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# Composite Adaptive Inverse Controller Design for Permanent Magnet Synchronous Motor

*Abstract. Permanent magnet synchronous motor (PMSM) servo system is a nonlinear, multi-variables strong coupling system. To improve the performance of the PMSM system, a composite adaptive inverse control strategy is proposed. This control strategy adopt improved radial basis function (RBF) neural network and FIR filter as nonlinear filter. The proposed filter is used to identify the system, inverse system and design the adaptive inverse controller. Meanwhile the chaos multi-population particle swarm optimization (CMPSO) algorithm is proposed to training the parameters of the nonlinear filter offline. And then an improved variable step size LMS (IVSLMS) algorithm is used to optimize the parameters online. These algorithm improves the convergence speed and accuracy, further improves the control performance of adaptive inverse control. The results of simulation and experiment indicate that the PMSM servo system has good dynamic, static performance and robustness by using proposed hybrid adaptive inverse control strategy.*

*Streszczenie. W celu poprawy parametrów silnika synchronicznego z magnesami trwałymi PMSM zaproponowano kompozytowa adaptacyjną strategię sterowania. Strategia wykorzystuje sieć neuronową i nieliniowy filtr SOI. (**Adaptacyjny, odwrotny system sterowania silnikami synchronicznymi z magnesem trwałym PMSM**)*

**Keywords:** PMSM; Adaptive inverse control; Nonlinear filter; CMPSO algorithm; IVSLMS algorithm
**Słowa kluczowe**: silnik synchroniczny PMSM, filtr nieliniowy

## 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 parameter variation, external load disturbance and nonlinear modeling error. Numerous methods have been proposed to improve the performance of PMSM servo system including model reference adaptive control [1], sliding mode control [2], neural network control [3] and so on. These methods have their own merit and defects.

The adaptive inverse control can eliminate the noise and disturbance of plant without compromise [4]. The whole disturbance between the plant and model drive both the plant and model, further this disturbance is subtracted from the input of plant by driving the inverse of the model. Ultimately the noise and disturbance of servo system are eliminated. Therefore, obtain the model and inverse model of PMSM servo system is the key for the adaptive inverse control [5].

Due to the characteristic that neural network can approximate any nonlinear function. A novel nonlinear adaptive filter is lead into adaptive control system, which is composed of improved RBF neural network and FIR filter. Meanwhile, an improved variable step size LMS (IVSLMS) algorithm is adapt to optimized the parameters of nonlinear filter online. By this method the convergence speed and accuracy of nonlinear filter is improved. Further improve the performance of adaptive inverse control system. Simulation comparative analysis and experiment results show that the PMSM servo system based on the proposed control strategy has good dynamic response, static accuracy and strong robust.

## 2 Adaptive inverse control

The 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.

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

(1)
$$H(z) = \frac{1 - G_m(z)G_q(z)}{1 + G_p(z)G_q(z) - G_m(z)G_q(z)}$$

where $G_p(z)$ is plant, $G_m(z)$ is plant model, $G_q(z)$ is plant inverse model. In the condition of ideal model and inverse model, namely $G_q(z) = G_m^{-1}(z)$, transfer function from disturbance to output is 1, restrain and eliminate the disturbance. Whereas in actual application, $G_q(z) \neq G_m^{-1}(z)$, the disturbance can't be delimited in dynamic process. Due to the parameters of controlled plant with the change in operating condition, so $G_c(z)$ and $G_q(z)$ have to adjusted adaptively to achieve follow the reference value, eliminate objective parameters variance and external disturbance.

### 2.1 Nonlinear adaptive filter

In adaptive inverse control system, the relationship between input and output of controlled plant, controller and disturbance cancelling is particular nonlinear. The nonlinear adaptive filter is the important unit in adaptive inverse control system. It is used to plant modeling, inverse modeling and plant disturbance canceling. The real-time performance, convergence ability and stability of nonlinear filter directly affect the performance of adaptive inverse control.

