Nonlinear Internal Model Control Using Echo State Network for Pneumatic Muscle System

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***Abstract*—Pneumatic muscle (PM) has many advantages such as light weight, high power to weight ratio and low price. However, it has strong time varying characteristic. The complex nonlinear dynamics of PM system poses some challenges for achieving accurate modeling and control. To solve these problems, we propose nonlinear internal model control (IMC) using echo state network (ESN) for PM system in this paper. The ESN based IMC is termed ESNBIMC, which fully embodies the virtues of ESN and IMC. In ESNBIMC, the dynamic model of PM system is identified by an ESN. The other ESN is trained to learn the inverse dynamics of the system, and then it can be used as a nonlinear controller. Recursive Least Square (RLS) algorithm can be applied to online training the ESN without affecting the previous weight structure, which is very suitable for real-time control problems. By using the identification ability of ESN and RLS, high accurate plant model of PM system without detailed model information can be built. In addition, strong robustness also can be attained by online self-tuning of controller and internal model. Experiment demonstrates the effectiveness of the proposed control algorithm. The results show that ESNBIMC achieves satisfactory tracking performance for PM system.**

***Index Terms*—internal model control, echo state network, pneumatic muscle, nonlinear control**

I. INTRODUCTION

Pneumatic muscle (PM) is a kind of an interesting actuator. During the last decade, there has been a significant increase in the medical, industrial and scientific utilization of PM [1]. PM is similar to human skeletal muscle in size, weight, and high power/weight output. Moreover, it can generate inherently compliant force and thus has excellent safety potential. These attractive features make that PM is feasible for using in rehabilitation engineering, which requires great compliance and high safety for patients [2-4]. However, the PM application also faces some challenges. Comparing to electric motor, PM has slower response time, time varying parameters depending on the load position and speed.

The complex nonlinear dynamics of the PM poses problems in achieving accurate modeling and control. In previous studies, various PM modeling approaches have been presented. The relationship between pressure and force of the PM was analyzed by Schulte firstly [5]. Complex theoretical equations were created relating the geometric structure and the contractile force [6-7]. The generated equations were functions of the input pressure, initial length and diameter of the PM, braid thread angle, thread length, and the number of thread turns. A static model was described based on static length-tension experiment and a theoretical approach by Chou and Hannaford [7-8]. A model that includes a non-linear, Mooney-Rivlin mathematical description of the actuator's internal bladder was presented in [9]. Inspired by the biomechanical model of skeletal muscle, the biomimetic approach models the PM by revising the Hill muscle model to include energetic and viscoelastic parameters [10]. Both biological muscles and PMs generate force only by the means of contraction. As pressure builds in the PM, it expands radially causing a force contraction in the axial direction mimicking biological muscle. A three-element phenomenological model is proposed and measured by Reynolds et al. [11]. Based on previous study, Serres et al. focused on the parameter characterisation of the three-element phenomenological model for commercially available pneumatic muscle actuators. The parameter profiles are defined in a linear manner for a specified operating range [12]. Doumit et al. presented a fully analytical braided pneumatic muscle static model that does not depend on experimentally determined parameters. Their approach is based on Newtonian mechanics that considers the mechanical and the geometrical properties of the muscle [13]. In addition there are some models which built based on fuzzy or time-series methods, but the expressions of the model have no clear physical meaning. However, there are some mathematic models of PM are built, but these models have a large numbers of parameters, which make the models are too complicated to be used. It is still difficult to attain an accurate and simple mathematic model of PM. It has restricted its widespread use in the past.

Internal model control (IMC) is proposed in [14]. Due to its simple structure, easy tuning property, strong robustness, and the ability of eliminating unpredictable disturbance, IMC could be used in linear systems successfully. However, it is difficult to obtain satisfactory control performance when IMC is directly introduced in

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nonlinear systems due to the inherent complexity of nonlinear systems. With the development of artificial neural networks (ANNs) for nonlinear modeling, the idea of using ANN for nonlinear IMC has been considered by Bhat and McAvoy [15]. ANNs have an inherent ability to approximate an arbitrary nonlinear function, and become an attractive way to model complex nonlinear system. ANNs have been increasingly used in many aspects of pattern classification, modeling and control in engineering applications [16-21]. Thus, ANNs can be used for building the plant model of complex system and controller in nonlinear IMC.

