switching control result, it is obvious that the switching control do not need to switch to 0 in most of time, so a fuzzy switching mechanism is constructed based on the system switching criterion function [9].

However, the original fuzzy switching mechanism has some useless switching problems which influence control accuracy. In order to solve the switching problems and to make the switching processing much more smooth, in this paper the improved fuzzy switching mechanism contained two new methods: one is to reduce the fluctuate of switching parameters, and the other is to design the new switching law.

This paper is organized as follows. Section 2 briefly describes the problem to be solved and the improved quasi-ARX prediction model is introduced based on a neural network by using an improved switching mechanism, then the parameter identification methods are given. Section 3 discusses the stability of the adaptive control with the improved switching mechanism. Section 4 provides the numerical simulations to demonstrate the effectiveness of the proposed method, and Section 5 presents the conclusions.

2 ADAPTIVE CONTROL USING IMPROVED FUZZY SWITCHING MECHANISM

2.1 Problem description

Consider a single-input-single-output (SISO) nonlinear time-invariant dynamical system with input output relation as

$$y(t+d) = g(\varphi(t)) \tag{1}$$

$$\varphi(t) = [y(t+d-1),...y(t+d-n),u(t),...,u(t-m+1)]^T \tag{2}$$

where $y(t)$ denotes the output at time t (t = 1, 2, ...), $u(t)$ the input, d the known integer time delay, $\varphi(t)$ the regression vector, and n, m the system orders. $g(.)$ is a smooth nonlinear function, and at a small region around $\varphi(t) = 0$, the value of C^∞ is continuous. The origin is an equilibrium point, then $g(0) = 0$. Now the following assumptions will be used:

Assumption 1 :

(i) $g(.)$ is a continuous function, and at a small region around $\varphi(t)$, it is C^∞ continuous;

(ii) there is a reasonable unknown controller which may be expressed by $u(t)=\tilde{\rho}(\tilde{\xi}(t))$, where $\tilde{\xi}(t)=$ $[y(t) \ldots y(t-n)u(t-1)\ldots u(t-m)y^*(t+1)\ldots y^*(t+1-l)]^T$ ($y^*(t)$ denotes reference signal);

(iii) the system has a global uniform asymptotically stable zero dynamics.

2.2 Quasi-ARX neural network

The elements of $\Theta(\xi(t), \chi(t))$ are unknown nonlinear function of $\xi(t)$ and $\chi(t)$, which can be parameterized by neural-fuzzy networks and neural networks as in Refs [8] [10]. In this paper, a neural network is chosen which can deal with higher dimensional problems. Parameterize Θ_ξ with a MIMO neural network, the quasi-ARX prediction model is expressed by:

$$N(\xi(t),\chi(t),\Omega) = \theta + \chi(t)W_2\Gamma(W_1\xi(t)+B) \tag{3}$$

where $\Omega = W_1$, W_2, B, θ are the parameters set of the neural network.

The $W_1 \in R^{MxN}$, and $W_2 \in R^{Mx(N+1)}$ are the weight matrices of the first and second layers, while $B \in R^{Mx1}$ is the bias vector of hidden nodes. The $\theta \in R^{(N+1)x1}$ represents the bias vector of output nodes, and Γ is the diagonal nonlinear operator with identical sigmoid elements σ (for example: $\sigma(x) = \frac{(1-e^{-x})}{(1+e^{-x})}$. Moreover, $\xi(t)$ is the input variables of neural network.

Then we can express the quasi-ARX neural network prediction model as:

$$\hat{y}(t+d|t,\xi(t)) = \Psi^T(t)\theta + \chi(t)\Psi^T(t)\cdot W_2\Gamma(W_1\xi(t)+B) \tag{4}$$

According the switching parameter $\chi(t)$, the quasi-ARX neural network predictor model is different from the conventional quasi-ARX model. When $\chi(t)=1$, the nonlinear prediction model can insure the prediction accuracy. In addition, when $\chi(t) = 0$, the linear prediction model can insure the control stability.

In this way the quasi-ARX prediction model uses only one model to achieve function of two or more models. The following assumption will be used to analyze the control system stability:

Assumption 2:

(i) The linear parameter θ lies in a compact region B;

(ii)The nonlinear term $\Psi^T.W_2\Gamma(W_1\xi(t)+B)$ is globally bounded, i.e. $\Psi^T.W_2\Gamma(W_1\xi(t)+B) < \Delta$.

2.3 Controller design

To control a given system, the controller design includes two steps: the first step for identifying the improved quasi-ARX prediction model; and the second step for deriving and implementing control law.