Recent years, the nonlinear filter composed of neural network has been widely used due to its powerful nonlinear mapping and function approximate ability, this provide new method for nonlinear control.
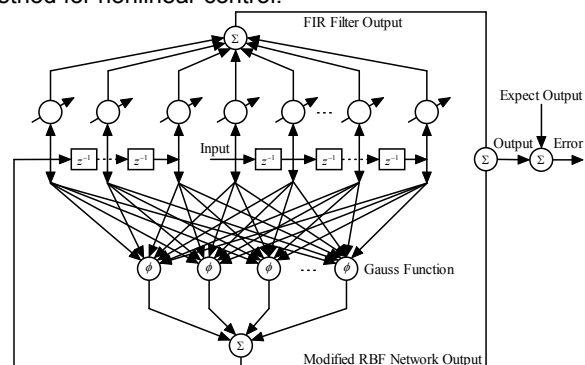


Fig. 1. Improved nonlinear adaptive filter

This paper constitutes a novel nonlinear filter combined with the advantage of FIR filter and RBF neural network [7] is shown in Fig. 2. The novel nonlinear filter is combined with improved RBF neural network [8] and FIR filter. And it has both the advantage of neural network and FIR filter.

The nonlinear filter input time series is $\mathbf{X}_k = [x_1, x_2, \cdots, x_m]$; The hidden layer unit number of improved RBF neural network is $\hat{\mathbf{W}}_k = [\hat{w}_1(k), \cdots, \hat{w}_m(k), \hat{w}_{m+1}(k), \cdots, \hat{w}_{m+n}(k)]$; The FIR filter weight factors is $\mathbf{W}_k = [w_1(k), w_2(k), \cdots, w_M(k)]$.

The nonlinear transfer function of the $j$th hidden node is $\phi_j$. The output of the $j$th hidden neuron can be written as:

$$(2) \qquad \phi_j = \exp\left(-\frac{\|\mathbf{X} - c_j\|^2}{2\sigma_j^2}\right)$$

Where $\mathbf{c}_j = [c_{j1}, c_{j2}, \cdots, c_{j(m+n)}]$ is the center vector of neuron; $\boldsymbol{\sigma}_k = [\sigma_1(k), \sigma_2(k), \cdots, \sigma_M(k)]$ is the center spread parameter. The output of nonlinear filter is the sum of FIR filter and improved RBF neural network as follows:

$$(3) \qquad y(k) = \sum_{j=1}^{M} w_j(k)\phi_j + \sum_{j=1}^{m+n} \hat{w}_j(k)\hat{x}(k-j+1)$$

The center vector $\mu$ and center spread parameters $\sigma$ of improved RBF neural network adopt gradient descent algorithm:

$$(4) \quad c_{ji}(k) = c_{ji}(k-1) + \eta\Delta c_{ji} + \alpha\left(c_{ji}(k-1) - c_{ji}(k-2)\right)$$

$$(5) \qquad \Delta c_{ji} = e(k) w_j \frac{x_j - c_{ji}}{\sigma_j^2}$$

$$(6) \quad \sigma_j(k) = \sigma_j(k-1) + \eta\Delta\sigma_j + \alpha\left(\sigma_j(k-1) - \sigma_j(k-2)\right)$$

$$(7) \qquad \Delta\sigma_j = e(k) w_j \phi_j \frac{\|\mathbf{X} - c_j\|^2}{\sigma_j^3}$$

where $\eta$ is learning rate; $\alpha$ is momentum factor.

The weight Coefficients of controller are improved by adopt variable step size LMS algorithm. For the online training, error function is defined as:

$$(8) \qquad J = \frac{1}{2}\left(y_d(k) - y(k)\right)^2 = \frac{1}{2}\left(e(k)\right)^2$$

where $y_d(k)$ is desired response, $e(k)$ is error.

