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Novel Adaptive Inverse Control for Permanent Magnet Synchronous Motor Servo System

Abstract. *The adaptive inverse control is a novel method in control system. It makes set signal, parameter disturbance and external disturbance separately controlled and makes them reach the optimal control without compromiseThe traditional adaptive inverse control system often used FIR filters. It madde the system costing long training time and slow convergence. So, it is unable to adapt the requirement of real-time control system. In this paper, a novel adaptive inverse control with adaptive neuro-fuzzy inference system (ANFIS) was designed for permanent magnet synchronous motor (PMSM) servo system. Meanwhile the microhabitat particle swarm optimization (MPSO) algorithm and RLS algorithm were used for updating parameters for ANFIS. This hybrid learning algorithm can reduce the computing costs and improve the convergence speed. Also, the ANFIS was used to for identification and inverse modeling of PMSM servo system. The simulation results show that the PMSM servo system based on novel adaptive inverse control strategy achieve higher tracking ability, steady precision and good robustness.*

Streszczenie. *Przedstawiono nowy adaptacyjny system sterowania odwrotnego wykorzystujący neuronowy-rozmyty system interferencji ANFIS. System zastosowano do układu serwomechanizmu z silnikiem synchronicznym o magnesach trwałych. Dodatkowo rojowy algorytm optymalizacji oraz algorytm RLS były wykorzystywane do zmiany parametrów. Badania symulacyjne potwierdziły, że nowy system ma dobra precyzję i odporność na zakłócenia. (**Nowy adaptacyjny odwrotny system sterowania silnikiem synchronicznym o magnesach trwałych**)*

Keywords: PMSM, adaptive inverse control, ANFIS, MPSO algorithm
Słowa kluczowe: adaptacyjny system sterowania, silnik synchroniczny, sieci neuronowe ANFIS

1. Introduction

PMSM has been widely used in industry, national defense and other social aspects. There are many advantages in PMSM servo system including high torque to current ratio, large power to weight ratio and high efficiency. But many uncertain factors can influence the performance of PMSM servo system such as parameters variation, external load disturbances and nonlinear modeling error. Numerous methods have been proposed to improve the performance of PMSM servo system including model reference adaptive control [1,2], sliding mode control [3], neural network control [1,2,4] and so on. These methods have their own merit and defects.

The adaptive inverse control has its own merit that it can eliminate the noise and disturbance of plant without compromise. It based on Wiener filtering theory and adaptive filtering theory [5]. The disturbance was eliminated by disturbance rejection method. The whole disturbance between the plant and model drive both the plant and model, farther, this disturbance was subtracted from the input of plant by driving the inverse of the model. Ultimately the noise and disturbance of servo system were eliminated. Therefore, obtain the model and inverse model of PMSM servo system are the key for the adaptive inverse control [6].

In this research, the mathematical model of PMSM was described in section 2. ANFIS and MPSO algorithm was presented in section 3. The novel adaptive inverse control strategy was proposed in section 4. The simulation results then followed to confirm the application in section 5. Finally, the advantages of the novel application were summarized.

2. Proposed Approach

2.1. ANFIS

The ANFIS combines two intelligent approaches including neural network and fuzzy system, so both fuzzy reasoning and network calculation will be available simultaneously [7].

Fig.1 shows the structure of ANFIS, which is composed of antecedent part and conclusion part. These are connected to each other by the fuzzy rules in network form.

The function of each layer as follows:

Layer 1: Executes a fuzzification process. Where: x is the input to the ith node and A_i is a linguistic label associated with this node.

(1) $$O_i^1 = \mu A_i(x), i = 1,2$$

(2) $$O_i^1 = \mu B_i(x), i = 3,4$$

Layer 2: Executes the fuzzy AND of the antecedent part of the fuzzy rules.

(3) $$O_i^2 = \omega_i = \mu A_i(x) \times \mu B_i(y)$$

Layer 3: Normalizes the member functions.

(4) $$O_i^3 = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}$$

Layer 4: Executes the conclusion part of the fuzzy rules. Where: $\bar{\omega}_i$ comes from the output of layer 3 and $\{p_i, q_i, r_i\}$ is the parameter of member functions.

(5) $$O_i^4 = \bar{\omega}_i f_i = \bar{\omega}_i (p_i x + q_i y + r_i)$$

Layer 5: Calculate the final output of the fuzzy system by summing up the incoming outputs of the fourth layer which is the defuzzification process.