This paper obtained the identified improved quasi-ARX prediction model from above parts, expressed by:

$$\hat{y}(t+1|t,\xi(t)) = \Psi^T(t)\hat{\Theta}(\xi(t),\lambda(t)) \tag{5}$$

where $\hat{\Theta}(\xi(t),\chi(t)) = [\hat{y_\xi}\,\hat{\alpha_{0,t}}\cdots\hat{\alpha_{n_y-1,t}}\hat{\beta_{0,t}}\cdots\hat{\beta_{n_u+d-2,t}}]^T$, will be used in controller design.

Consider a minimum variance control with the criterion function as follows:

$$M(t+1) = [\frac{1}{2}(y(t+d) - y^*(t+d))^2 + \frac{\lambda}{2}u(t)^2] \tag{6}$$

where λ is weighting factor for the control input.

The controller can be obtained by solving:

$$\frac{\partial M(t+1)}{\partial u(t)} = 0 \tag{7}$$

In the case where a conventional neural network is used as a prediction model, a controller can't be derived directly from an identified model because of the nonlinearities.

However, the improved quasi-ARX neural network model is linear in the input variable $u(t)$.

Therefore, a controller is derived from the proposed model:

$$u(t) = \frac{\hat{\beta_{0,t}}}{\hat{\beta^2_{0,t}}}((\hat{\beta_{0,t}} - \hat{\beta}(q^{-1},\xi(t)))q)u(t-1) + y^*(t+1) - \hat{\alpha}(q^{-1},\xi(t))y(t) - \hat{y}_{\xi,\chi}. \tag{8}$$

where the controller parameters $\hat{\alpha}_{i,t}$ and $\hat{\beta}_{i,t}$ come from the predictor.

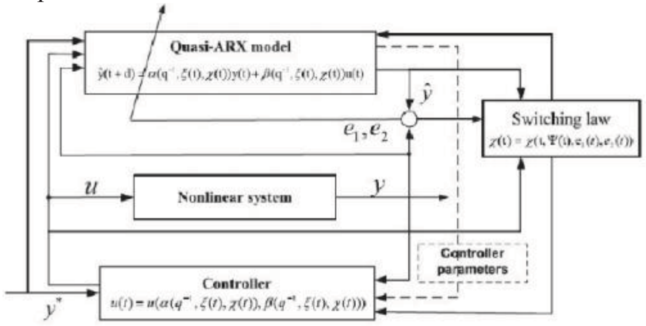

Fig. 1 Switching control structure based on quasi-ARX model

The Fig. 1 shows the adaptive switching controller based on the improved neural network prediction model for unknown nonlinear systems. The switching parameters c(t) is is calculated from input and output signals and model errors, then is used into the identified model and controller.

The proposed control mechanism has several distinctive features:

(1) it is linear for the variables synthesized in control systems;
(2) the parameters have explicit meanings;
(3) it uses one controller which combines a switching algorithm;
(4) with the improved switching mechanism, it improves the accuracy;

2.4 The improved switching mechanism

According to the original fuzzy switching mechanism control, the switching parameter is fluctuant so that there still have some unnecessary switching problems.

After analyzing the control processing, there are still exist some problems:

(i) Since the control result of nonlinear predictor is better than the linear predictor in most of time, in order to improve the accuracy, it is better to remain nonlinear predictor while ensuring the stability of the control.
(ii) By updating of linear parameters, the errors of the predictor e_1 and e_2 change a lot, so the stability of control system is proved. In order to improve the accuracy of the control result, we may not only consider a single $\chi(t)$, but also the tendency of $\chi(t)$. In this way, we can reduce the unreasonable switching occurred by the unstable $J_1(t)$, $J_2(t)$.
(iii) The switching control method is used to guarantee the stability of control system with the switching between linear and nonlinear model. But $J_2(t)$ is bounded in most of time, so there are so many useless switching in original fuzzy switching method.

Motivated by the reasons mentioned before, in this paper, the improved fuzzy switching mechanism is designed to increase the control accuracy with two methods:

Method 1 : Moving average filter

In order to make the switching control more smoothly, the first improved method adds a moving average filter in the switching parameter $\chi(t)$, with the preset threshold parameters k and K to improve the accuracy and the adaptation in the controller by reducing the unreasonable switching in the control process.

$$\chi(t)=\begin{cases} 1 & \text{if} \quad \eta(t)>K \\ \dfrac{1}{\sum_{i=0}^{M-1}\zeta_i}\sum_{i=0}^{M-1}\zeta_i\chi(t-i) & \text{if} \quad k\le\eta(t)\le K \\ 0 & \text{if} \quad \eta(t)<k \end{cases} \tag{9}$$

Method 2 : New switching law

As mentioned before, in order to ensure the stability of the control system, the switching mechanism should firstly consider the error of nonlinear predictor, while the linear predictor error $e_1(t)$ is globally bounded. Furthermore the nonlinear predictor is bounded in most control processing.