## 2.2 Chaos multi-population particle swarm optimization algorithm

The particle swarm optimization (PSO) algorithm as an intelligent algorithm was first introduced by Kennedy and Eberhart in 1995 [9]. 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. Each particle updates its status according equation (9) and (10) as follows.

$$(9) \quad \begin{aligned} V_i(k+1) &= \omega(k)V_i(k) + \xi_1(k)r_1\left(P_i - X_i(k)\right) \\ &+ \xi_2(k)r_2\left(P_g - X_i(k)\right) \end{aligned}$$

$$(10) \qquad X_i(k+1) = X_i(k) + V_i(k+1)$$

Where $\omega$ is time varying inertia weight factor, $\xi_1$ and $\xi_2$ are the time-varying cognitive and social parameters. $r_1$

and $r_2$ are random number in the range of [0,1]. Every new position must be evaluated by fitness function.

In this paper, chaos and multi-population were introduced. The chaos system to initialization particles, which is shown in equation (11). This strategy can make particles have good randomness and diversity [10].

$$(11) \qquad z_{n+1} = \mu z_n(1 - z_n) \quad n = 0, 1, 2, \cdots$$

Where $\mu \in [3.56, 4.0]$ is the control parameter. It decide the chaotic degree of chaos system; $z_0 \in [0,1]$. Through equation (11), we can get chaotic sequence $z_1, z_2, z_3 \cdots$.

The populations is arranged in accordance with the fitness value and then divided into the optimal population, the general population and the poorest population.
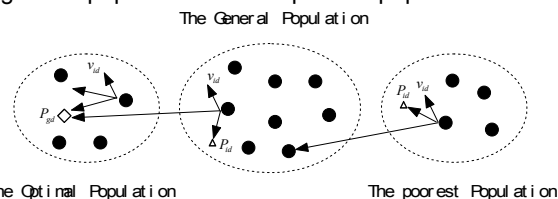


Fig.2. Division of particle population

$$(12) \qquad f_{avg} = \frac{1}{N}\sum_{i=1}^{N} f_i$$

$$(13) \qquad \Delta = \left| f_g - f'_{avg} \right|$$

where $f_{avg}$ is average fitness value of particles; $f_i$ is the current iteration fitness value; $N$ is particle number; $f_g$ is fitness value of the optimal particle; $f'_{avg}$ is the average value which are better than $f_{avg}$; $\Delta$ precocious is evaluation factor, it indicate the precocious degree.

For the optimal population, the fitness value is relatively high. It means the population closer to the global optimal solution. We update the particles according to equation (14) and equation (15):

$$(14) \qquad v_{id}(k+1) = \omega v_{id}(k) + \xi_1 r_1\left(p_{gd} - x_{id}(k)\right)$$

$$(15) \qquad \omega = \omega - (\omega - \omega_{min})\left|\frac{f_i - f'_{avg}}{f_g - f'_{avg}}\right|$$

where $\omega_{min}$ is the minimum inertia factor.

For the general population, particle has both global and local optimize ability. We update the particles according to equation (9) and equation (16):

$$(16) \qquad \omega = \omega_{min} + (\omega_{max} - \omega_{min}) \times \frac{(iter_{max} - iter)}{iter_{max}}$$

For the poorest population, particles have poor search ability. So the position information from the general population is introduced into the poorest population. We update the particles according to equation (17) and equation (18):

$$(17) \quad \begin{aligned} v_{id}(k+1) &= \omega v_{id}(k) + \xi_1 r_1\left(p_{id} - x(k)\right) \\ &+ \xi_2 r_2\left(p'_{id} - x_{id}(k)\right) \end{aligned}$$

$$(18) \qquad \omega = 1.5 - 1/\left(1 + k_1 \cdot \exp(-k_2 \cdot \Delta)\right)$$

where $p'_{id}$ is the position which particle has the highest premature convergence factor in the general population; $k_1$ determines the maximum value of $\omega$; $k_2$ determines the adjustment ability of equation(17).

## 2.3 VSLMS algoritm

LMS algorithm based on gradient descent algorithm, it has low computational complexity and easy to realize. And the fixed step size LMS algorithm has equilibrium problem in convergence speed and convergence accuracy aspect. In order to overcome these weaknesses, people proposed many variable step size adaptive filter algorithms.