Recently, the Echo State Network (ESN) has been introduced as a novel approach by Herbert Jaeger for time series modeling and nonlinear system identification [22-23]. As a typical recurrent neural network (RNN), the notable character of ESN is that its internal layer is composed of a large number of neurons and these neurons are sparsely connected to each other. This layer is the so-called "Dynamic Reservoir" (DR), it can map inputs into high-dimensional space and reserve information of the past. This makes the ESN not only holds self-organization, self-learning, adaptive ability, but also has short-term memory. Moreover, in contrast to normal RNNs, whose training algorithms are computationally very costly, an ESN only adjusts the output weights, which lead from the internal nodes to the output nodes. Therefore the learning algorithms of ESN are computationally efficient and easy to use. Among these algorithms, the Recursive Least Square (RLS) algorithm can be applied to online training the ESN without affecting the previous weight structure, which is very suitable for real-time control problems. An ESN together with RLS training algorithm is called a RLSESN. Nevertheless, to the best of our knowledge there are few applications of utilizing an ESN-based method in the control filed.

The ability of ESN to represent nonlinear function leads to the idea of combining ESN with IMC in nonlinear system control. Thus, we propose a nonlinear IMC using ESN for PM system. In this paper, the ESN based IMC is termed ESNBIMC, which fully embodies the virtues of ESN and IMC. Here, an ESN is employed to learn the process dynamics of PM system for identifying the plant model, The other ESN is trained to learn the inverse dynamics so that it can be used to construct nonlinear controller. The proposed ESNBIMC control algorithm can build high accurate plant model and nonlinear controller without detail model information, as well as attain strong robustness by online self-tuning of internal model.

This paper is organized as follows. Section II describes the PM control system. Section III presents the structure of ESN and its echo state property. In Section IV, we take advantage of both ESN and IMC to propose ESNBIMC for the control of PM system. In Section V, the experiment of the trajectory tracking control of PM system is undertaken by employing ESNBIMC. The results show that the ESNBIMC is effective. By using ESNBIMC, satisfactory tracking performance is achieved for the control of PM system. Finally, the discussion and conclusion are given.

II. PM CONTROL SYSTEM

A PM is made from inexpensive materials, such as a natural latex tube, a braided sleeving and so on. The maximum contraction ratio of PM which made in lab is about 25%. The operational principle of a PM can be shown in Fig. 1. As the rubber bladder expands due to an increase in pressure, the diameter of the combined sheath and bladder assembly easily changes in the radial direction and the muscle shortens in the axial direction. Thus, the force exerted on the environment occurs in the axial direction.

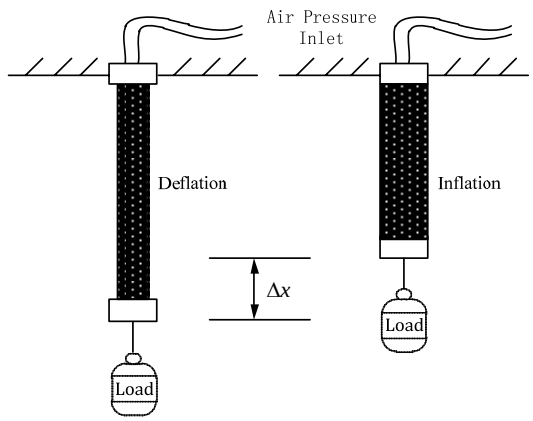

Figure 1. The operational principle of a PM.

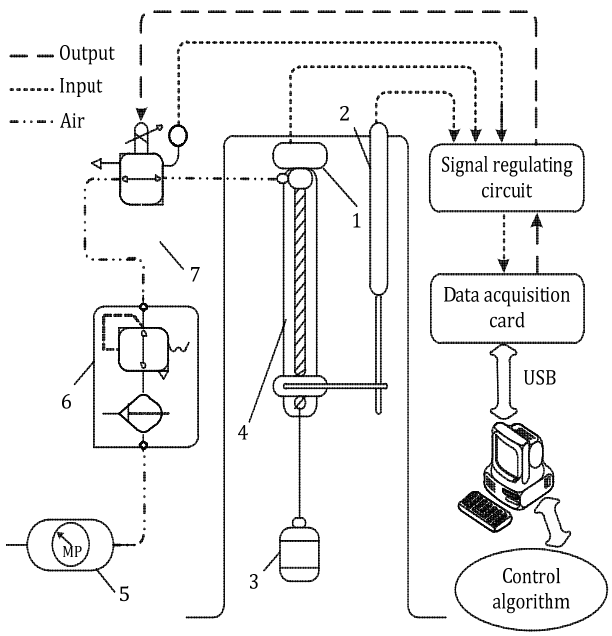

Figure 2. The experimental schematic diagram of PM platform (1-force sensor, 2-displacement transducer, 3-load/weights, 4-pneumatic muscle, 5-mute air compressor, 6-pessure regulating valve, 7-electromagnetic proportion valve).