Motivated by this condition, the switching law is designed in order to make the switching mechanism remains in nonlinear predictor as much as possible.

The other goal of the design is to improve the control accuracy in the nonlinear predictor which has better performance than the linear predictor.

3 STABILITY ANALYSIS

In this section, the proof that all the signals are bounded will be given. This is the basis for using multiple models to improve performance while maintaining stability.

Theorem: For the system with adaptive controller, all the input and output signals in the closed-loop system are bounded. Moreover, the tracking error of the system can converge on zero when a properly neural network is determined.

Proof: Firstly, the model error $e(t)$ is defined by:

$$e(t)=y(t+d)-\Psi(t)^T\hat{\theta}(t)-\chi_t\Psi^T(t)\cdot\hat{W}_2(t)\Gamma\hat{W}_1(t)\xi(t)+\hat{B}(t)) \tag{10}$$

Subtracting θ_0 from both sides and gives:

$$\tilde{\theta}(t)=\tilde{\theta}(t-d)-\frac{a(t)\psi(t-d)(\psi(t-d)^T\tilde{\theta}(t-d)-\omega(t))}{1+\psi(t-d)^T\psi(t-d)} \tag{11}$$

where $\tilde{\theta}(t)=\hat{\theta}(t)-\theta_0$ and $\omega(t)=y(t+d)-\psi(t)^T\hat{\theta}(t)$.
Consider the following functional:

$$V(t)=\|\tilde{\theta}(t)\|^2 \tag{12}$$

then it can be obtained that:

$$\begin{aligned} V(t)&=V(t-d)-\frac{2a(t)(e_1(t)-\omega(t))e_1(t)}{1+\Psi(t-d)^T\Psi(t-d)}+\frac{a_1(t)^2\Psi(t-d)^T\Psi(t-d)e_1(t)^2}{(1+\Psi(t-d)^T\Psi(t-d)^2)} \\ &\le V(t-d)+\frac{a_1(t)(2e_1\omega(t))}{1+\Psi(t-d)^T\Psi(t-d)}-\frac{a(t)e_1(t)^2}{1+\Psi(t-d)^T\Psi(t-d)} \end{aligned} \tag{13}$$

From $2ab\le\kappa a^2+b^2/\kappa,\forall\kappa$, the following inequality holds:

$$\begin{aligned} v(t)&\le V(t-d)+\frac{a(t)(e_1^2(t)/2+2\omega^2(t))}{1+\Psi(t-d)^T\Psi(t-d)}-\frac{a(t)e_1(t)^2}{1+\Psi(t-d)^T\Psi(t-d)} \\ &\le V(t-d)+\frac{2a(t)\Delta^2}{1+\Psi(t-d)^T\Psi(t-d)}-\frac{1}{2}\frac{a_1(t)e_1(t)^2}{1+\Psi(t-d)^T\Psi(t-d)} \end{aligned} \tag{14}$$

Two conclusions can be drawn from inequality (14):

(1) Since $a(t) = 1$ for $|e(t)| > 2\Delta$ and ~~is~~ 0 otherwise, $\|\tilde{\theta}(t)\|^2$ is a non-increasing sequence. Hence $\hat{\theta}(t)$ is bounded. Moreover;

(2)
$$\lim_{N\to\infty}\sum_{t=1}^{N}\frac{(a(t)(e^2(t)-4\Delta^2))}{(2(1+\Psi(t-d)^T\Psi(t-d)))} \le |\theta(0)|^2 - |\theta(N)| < \infty \quad (15)$$

and hence,
$$\lim_{N\to\infty}\frac{a(t)^2(e_1(t)^2-4\Delta)}{2(1+\Psi(t-d)^T\Psi(t-d))} \to 0 \quad (16)$$

The proof that all signals are bounded is by contradiction.