This paper proposed a novel nonlinear function, adjust the the step size factor flexible [11]. The parameter $\alpha$ adjust the shape of step size function and parameter $\beta$ adjust the step size. Meanwhile, eliminate the disturbance come from uncorrelated noise utilize autocorrelation estimation of current error $e(k)$ and previous error $e(k\text{-}1)$ control iterative step size.

The relationship of step size function is shown as follows:

$$(19) \qquad \mu(k) = \beta\left(1 - \frac{1}{\alpha p(k)+1}\right)$$

$$(20) \qquad p(k) = \gamma p(k-1) + (1-\gamma)e(k)e(k-1)$$

$$(21) \qquad \alpha = \begin{cases} \alpha_1 & |e(k)/e(k-1)| < \delta \\ \alpha_2 & |e(k)/e(k-1)| > \delta \end{cases}$$

where $\mu(k)$ is step factor; $p(k)$ is autocorrelation estimate of $e(k)$ and $e(k-1)$; $\gamma$ is the relevance factor of $p(k)$ and $p(k-1)$, $0 < \gamma < 1$. The shape is depend on parameter $\alpha$. The rang of step size function depend on parameter $\beta$. $e(k)$ and $e(k-1)$ are error signal at time step $k$ and $k-1$. Under the condition of other parameters are same, the bigger $\alpha$ is, the longer the time of step size get bigger value. This may lead to fast convergence speed. But the defect is when $e(k)$ approach 0, step size has steep descend. It means little $\Delta e(k)$ may lead to large $\Delta\mu(k)$ and the steady state error may improve. Otherwise, the smaller $\alpha$ is, the shorter the time of step size get bigger value. This may lead to slow convergence speed. So in order to get faster convergence speed, the value of parameters $\alpha$ should change bigger. Otherwise the value of parameters $\alpha$ should change smaller.

This algorithm adaptive adjust $\alpha$ through compare $|e(k)/e(k-1)|$ and threshold $\delta$, when $|e(k)/e(k-1)|$ changes big, $\alpha$ adjust to a bigger value according to $\alpha_1$, enlarge the adjustment range of $\mu(k)$, thus get bigger convergence speed . Otherwise, when $|e(k)/e(k-1)|$ changes small, $\alpha$ adjust to a bigger value according to $\alpha_2$, reduce the adjustment range of $\mu(k)$, thus get smaller steady state error. By this method, when system occur jump, the algorithm can convergence to steady state quickly. It can improve tracking jump ability of adaptive algorithm. Meanwhile, utilize autocorrelation estimate $p(k)$ of $e(k)$ and $e(k-1)$ replace $e(k)$, make step size $\mu(k)$ is only related to input signal without noise[12], and then the adaptive system dismiss the disturbance of uncorrelated noise.

## 3 Composite adaptive inverse control system

PMSM position control system based on adaptive inverse control can improve the tracking performance and anti-disturbance ability. This paper make PMSM system as controlled plant, adopt improved RBF neural network and FIR filter to construct the nonlinear adaptive filter for plant modeling, plant inverse modeling and disturbance canceller designing.
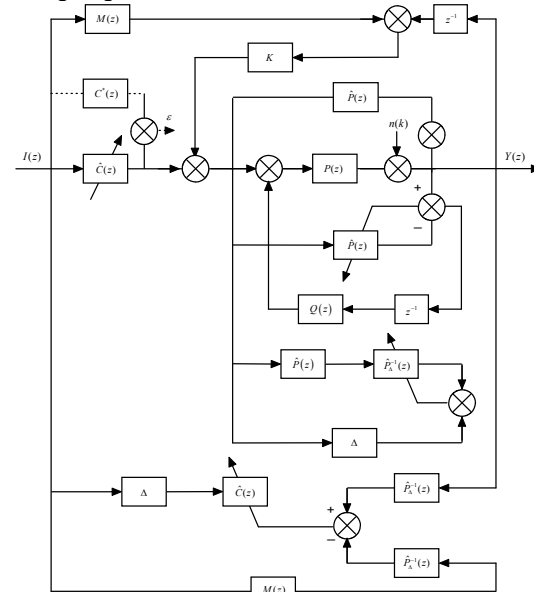


Fig.1. Composite adaptive inverse control system

Plant modeling is the premise and foundation of plant inverse modeling. It requires fast convergence character and good tracking character when establish positive model. This paper adopt nonlinear filter and variable step size LMS algorithm identify the system, establish the plant model.