(6) $$O_i^5 = f = \sum_i \bar{\omega}_i f_i = \frac{\omega_1 f_1 + \omega_2 f_2}{\omega_1 + \omega_2}$$

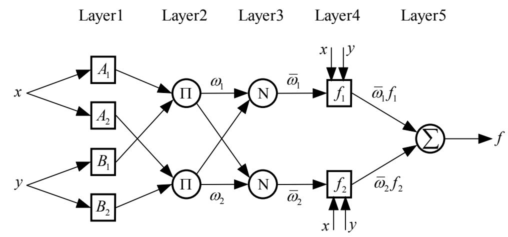

Fig.1. Structure diagram of ANFIS

2.1. MPSO Algorithm

The particle swarm optimization (PSO) algorithm as an intelligent algorithm was first introduced by Kennedy and Eberhart in 1995 [8], in recent years it has been widely applied because it is easy to realize, has little information about the optimal problem and fewer parameters to adjust. Meanwhile, PSO algorithm has the merit like to other intelligent algorithm, such as genetic algorithm. But PSO has such problems as the rate of convergence, local extreme, premature and halt condition in searching process.

In order to overcome these defects additional operators have been incorporated into the basic MPSO, such as DPSO, GA-MPSO, MPSO, etc [8-13]. The MPSO share the overall optimal information in the group to improve the overall convergence and avoid prematurely. After each groups divided, choose the group which has the largest population as the center.

In this paper, a random wheel shape structure was used, it defines a particle subgroup as a central subgroup, other subgroups as the neighborhoods around the center [14]. The center subgroup can communicate with other subgroup which around it. But the other subgroups cannot communicate with each other. With this method the information can transmit faster and improving the algorithm efficiency. Fig.2 shows the random wheel shape structure.

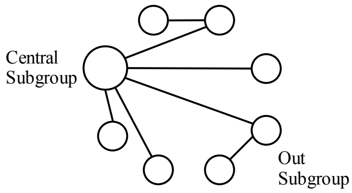

Fig.2. Random wheel shape structure

According to the space position of each particle, the distance of two vectors was calculated. The $L_{\max}$ was marked as the maximum distance of any two particles. Meanwhile $\left\|X_i(k)-X_j(k)\right\|/L_{\max}$ was also calculated, Where: $\left\|X_i(k)-X_j(k)\right\|$ is the distance between current particle $X_i(k)$ to another particle $X_j(k)$. Two particles merge into one group when the ratio smaller than a certain value, otherwise they should be divided from the group.

Each particle updates its status according Eq. (7) and (8) as follows.

(7) $$V_i(k+1)=\omega(k)V_i(k)+c_1(k)r_1(P_i-X_i(k)) \\ +c_2(k)r_2(P_g-X_i(k))$$

(8) $$X_i(k+1)=X_i(k)+V_i(k+1)$$

where: ω is time varying inertia weight factor, c_1 and c_2 are the time-varying cognitive and social parameters. r_1 and r_2 random functions in the range of [0,1]. Every new position must be evaluated by fitness function.

In order to expedite the speed of be optimized and to avoid particle swarm algorithm to get into a local optimum, it is necessary to properly adjust the value of ω. In the early stages, a big speed-weight ω can prevent algorithm from getting into a local optimization. In the later stage, small one is propitious to accelerate algorithm converge. In this algorithm, a quasi-linear speed-weights way is used in the iterative process. This way can be described as follows:

(9) $$\omega(k)=\omega_{initial}+(\omega_{initial}-\omega_{final})(1-k/K)$$

(10) $$c_1(k)=c_{1initial}+(c_{1initial}-c_{1final})(1-k/K)$$

(11) $$c_2(k)=c_{2initial}+(c_{2initial}-c_{2final})(1-k/K)$$

Where: $\omega_{initial}$ and ω_{final} are the initial and final values of the weight factor; $c_{1initial}$ and c_{1final} are the initial and final values of the cognitive parameter; $c_{2initial}$ and c_{2final} are the initial and final values of the social parameter; k is the current iterate time; K is the maximum iterate time.