Proof: Assume that y is unbounded. Then,

1. By certainty equivalent, $u(k)$ is always chosen such that $\hat{y}(t+1) = y^*(t+1)$, and therefore
$$e(t) = \hat{y}(i)\text{-}y(t) = y^*(t)\text{-}y(t)$$
Since $y^*(t)$ is bounded, we have
$$e(t) \sim y(t)$$
or $e(t)$ grows at the same rate as $y(t)$.
2. By the assumption that the system has an asymptotically stable zero dynamics, i.e., any input sequence $u(t\text{-}1)$ cannot grow faster than the output sequence $y(t)$, then we have
$$u(t\ \text{-}1) = O[y(t)]$$
Since
$$\phi(t) = [y(t)\ldots y(t\text{-}n\text{+}1)u(t)\ldots u(t-m\text{-}d\text{+}2)]^T$$
it follows that
$$\phi(t) = O[y(t)]$$
or, $\phi(t)$ is not grow faster than $y(t)$.
3. By the adaptation law [6],
$$e(t) = o[\phi(t)]$$
or $e(t)$ grows slower than $\phi(t)$.
4. Therefore, from the adaptation law [8] [11][12],
$$y(t) = o[y(t)]$$
or, $y(t)$ grows slower than itself.

This cannot happen if $y(k)$ is assumed to be unbounded. Therefore $y(k)$ is bounded, and the boundedness of other signals follows in a straight forward fashion.

It is seen from the proof that the characteristics of the identifier is follows $e(t) = o[\phi(t)]$. The identification error grows at a lower rate than the regression vector, plays a central role.

So when multiple models are used, the objective of the switching mechanism is to maintain this relationship. This will be demonstrated in the next section.

As J_1 is bounded with the Eq. (16), and with the improved switching mechanism, we need to prove all the signals in the closed-loop switching system described above and bounded with J_2 in two cases:

(i) $J_2(t)$ is also bounded. By the equation
$$\lim_{N\to\infty}\frac{a(t)^2(e_1(t)^2-4\Delta)}{2(1+\Psi(t-d)^T\Psi(t-d))} \to 0$$
holds and similar to the boundedness proof of $e_1(t)$, the error $e_2(t)$ is also bounded. Since the control error $e(t) = (1\text{-}\chi(t))e_1(t)\text{+}\chi(t)e_2(t)$, where $\chi(t) \in [0,1]$, therefore $e(t)$ is bounded.

(ii) If $J_2(t)$ is unbounded, we will discuss the stability of the two new method separately;

Method 1: Moving average filter:

Since $J_1(t)$ is bounded, from the equation of switching function $J_i(t)$ and the moving average filter with switching parameter $\chi(t)$, there is exist a constant t_k such that $\forall t > t_k$, $\chi(t) = 0$, so that the control error $e(t) = e_1(t)$ is bounded with $e_1(t)$.

Method 2: New switching law:

Since $J_1(t)$ is globally bounded, and $J_2(t)$ is smaller than $\max(J_1(t))$, we can consider $J_2(t)$ is bounded with $J_1(t)$ and prove the stability same as case (i). In addition, while $J_2(t)$ is larger than $\max(J_1(k))$, where $J_2(k)$ is bounded or not, we can calculate switching parameter $\chi(t)$ with the fuzzy switching control equation in the new switching law. This condition is also exist in a constant t_k such that $\forall t > t_k$, $\chi(t) = 0$, so that the control error $e(t) = e_1(t)$ is bounded with $e_1(t)$.

With the improved switching mechanism, from above inequalities, the input and output of the closed-loop switching control system are bounded.

4 NUMERICAL SIMULATIONS

The reference output of this example is shown as:

$$y^*(t) = \begin{cases} 0.4493y^*(t-1)+0.57r(t-1) \\ \qquad t\in[1,100]\cup[151,200] \\ 0.7sign(0.4493y^*(t-1)+0.57r(t-1)) \\ \qquad t\in[101,150] \end{cases} \quad (17)$$

where $r(t) = 1.2\text{*}\sin(2\pi t/25)$, and the parameters of switching criterion function are chosen to be $c = 1.2$, $N = 3$. Then, we can get the control result with different method:

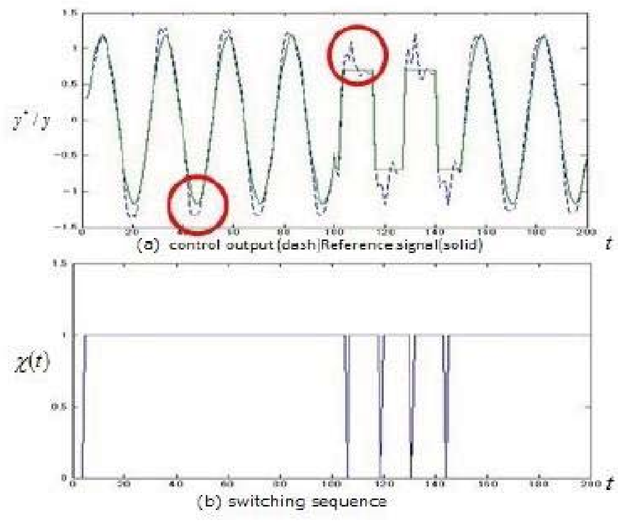

Fig. 2 Control result of 1/0 switching mechanism

From the control processing, we find that with the original proposed switching mechanism, the switching processing is not smooth as the switching parameter $\chi(t)$ when changes a lot.

This condition causes the useless switching problems as the red circle showing in Fig. 2 and Fig. 3. Moreover, while using the improved switching mechanism with the two new proposed methods, $M = 5$, $[\zeta_0, \zeta_1, \zeta_2, \zeta_3, \zeta_4] = [1, 1, 1, 1, 1]$, $k = 0.1$, $K = 0.9$ we can get the control results as follows:

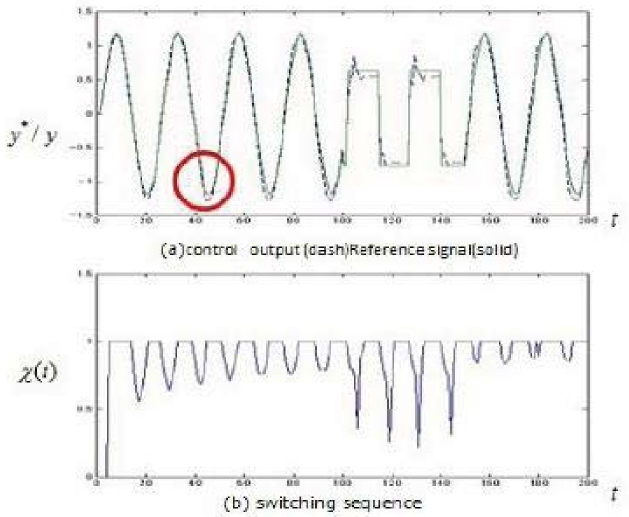

Fig. 3 Control result of original fuzzy switching mechanism

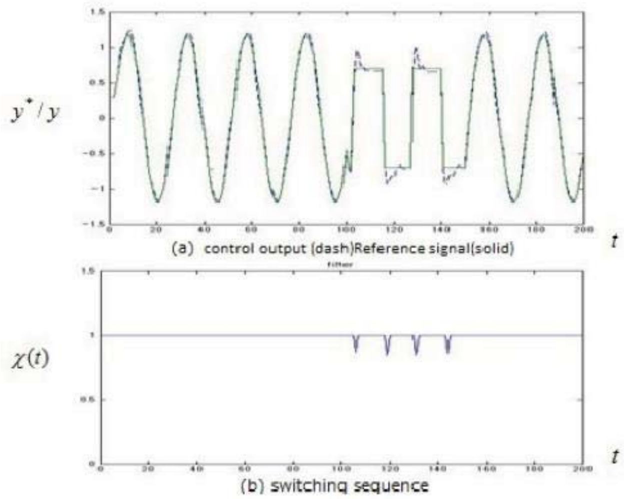

Fig. 4 Control result of fuzzy switching mechanism with filter

From the control result in Fig. 4 and Fig. 5, we find that by improved the fuzzy switching mechanism, the adaptive control can reduce the useless switching with the switching parameter $\chi(t)$ and remain in the nonlinear control as much as possible.

In this way, the control processing is smoother and can improve the control performance with the reference signal.

The control performances of the proposed switching mechanism become much better when the reference signal has more linear properties.

Comparing the different control results with root mean squared error (RMSE)