In order to improve convergence speed and get smaller overshot, variable step size LMS algorithm is adopt to get inverse model, the nonlinear filter weights form offline inverse modeling is used as the original value of online inverse modeling controller.

In order to eliminate disturbance and do not change dynamic performance, feedback method is adopted. For guarantee inverse model has fast adaptive process, the positive model should tracking time-varying plant quickly and the disturbance canceller should finish adaptive process quickly. Online disturbance canceller initial value is the nonlinear filter weights, which is obtained from offline disturbance canceller. The disturbance canceller must turn off when plant character changes until plant model $\hat{P}(z)$ convergence to $P(z)$.

During this period the disturbance may occur in output. So we add PID controller into adaptive inverse control system. Fig. 3 shows the composite adaptive inverse control system. The PID controller can eliminate the disturbance when disturbance canceller turned off. Meanwhile the PID controller can eliminate static error when plant model has modeling error. Also the PID controller can decrease overshoot when $\hat{C}(z)$ lose control effect.

## 4 Simulation and experiment results

The simulation study is carried out using MATLAB/SIMULINK. The selected PMSM with rated voltage is $138V$, rated current is $11A$, zero speed torque is $5N\cdot M$, rated speed is $2000\text{rpm}$, moment of inertia

$1.06 \times 10^{-3} kg \cdot cm^2$ . Fig.4 to Fig.6 show the performance of modeling, inverse modeling and disturbance cancelling.
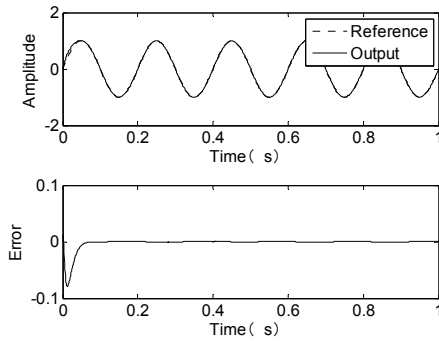


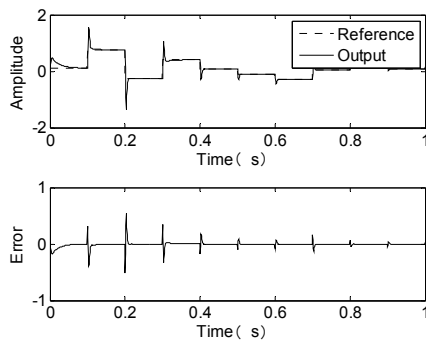Fig. 4. Performance of plant modeling



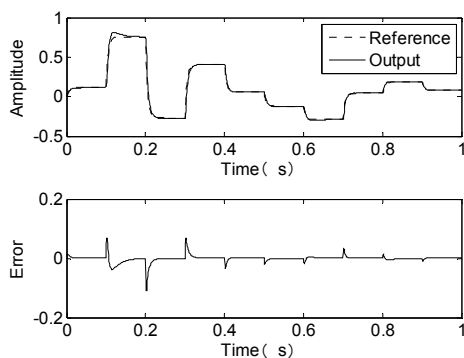Fig. 5. Performance of inverse modeling



Fig.6. Performance of disturbance canceller

The experiment system based DSP is designed to verify the reality control performance. The processer in experiment system adopt TMS320F28335 product by TI Company. It implements proposed control algorithm and executes in real time. The photoelectricity coder is used for position detect, then the output signal of photoelectricity coder is sent to DSP pass by the filter and amplify circuit. DSP uses an integrated 12-bit analog-to-digital converter to read the position sensor output and produces SVPWM control signal drive PMSM. Finally position control is realized.