2.3. Hybrid Learning Algorithm for ANFIS

There are four methods were introduced to update the parameters of ANFIS in [9] as follows:

1. Gradient decent only: all parameters are updated by the gradient descent.
2. Gradient decent only and one pass of LSE: the LSE is applied only once at the very beginning to get the initial values of the consequent parameters and then the gradient decent takes over to update all parameters.
3. Gradient decent only and LSE: this is the hybrid learning.
4. Sequential LSE: using extended Kalman filter to update all parameters.

The most training methods in the antecedent part are based on gradient decent. Due to the gradient decent method should go through all layers which cause much calculation. So this method is complexity and slow convergence.

Here, the MPSO and RLS were employed for updating the ANFIS parameters including the antecedent part parameters and the conclusion part parameters. The MPSO algorithm was employed to update the antecedent part. It was easier and faster than the gradient method. In the gradient method convergence of parameters is very slow and depends on initial value of parameters and finding the best learning rate is very difficult. But, in the MPSO method, the learning rate does not needed.

The RLS algorithm for training the conclusion part is used and for training the antecedent part parameters apply MPSO algorithms. Table 1 shows the hybrid learning algorithm for ANFIS.

Table 1. Hybrid learning algorithm for ANFIS

	Forward Pass	Backward Pass
Antecedent Parameters	Fixed	RLS
Conclusion Parameters	MPSO	Fixed
Signals	Node Outputs	Error Rates

3. Adaptive Inverse Control for PMSM Servo System

3.1. Adaptive Inverse Control Concept

Adaptive inverse control which has been widely used in unknown nonlinear system, has received much attention in recent years. The basic idea is to use a signal that comes from the controller to drive the plant while the model of the controller is the inverse model of the plant, the output of the plant follows the input to the controller and then realizing the anticipate control effects [6].

The transfer function from disturbance input to plant output was described as follows:

(12) $$W(s)=\frac{1-G_m(s)\cdot G_q(s)}{1+G_p(s)G_q(s)-G_m(s)\cdot G_q(s)}$$

where: $G_p(s)$ is plant, $G_m(s)$ is plant model, $G_q(s)$ is plant inverse model. In the condition of ideal model and inverse model, namely $G_q(s)=G_m^{-1}(s)$, transfer function from disturbance to output is 1, restrain and eliminate the disturbance.

Fig.3 shows the structure of adaptive inverse control system. The plant model and inverse model which we need can get through identification. The adaptive inverse control can divided into two parts: (a) control of plant dynamic response (b) restrain of plant noise.

It is obviously that the adaptive inverse control needs model and inverse model of plant. The accuracy of model and inverse model directly affect the control performance. So how to get the accuracy model and inverse model of plant is important. Due to PMSM servo system is a nonlinear system, so it is infeasible the uses linear adaptive filter to modeling. In contrast, ANFIS has obviously superiority in this aspect. We can train the ANFIS to get model and inverse model of PMSM servo system.

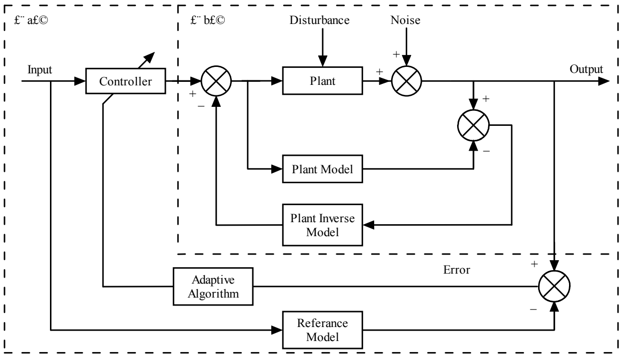

Fig.3. Structure of model reference adaptive inverse control system

3.2. Nonlinear System Modeling

The series-parallel modeling method has simple structure and guarantees converge. Due to the parallel model can't about system identification, series-parallel identification structure was adopted[15,16], it can be described in Eq. (13):

(13) $$y_m(k) = f[y(k-1)\cdots y(k-n), u(k)\cdots u(k-m)]$$

Fig.4 shows the structure diagram of PMSM servo system modeling. Where: $u(k)$ is modeling signal, $n(k)$ is noise or disturbance, $y_p(k)$ is dynamic output, $y_m(k)$ is output of identify model, $y(k)$ is the total output of plant, $P(z)$ is PMSM servo system, $\hat{P}(z)$ is the identification model.

The output of model $y(k)$ depends on the system input $u(k\text{-}1)$ and output $y(k-1)$ previous time, because of the system is bounded in bounded out stability, so the ANFIS input signal and other signal from identification are bounded. As far as select proper learning rate, we can guarantee identification model convergence.