$$RMSE = \sqrt{\frac{\sum_t (y(t) - \hat{y}(t))^2}{N}} \quad (18)$$

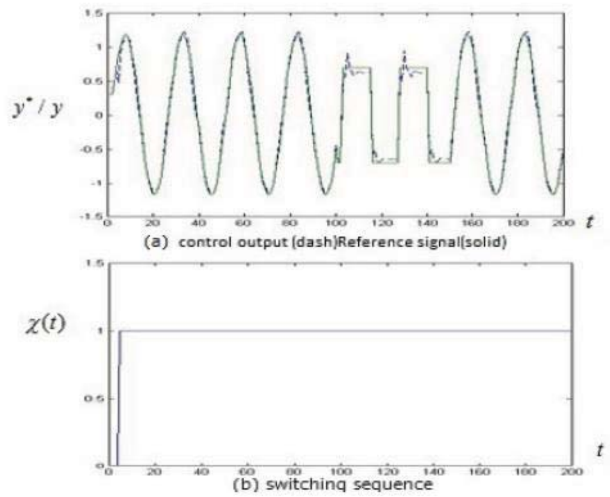

Fig. 5 Control result of fuzzy switching mechanism with new switching law

	1/0 switching	Fuzzy switching	Fuzzy switching with filter	Fuzzy switching with new law
Control error(RMSE)	0.1393	0.1009	0.0677	0.0730

Table 1 Control result with RMSE

From the control error in Table 1, it is obvious that the improved switching mechanism improve the control accuracy when comparing with the original method.

5 CONCLUSIONS

In this paper, the quasi-ARX neural network is divided into two parts: the linear part used to ensure the nonlinear control stability, and the nonlinear part utilized to improve the control accuracy. In order to combine both the stability and universal approximation capability in the controller, a switching law is established based on system input-output variables and prediction errors. An adaptive control law is proposed for nonlinear dynamical systems and then the control system stability is proved.

In such a way the adaptive switching control mechanism can satisfy the stability, response and performance requirement with only one model used. By the hard switching laws used, the linear and nonlinear predictors are alternately used. However from the 1/0 switching control result, we can find that the switching control does not need to switch to 0 in most of time so that we can design the fuzzy switching to improve the control result.

According to the control processing, we find that the original fuzzy switching mechanism is not smooth enough by updating the linear and nonlinear predictor. Hence, in order to improve the performance of the switching control an improved switching mechanism is designed with two methods: one improves calculation of switching parameters and the other design a new switching law. The switching mechanism has compared in the simulations, and the improved fuzzy mechanism with both methods increases the control accuracy by solving the useless switching problem while ensuring the control stability.

REFERENCES

[1] T. Y. Chai (1988), A self-tuning decoupling controller for a class of multivariable systems and global convergence analysis. IEEE Transactions on Automatic Control, Vol. 33, No. 8, pp. 767-771

[2] F. Chen and H. Khalil (1995), Adaptive control of a class of nonlinear discrete time systems using neural networks. IEEE Transactions on Automatic Control, Vol. 40, No. 5, pp. 791-801

[3] J. Y. Choi and J. A. Farrell (2000), Nonlinear adaptive control using networks of piecewise linear approximators. IEEE Transactions on Neural Networks, Vol. 11, No. 2, pp. 390-401

[4] H. Lee and M. Tomizuka (2000), Robust adaptive control using a universal approximator for siso nonlinear system. IEEE Transactions on Fuzzy Systems, Vol. 8, No. 1, pp. 95-106

[5] K. Funahashi (2000), On the approximate realization of continuous mappings by neural networks. Neural Networks, Vol. 2, No. 3, pp. 183-192

[6] M. K. Hornik and H. White (2000), Multilayer feedforward networks are universal approximators. Neural Networks, Vol. 2, No. 5, pp. 359-366

[7] J. Hu and K. Hirasawa (2004), A method for applying neural networks to control of nonlinear systems. Neural Information Processing:Research and Development, J. Rajapakse and L. Wang, Eds., Springer, pp. 351-369

[8] J. Hu and K. Hirasawa (2003), Neural network based prediction model for control of nonlinear systems. Transactions of the Society of Instrument and Control Engineers, Vol. 39, No. 2, pp. 166-175

[9] Lan Wang, Yu Cheng and Jinglu Hu (2010), Nonlinear adaptive control using a fuzzy switching mechanism based on improved quasi-ARX neural network. In Proc. of the 2010 International Joint Conference on Neural Networks (IJCNN), pp.1-7

[10] J. Hu, K. Hirasawa and K. Kumamaru (1999), A neurofuzzy-based adaptive predictor for control of nonlinear systems. Transactions of the Society of Instrument and Control Engineers, Vol. 35, No. 8, pp. 1060-1068

[11] L. Chen and K. S. Narendra (2004), Identification and control of a nonlinear discrete-time system based on its linearization, A unified framework. IEEE Transactions on Neural Networks, Vol. 15, No. 3, pp. 663-673

[12] L. Chen and K. S. Narendra (2001), Nonlinear adaptive control using neural networks and multiple models. Automatica, Vol. 37, No. 8, pp. 1245-1255