The experiment test curve is real-time collected by experiment system is shown as follows. Fig.7 is the performance comparison of PID control strategy and proposed adaptive inverse control strategy. We can see that the output error of adopt PID control strategy is larger and the time of reach steady state is longer than the proposed algorithm. The proposed control strategy has better dynamic response and steady state accuracy.
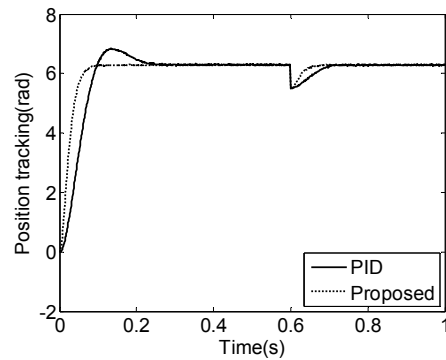


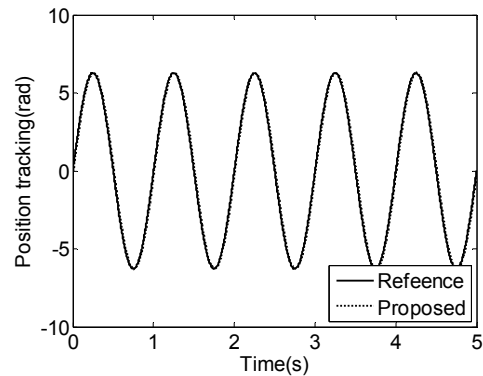Fig. 7. Comparison with different controllers
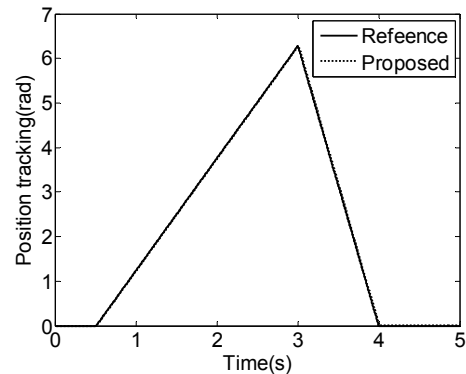


Fig.8 Responses of sinusoidal command



Fig.9. Responses of triangular command

Fig.7 also shows the comparison of the load disturbance responses between PID controller and the proposed controller. When system has disturbance at $0.6s$ , the output of PID control strategy is effected large and error obviously change large. But the proposed algorithm performance better. The proposed adaptive inverse control strategy has strong robustness. Fig.8 and Fig.9 show the response that servo system with different input signal. It can be seen from the experiments that the servo system has faster dynamic response and higher steady state accuracy by using the proposed adaptive inverse controller.

Fig.10 to Fig.12 shows the experiment results of the PMSM system. Fig.10 shows the speed respose of PMSM system. Fig.11 and Fig.12 show the current and voltage response of PMSM system. From these experiments we can see that the PMSM system based on proposed control strategy has good tracking performance and steady state accuracy.
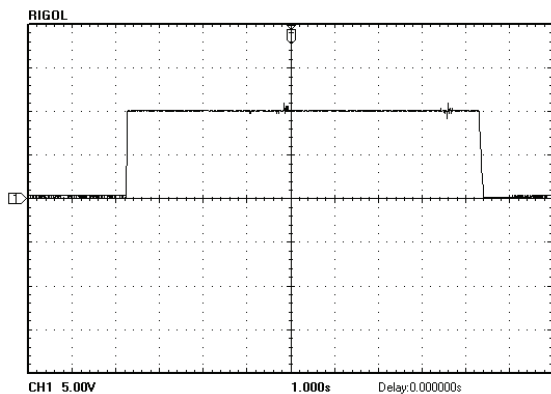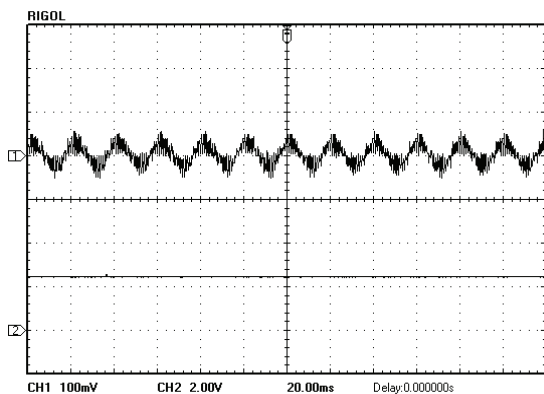
Fig.10. Speed response of proposed control strategy
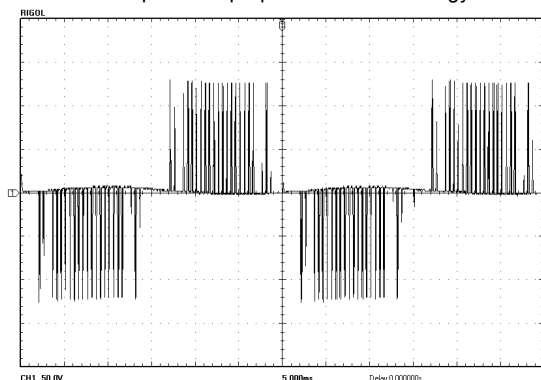