The experimental schematic diagram of PM platform is shown as Fig. 2. The change of PM length is measured by a displacement transducer which is attached to the

moving lower end of the PM. In addition, there is also a pressure sensor integrated in the electric proportional valve to provide the pressure feedback. Data are collected by a multichannel real-time data acquisition card (Advantech USB-4716). The prototype of the experimental platform is shown as Fig. 3.

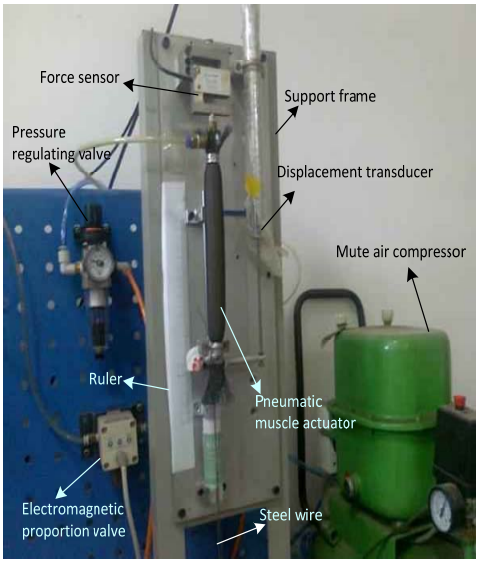

Figure 3. The prototype of PM platform.

III. Echo State Network

PM modeling is still difficult to attain an accurate and simple mathematic model of PM due to its complex nonlinear dynamics. Fortunately, It has been witnessed that neural networks have been increasingly adopted in the nonlinear control systems, due to their model-free approximation and predictive capability. Compared with the static neural network, ESN is a recurrent neural network and more suitable for the dynamic representations to efficiently capture the dynamic behavior of a complex nonlinear system. Thus, we employ ESN for the PM control in this paper.

A. Topological Structure of ESN

As both work using the mechanism of reservoir computing, the ESN proposed by Herbert Jaeger [22], shares some similarities with the Liquid State Machine (LSM) [24].

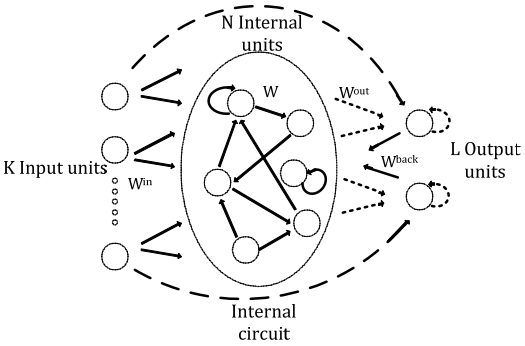

Figure 4. The structure of ESN (the dash arrows represent the weight matrix that need to be trained while the solid ones represent those that are fixed).

The ESN is a novel RNN model which has superior ability for modeling complex dynamic systems. The structure of ESN is illustrated in Fig. 4. An ESN is a recurrent discrete-time neural network with K input units, N internal (reservoir) units and L output units. It is notable that the internal neurons are sparsely connected to each other. The activations of input, internal and output units at time step k are denoted by $u(k)=(u_1(k),...,u_K(k))^T$, $x(k)=(x_1(k),...,x_N(k))^T$ and $y(k)=(y_1(k),...,y_L(k))^T$, respectively. The real-valued input, internal, and output weights are collected in a $N\times K$ matrix $W^{in}=(w_{ij}^{in})$, a $N\times N$ matrix $W=(w_{ij})$, a $L\times(K+N+L)$ matrix $W^{out}=(w_{ij}^{out})$, respectively. The output units may optionally project back to internal units with connections whose weights are collected in a $N\times L$ matrix $W^{back}=(w_{ij}^{back})$.