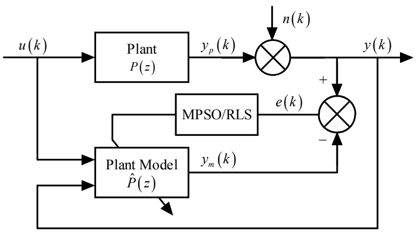

Fig.4. Structure diagram of modeling for PMSM servo system

In order to identify the plant, the input and output data should be sampled first. When train ANFIS the input and output data were normalized and calculate the output anti normalized.

We select multi-frequency sine signal as the input signal which was showed as follows:

(14) $$u(k) = 300\sin\frac{k\pi}{250} + 350\sin\frac{k\pi}{500}$$

The membership function of ANFIS was described as gauss functions in Eq. (15). It was used for two input variables.

(15) $$O_i^1 = \mu A_i(x) = e^{\frac{(x-b_i)^2}{2a_i^2}}$$

where: a_i and b_i are the premise parameters. Training algorithm requires a training set defined between inputs and output [3]. The numbers of member functions for input variables including $u(k\text{-}1)$ and $y(k-1)$ are 5 and 5. The numbers of rules are 25 (5×5). It is clear that the gauss member function was specified by two parameters. Therefore, the ANFIS contains a total of 95 parameters including 20 (2×5+2×5) premise parameters and 75 (25×3) consequent parameters.

The MPSO was used to update the antecedent parameters which was described before and updating conclusion parameters with RLS algorithm. We selected 30 particles and each particle had a vector with 20 dimensions. The number of training epochs was 200. The fitness function defined as the mean squared error.

The modeling error between plant output and model output Fig.5 shows, which is evident that ANFIS achieve good performance after first iteration.

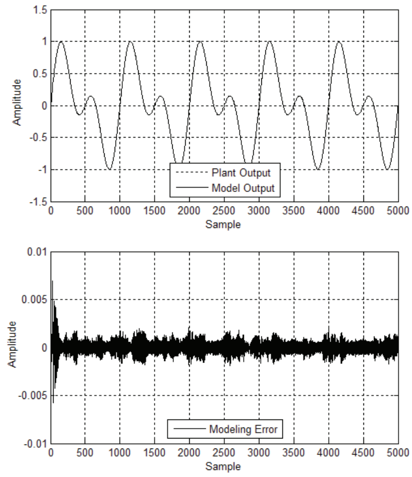

Fig.5. Curve of modeling error between plant output and model output

3.3. Nonlinear System Inverse Modeling

Due to adopt adaptive inverse control we need inverse model of nonlinear controlled plant. The direct modeling method has simple principle, but the trained inverse model cannot be used as controller directly.

The indirect modeling method can resolve the problem and it can get inverse model both online and offline. By the premise of getting plant identification model, we adopt indirect inverse modeling model to get inverse model. Fig.6 shows the structure diagram of indirect inverse modeling for PMSM servo system [19].

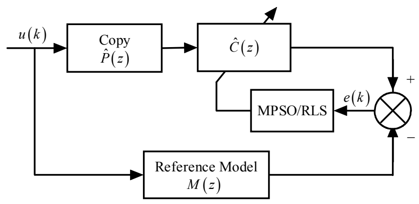

Fig.6. Structure diagram of inverse modeling for PMSM servo system

Where: $u(k)$ is the white noise as modeling signal. $\hat{C}(z)$ was obtained off line by $\hat{P}(z)$ which is an exact digital copy of identification model of PMSM servo system. The $u(k)$ drives the reference model $M(z)$ and the output was compared with the output of $\hat{C}(z)$ to obtain the error $e(k)$. $\hat{C}(z)$ was adopted to minimize the mean square of $e(k)$ by using ANFIS.

The membership function was described as gauss functions in Eq. (28). The numbers of member functions for input variables including $u(k\text{-}1)$ and $y(k-1)$ are 5 and 5. The numbers of rules are 25 (5×5). It is clear from Eq. (29) that the gauss member function is specified by two parameters. Therefore, the ANFIS contains totally 95 parameters including 20 (2×5+2×5) premise parameters and 75 (25×5)) consequent parameters.