Fig. 11. current response of proposed control strategy



Fig. 12. voltage response of proposed control strategy

## 5 Conclusion

This paper proposed a hybrid adaptive inverse control strategy aim at the nonlinear control system. Improved RBF neural network and FIR filter compose the nonlinear filter for system modeling, inverse modeling and disturbance cancelling. CMPSO algorithm and IVSLMS algorithm was adapt to training he parameters of nonlinear filter offline and online. Simulation and experiment results show that the proposed composite adaptive inverse control strategy has good dynamic response and steady state accuracy. The position can tracking command fast and precise. The system will be widely used in robot, NC machine and other field which need high position precision.

REFERENCES

[1] Ting-na SHI, Xiang-chao WANG, Chang-liang Xia, et al. Adaptive Speed Control of PMSM Based on Wavelet Neural Network. Industrial Electronics, (2007), 2842-2847.
[2] Cetin Elmas, Oguz Ustun. A hybrid controller for speed control of a permanent magnet sychronous motor drive. Control Engineering Practce, 16(2008), 260-270.
[3] Jong-Sun Ko, Byung-Moon Han. Precision Position Control of PMSM using Neural Network Disturbance Observer and Parameter Compensator. IEEE International Conference, (2006), 316-320.
[4] Guo Qingding, Sun Yibiao, Wang Limei. Modern Permanent Magnet Synchronous Motor Servo System. Beijing: Chinese Electric Power Press, (2006).
[5] Bernard Widrow. Adaptive Inverise Control. IFAC Adaptive Inverise Control and Signal Proceing, Lund, Sweden, (1986).
[6] Liu XiaoQing, Yi Jianqiang, Zhao Dongfu, et al. a nonlinear adaptive inverse control system based on RBF network[J]. Control and Decision, 19(2004), 1175-1177.
[7] Han Hua. The research of adaptiveinverse control based on LMS algorithmf. Central South University Doctoral Dissertation, (2008).
[8] Selami Beyhan, Musa Alci. Stable modeling based control methods using a new RBF network. ISA Transactions, 49(2010), 510-518.
[9] Kennedy J, Eberhart R. Particle Swarm Optimization [C].IEEE Int Conference on Neural Networks, Perth, Australia, 1995:1942-1948.
[10] D C Huynh, M W Dunnigan. Parameter estimation of an induction machine using advanced particle swarm optimization algorithms[J]. IET Electric Power Applications, 2010, 4(9):748-760.
[11] J Moody, C J Darken. Fast learning in networks of locally tuned processing units. Neural Computation, (1989), 281-294.
[12] Yang Zhidong, Huang Qitao, Han Junwei,et al. Adaptive inverse control of random vibration based on the filtered-X LMS algorithm. Earthquake engineering and engineering vibration, 9(2010),141-146.

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