The next activation state $x(k+1)$ of internal units is updated according to

$$x(k+1)=f(W^{in}u(k+1)+Wx(k)+W^{back}y(k)). \quad (1)$$

where $f=(f_1,...,f_N)$ are the internal units' activation functions (usually sigmoid fuctions).

The next output $y(k+1)$ of ESN is computed according to

$$y(k+1)=f^{out}(W^{out}(u(k+1),x(k+1),y(k))). \quad (2)$$

where $f^{out}=(f_1^{out},...,f_L^{out})$ are the output units' activation functions. $(u(k+1),x(k+1),y(k))$ denotes the concatenation vector made from input, internal, and output activation vectors. In our study, we choose sigmoid neurons to form the hidden layer, and linear units to form the output layer, and assume the ESN without feedback connections from the output to the reservoir as used in [25] and [26]. This common-used ESN structure not only keeps the nonlinear approximation capability and the echo state property, but also to some extent decreases computational complexity for real-time control.

B. Echo State Property

The most important property of ESN is the echo state property which was illustrated in [22-23]. Under certain conditions, the network state vector $x(k)$ is uniquely determined by the left-infinite input histories $...,u(k-1),u(k)\in U^{-N}$. More precisely, we say that the network has echo state property, if there exists input echo function $E=(e_1,...,e_N)$, where $e_i:U^{-N}\to R$, so that, for all left-infinite input histories $...,u(k-1),u(k)\in U^{-N}$, the current network state is $x(k)=E(...,u(k-1),u(k))$. Then the question is: under what condition can this property be satisfied? This problem is theoretical and somehow complicated. For a practical use, we simply apply the conclusion obtained in [22]. That is, it is sufficient to ensure this property by

scaling the spectral radius of internal weight matrix to $|\lambda_{\max}|<1$ for an ESN with normal sigmoid units in the internal layer.

IV. ESNBIMC FOR THE CONTROL OF PM SYSTEM

Inspired by the approximation theorem of ESN, a nonlinear internal model control (IMC) using echo state network (ESN) is proposed for PM system. The ESN based IMC is termed ESNBIMC. In the ESNBIMC, we employ the framework of internal model control, while the identification model of plant and internal model controller are structured by ESN.

A. Internal Model Control

IMC is a mathematical model of plant/process based control strategy for the design of controller. The classical structure of IMC is demonstrated in Fig. 5. In the diagram, R is the reference input of the control system, Y is the system output, U is the controller output, d is the unknown disturbance, G_c is the controller, G_p is the plant and $\tilde{G}_p$ is plant model, which is used as the internal model.

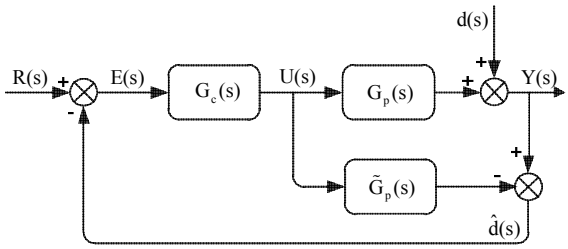

Figure 5. The structure of internal model control.

According to the IMC architecture, the output of the closed loop IMC system is:

$$Y(s)=\frac{G_c(s)G_p(s)R(s)+[1-G_c(s)\tilde{G}_p(s)]d(s)}{1+[G_p(s)-\tilde{G}_p(s)]G_c(s)}. \quad (3)$$

From (3), we can see that if there exists the perfect match between the plant model and plant, that is $\tilde{G}_p(s)=G_p(s)$, perfect tracking of R and Y is attained, as well as disturbance rejection is achieved by selecting $G_c(s)=\tilde{G}_p(s)^{-1}$. Note that, theoretically, even if $G_p(s)\neq\tilde{G}_p(s)$, perfect disturbance rejection can still be realized when $G_c(s)=\tilde{G}_p(s)^{-1}$.

B. ESN Based IMC

The proposed ESNBIMC is shown in Fig. 6, the plant model and controller are constructed by ESN in this paper. Here, the plant model can be termed as the neural network identifier (NNI) of plant, which can be approximated according to the input and output data of plant by ESN. As the Fig. 6 shown, Y is the plant output, Y_m is the NNI estimation output of the plant. Through the error between the real output Y and the computed output Y_m, the weight of NNI is updated online. It makes the NNI can accurately represent the dynamic characteristic of the plant.