We use MPSO to updating the antecedent parameters which was described before and updating conclusion parameters with RLS algorithm. Each particle was a vector with 20 dimensions. We selected 30 particles to train. The number of training epochs was 200. The fitness function defined as the mean squared error.

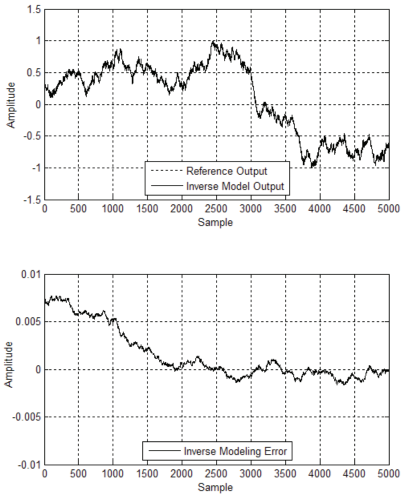

Fig.7. Curve of inverse modeling error between plant output and inverse model output

The inverse modeling error between plant output and inverse model output Fig.7 shows, which is evident that ANFIS achieve good performance after first iteration.

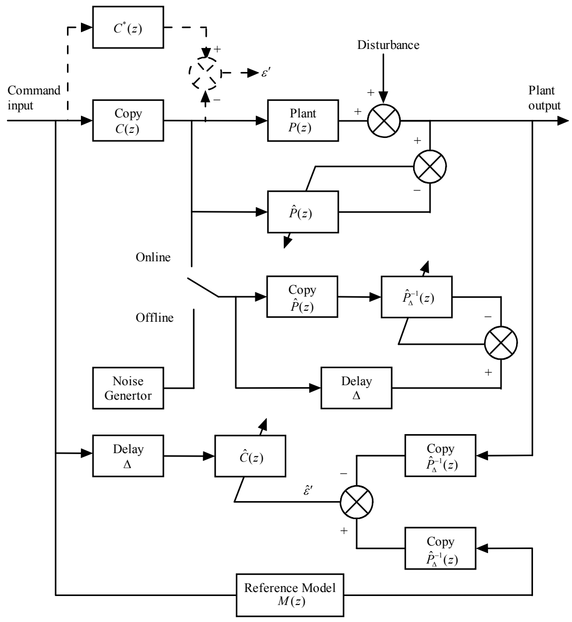

Fig.8. Nonlinear adaptive inverse control system based on ε -filtering

3.4. Nonlinear Adaptive Inverse Control System Integeration

First, the ANFIS was trained with hybrid algorithm for plant modeling and plant inverse modeling offline, and then the trained ANFIS was adjusted online. The controller model trained and adjusted online. Fig.8 shows the nonlinear adaptive inverse control based ε - filtering system [20].

The output of $\hat{P}(z)$ is used in generating the error signal for the adaptive process for finding $\hat{C}(z)$. The advantage is that the output of $\hat{P}(z)$ does not contain plant disturbance. The disadvantage is that differences between $\hat{P}(z)$ and $P(z)$ could bias the adaptive process for finding $\hat{C}(z)$. Thus, the controller could differ from the ideal. The control engineer must trade advantages against disadvantages in each practical case.

4. Simulations and Experiments

The simulation study was carried out using MATLAB/SIMULINK. The simulations results of the PMSM servo system are presented to demonstrate the performance of the proposed novel adaptive inverse controller under various operating conditions. The parameters of simulated PMSM as follow: rated voltage is 220 V, rated current is 2.5A, stator resistance is 1.6 Ω, d axis inductance 1.54 mH, q axis inductance1.54 mH, number of magnetic poles is 2, moment of inertia 0.0156 kg m^2.