The internal model controller is the inverse of the plant, which can be termed as the neural network controller (NNC). It also can be approximated according to the input and output data of plant by ESN. Unlike the NNI, the output data of plant is considered as the NNC input, the input data of plant is considered as the NNC output for NNC training. Through the error between the desired output R and the real output Y, the weight of NNC is also adjusted online.

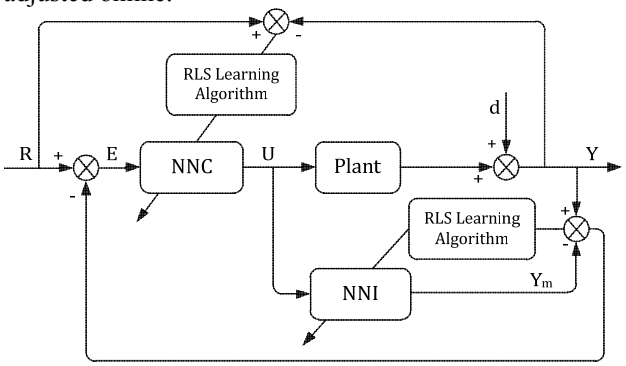

Figure 6. The structure of echo state network based internal model control.

After the training of the NNI and NNC, the control strategy of ESNBIMC can be implemented. Due to the online adjustment of NNI and NNC, the two ESNs can optimize the weighs to achieve higher accuracy. Besides, if there are some uncertainties or disturbances making the system change, the online adjustment also can make the control system has strong disturbance rejection.

C. Online Training Algorithm

The training of an ESN is simple. The values of the input weight matrix W^{in}, the internal weight matrix W and the output back projection weight matrix W^{back} are randomly chosen and fixed without adaptation, whereas only the output weight matrix W^{out} will be trained and updated. Thus, the computational complexity for the ESN training would be lower than most other neural network.

The recursive least square (RLS) algorithm has been extensively used in adaptive identification, prediction, filtering, and many other fields. It can be applied to the online training of the ESN without affecting the previous weight structure, which is very suitable for real-time control problems. In our study, ESN is conjoined with the RLS for online self-adaption after the initial steps.

If $W^{out}(k)$ is the output weight of ESN at the k-th step, while the desired output of ESN is $y(k)$. $e(i\,|\,k)=y(i)-W^{out}(k)x(i\,|\,k)$ represents the i-step-ahead prediction error of based on the k-th step. The goal of RLS algorithm is to minimize the following objective function at the k-th step.

$$J=\sum_{i=1}^{k}\gamma^{k-i}e^2(i\,|\,k). \quad (4)$$

where γ is forgetting parameter, it is usually set to the value smaller or equal to 1.0.

According to the principle of least mean square error, RLS algorithm can be expressed as follows.

$$\lambda(k) = \frac{P(k-1)v(k)}{v^T(k)P(k-1)v(k)+\gamma} \tag{5}$$

$$P(k) = \gamma^{-1}(P(k-1) - \lambda(k)v^T(k)P(k-1)) \tag{6}$$

$$e(k) = y(k) - \hat{y}(k) = y(k) - v^T(k)W^{out}(k-1) \tag{7}$$

$$W^{out}(k) = W^{out}(k-1) + \lambda(k)e(k)\,. \tag{8}$$

where λ stands for the innovation vector calculated in every time step, W^{out} is the vector of output weight, v is the vector of state activities of ESN, y is the vector of target values, and $\hat{y}$ is the output vector which is calculated by the input vector and the ESN. P is the error covariance matrix initialized with large diagonal elements and updated in every time step. It is initialized as:

$$P(0) = \delta^{-1}I \quad (\delta > 0)\,. \tag{9}$$

where δ is a small positive number. I is used to denote a unit matrix.

In addition, the reset of the covariance matrix is introduced to avoid instability problem caused by long-term non-static signal [27]. If the track of the matrix $P(k)$ is lower than a small positive constant, then $P(k)$ is reset.

The detail algorithm used in ESNBIMC can be described as follows.

Step 1: Initialize the weights of ESNs and the error covariance matrix P ;

Step 2: Attain the vector v of state activities of ESN, and then calculate the innovation vector λ ;

Step 3: calculate the error between the output of the plant and the output of ESN for NNI, while calculate the error between the reference input and the output of plant for NNC;

Step 4: Update the output weights of the NNI or the NNC by using RLS;

Step 5: Update the error covariance matrix P ;

Step 6: The controller produces the new control value to drive the plant;

Step 7: Collect the new sample values for the next control;

Step 8: If the control process is not completed, then go to Step 2, otherwise go to Step 9;

Step 9: Quit the control process successfully.

V. Experiment

The experiment is to demonstrate that the validity of the proposed ESNBIMC. First, the experiment is set up according to Fig. 2. In our experiment, the initial length of PM is 200mm. The initial diameter is 12.26mm, the initial angle of mesh grid is 22º, and the thickness of rubber sleeve is 1.64mm. The main experimental apparatus includes mute air compressor, pressure regulating valve, electromagnetic proportional valve, displacement transducer, data acquisition card and so on. The physical parameters of experimental equipment are summarized and listed in Table I. The software is developed by VC++ 6.0.

TABLE I.
The Main Performance Parameters of Experimental Equipment.

Name	Model	Performance
Mute air compressor	FB-0.017/7	Rating exhaust pressure: 0.7Mpa
Pressure regulating valve	AW20-02BCG	Range: 0.05-0.85Mpa
Electromagnetic proportion valve	ITV1030-211BS	Input: 0-5V Output: 0.005-0.5Mpa
Displacement transducer	DA-75	Range: 0-150mm Linearity: <0.1% (=0.09%) Output: 0-5V
Data acquisition card	USB-4716	8 DI, 8 DO, 16 AI, 2 AO Sampling rate: 200 kS/s
Others	Joints connector, air pipe, etc	

First, in order to survey the approximation effect of PM system by using ESN, we select the input voltage of electromagnetic proportion valve is shown in (10). The unit of input voltage is volt (V). The duration of the incentive process is 48s. Here, the relationship between input pressure and output position of PM system can be simplified as a black-box model. Based on the collected data, the black-box model of PM system can be built by an ESN. The numbers of input units, internal units and output units of the ESN are 1, 20 and 1, respectively. The predictive result of PM position by ESN is shown in Fig. 7. The corresponding predictive error of PM position is shown in Fig. 8.

$$\begin{cases} V(t) = 1.2+0.3(\sin(2\pi f_1 t)+\sin(2\pi f_2 t)+\sin(2\pi f_3 t)),\ 0 \le t < 20\text{s} \\ V(t) = 1.2+0.4\sin(2\pi f_1 t)\cos(2\pi f_2 t)\sin(2\pi f_3 t),\ t \ge 20\text{s} \end{cases} \tag{10}$$

with $f_1 = 0.2\text{Hz}, f_2 = 0.05\text{Hz}, f_3 = 0.1\text{Hz}$.

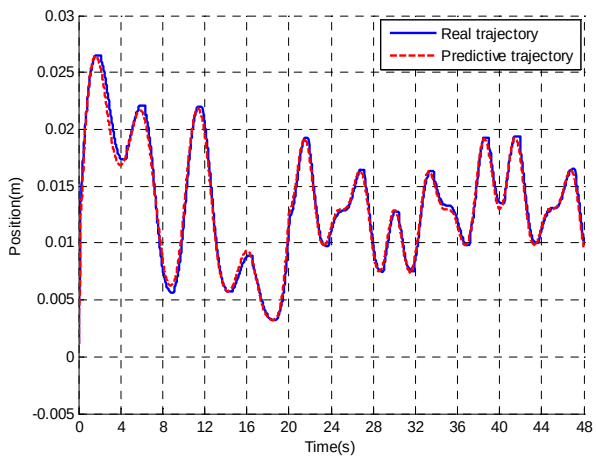

Figure 7. The predictive result of PM position by ESN.

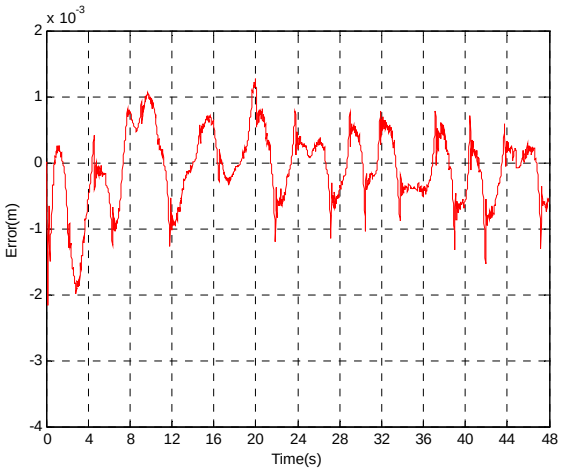

Figure 8. The predictive error of PM position by ESN.