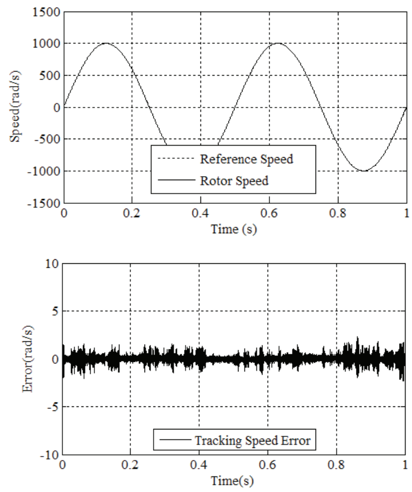

Fig.9. Dynamic speed response for PI controller

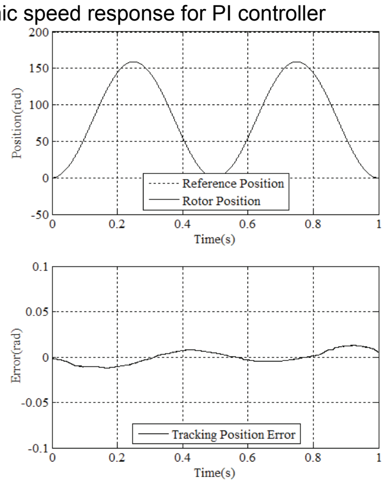

Fig.10. Dynamic position response for PI controller

Fig.9 and Fig.10 show the dynamic response for the PI controller. Fig.11 and Fig.12 show the dynamic response for the proposed adaptive inverse controller. These simulation results clearly demonstrate the adaptive inverse controller has good dynamic performances in command tracking characteristics than PI controller.

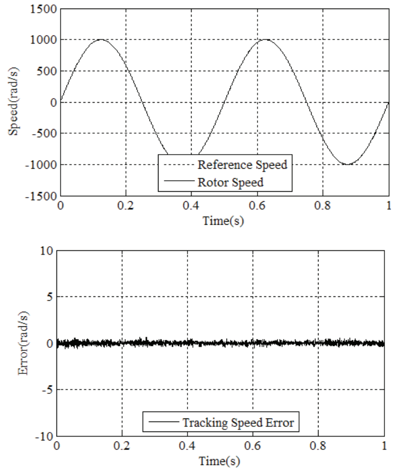

Fig.11. Dynamic speed response for proposed adaptive inverse controller

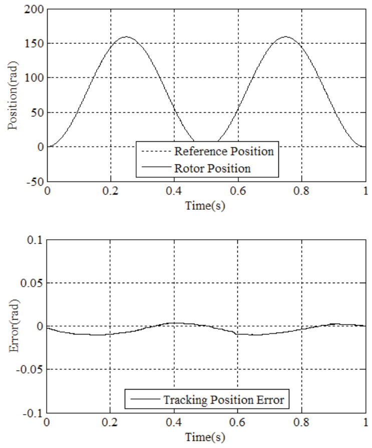

Fig.12. Dynamic position response for proposed adaptive inverse controller

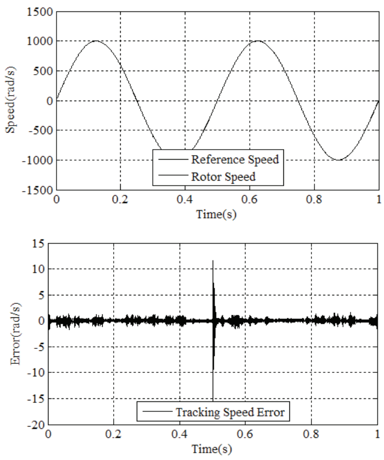

Fig.13. Dynamic response for PI controller when a load of 3 N·m is applied at t=0.3s

The disturbance rejection capabilities have been checked when a load of 3N·m is applied to the shaft at t=0.5s. Fig.13 and Fig.14 show the dynamic response for the PI controller.

Fig.15 and Fig.16 show the dynamic response for the proposed adaptive inverse controller. These simulation results clearly demonstrate the adaptive inverse controller has good dynamic performances in load regulation characteristics than PI controller. Meanwhile, the proposed novel adaptive inverse controller provided a rapid and accurate response under load change compared with the PI controller.

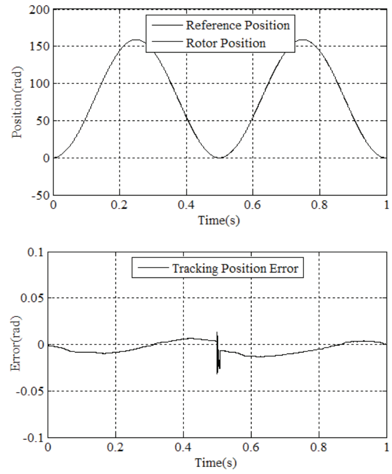

Fig.14. Dynamic response for PI controller when a load of 3 N·m is applied at t=0.3s