According to the predictive result, the relative approximation error between the predictive trajectory and the real trajectory of PM position is ±1-2mm. The approximation effect is satisfied. The predictive error of the beginning is relatively big without suitable initial output weights of ESN. Due to the earlier collection of training data and online learning of ESN output weights, the approximation error is relatively small.

In order to compare the control effectiveness and attain the training data for identifying NNI and constructing NNC in ESNBIMC, both the performance of the PID and the ESNBIMC controllers are evaluated using sine and square waves as the desired trajectory for PM control. The parameters of PID controller are: k_p =0.012, k_i =0.0002 and k_d =0.0002. The collected data by using PID controller is used for the training of NNI and NNC in ESNBIMC. The numbers of input units, internal units and output units of NNI are 1, 20, and 1, respectively. The NNC has the same network structure with NNI.

In sine trajectory tracking, the reference signal serves as a desired trajectory which is given by

$$x_d(t) = 0.012\sin\left(2\pi f_1 t - \pi/2\right) + 0.012 \ . \qquad (11)$$

with $f_1 = 0.125\text{Hz}$.

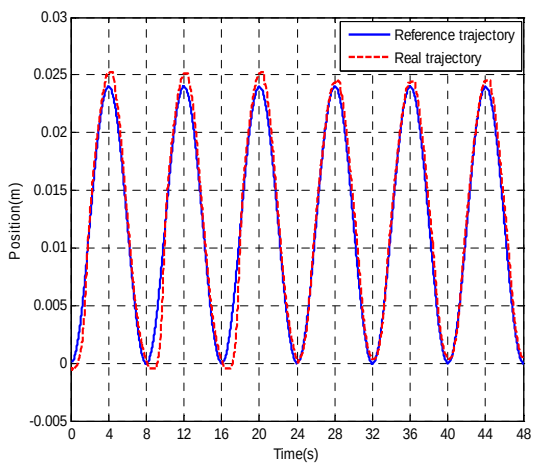

Figure 9. The sine tracking result of PM system by employing PID and ESNBIMC.

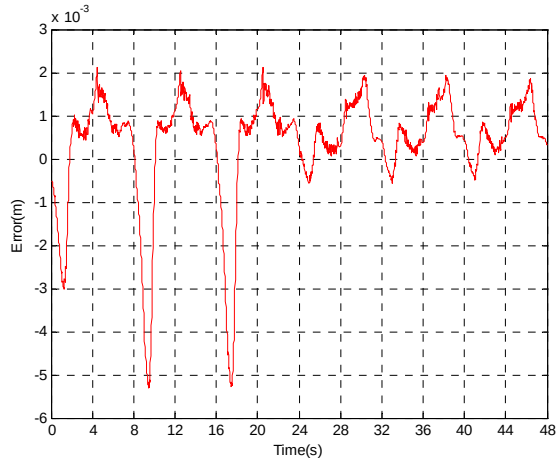

Figure 10. The sine tracking error of PM system by employing PID and ESNBIMC.

At the beginning of the ESNBIMC control strategy, we use the PID control and make the ESN update the internal state without the update of the output weight from 0s to 24s (the primitively three periods of tracking trajectory). Then the controller is switched to the ESNBIMC control with self-adaption. In the practical experiment, after several sampling control periods, the output of ESNBIMC can present a good performance. However, we still select the end of the third period of tracking trajectory as the switch time for the following reasons.

1): To conveniently compare the performance of the PID control and the ESNBIMC control. In the primitively three periods of tracking trajectory, we investigate the performance of PID control, while we investigate the performance of ESNBIMC control in the rest time;

2): To provide enough time for updating the internal state of ESNs and to obtain enough input history for using short term memory capability of ESN.

The tracking result of sine wave for PM system by employing PID and ESNBIMC is shown in Fig. 9. The corresponding tracking error using the two control strategies is shown in Fig. 10. From the comparison of the sine tracking result, the performance of the ESNBIMC control algorithm outperforms the conventional PID, especially in the turning of curve.