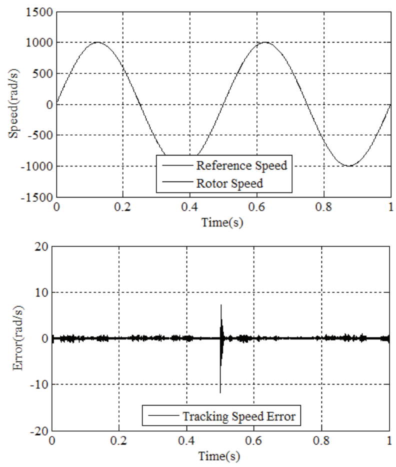

Fig.15. Dynamic response for proposed adaptive inverse controller when a load of 3 N·m is applied at t=0.3s

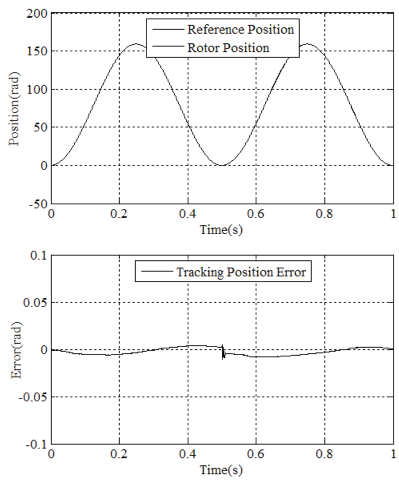

Fig.16. Dynamic response for proposed adaptive inverse controller when a load of 3 N·m is applied at t=0.3s

The PMSM servo system was designed in order to further demonstrate the effectiveness of the proposed control strategy. The PMSM servo system was based on TMS320F2812 DSP. The system main loop composed of inverter, PMSM, rotor position detector, current sensor and speed sensor. Control loop composed of adaptive inverse position controller, speed controller, vector conversion circuit, current controller, SVPWM generator, drive circuit and speed conversion circuit.

The real-time collection curves of experiment system were shown in Fig.17 and Fig.18.

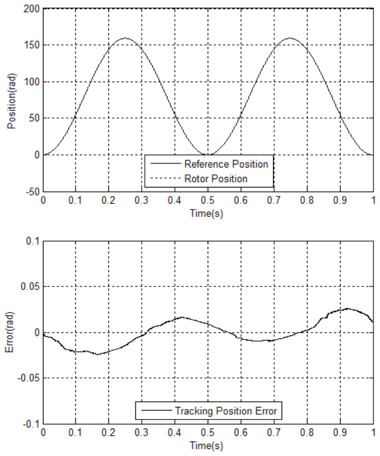

Fig.17. Experiment result of position tracking performance

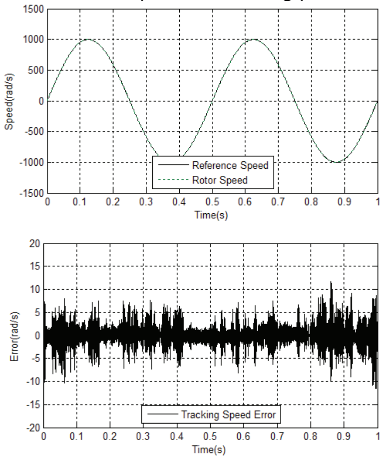

Fig.18. Experiment result of speed tracking performance

It is obvious that good position tracking responses of the PMSM servo system was obtained. The robust control characteristic was clearly observed under the occurrence of load disturbance.

Conclusions

This study has successfully demonstrated the effectiveness of the proposed novel adaptive inverse control with ANFIS for the position control of PMSM servo system. First, the principle of the field-oriented PMSM drive system was derived. Then, the network structure and theoretical bases of the proposed adaptive inverse control with ANFIS was described in detail. In the ANFIS neural network, the MPSO and RLS algorithm have been adopted to adjust the parameters to replace the traditional method. The antecedent parameters were updated by MPSO and conclusion parameters were updated by RLS. We adopt ANFIS to obtain the plant model, plant inverse model and construct nonlinear adaptive inverse control based on ε-filtering LMS system. Finally, the control performance of the adaptive inverse control based on ANFIS has been confirmed by some simulated results. Simulation result shows the proposed adaptive inverse control greatly enhances the position tracking ability and has strong robustness when parameters changes.

The major contributions of this study are: (1) the successful adoption of an MPSO-RLS algorithm to adjust the parameters of ANFIS; (2) the successful application of the adaptive inverse control based on ANFIS for PMSM servo system.

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