Through sine trajectory tracking, it is shown that the control accuracy of the ESNBIMC is satisfactory. For the verification of response speed of the ESNBIMC, square trajectory tracking of PM system is carried out.

In square trajectory tracking, the reference signal serves as a desired trajectory which is given by

$$\begin{cases} x_d(t) = 0.0225, & 8N\text{s} \le t < 4(2N+1)\text{s} \\ x_d(t) = 0.0028, & 4(2N+1)\text{s} \le t < 8(N+1)\text{s} \end{cases} . \qquad (12)$$

with $N = 0, 1, 2, 3, 4, 5$.

The tracking result of square wave for PM system by employing PID and ESNBIMC is shown in Fig. 11. The corresponding tracking error using the two control strategies is shown in Fig. 12. From the comparison of the square tracking result, the ESNBIMC control algorithm is superior to the conventional PID in response speed.

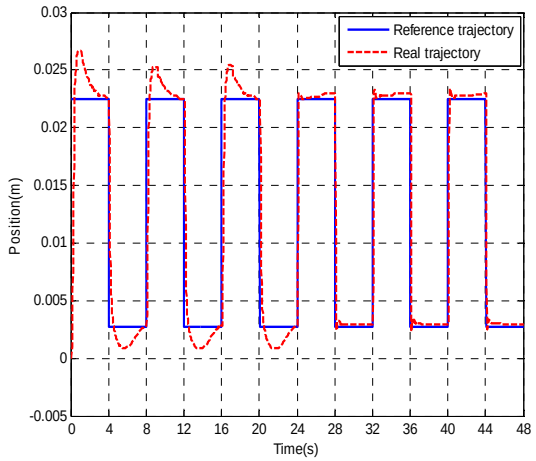

Figure 11. The square tracking result of PM system by employing PID and ESNBIMC.

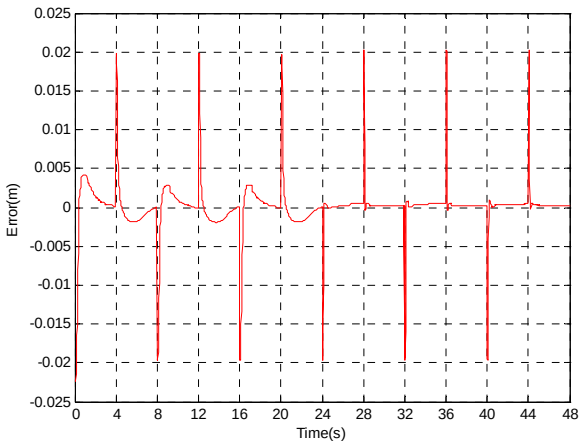

Figure 12. The square tracking result of PM system by employing PID and ESNBIMC.

From these results, it shows that the performance of the ESNBIMC is effective and satisfactory.

VI. Conclusions

In this paper, nonlinear internal model control using echo state network is proposed the control of PM system. The ESN based IMC is termed ESNBIMC. IMC has the advantages, such as simple structure, easy tuning property, strong robustness, the ability of eliminating unpredictable disturbance and so on. The traditional framework of IMC is designed by employing the plant model. However, PM system is complex nonlinear and time-varying system. It is difficult to establish the accurate mathematic model of plant. Fortunately, the ESN has the echo state property and the strong ability of nonlinear approximation. The proposed ESNBIMC algorithm is an optimized method which can fully embody the virtues of ESN and IMC. Based on the ability of ESN approximation, we don't need too much priori knowledge about the detailed model of the plant to identify the plant and construct the controller. Moreover, in ESNBIMC algorithm, the identified plant model and the constructed controller can be updated by the online learning of ESN for achieving accurate control.

By employing ESN, it can be found that ESN has good approximation effect for the prediction of PM system. The approximation error between the predictive trajectory and the real trajectory of PM is small. In sine trajectory tracking, it shows that the ESNBIMC control algorithm has good tracking accuracy, especially in the turning of tracking curve. Besides, in square trajectory tracking, the ESNBIMC control algorithm can respond rapidly. The experiment results demonstrate that the effectiveness of the ESNBIMC algorithm is satisfactory. Furthermore, it has better performance than the PID controller.

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