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Adaptive Neural Backstepping PID Global Sliding Mode Fuzzy Control of MEMS Gyroscope

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ABSTRACT An adaptive global sliding mode fuzzy control using radial basis function (RBF) neural network (NN) based on backstepping technique is presented for a micro electromechanical systems (MEMS) gyroscope. The proportion integral differential (PID) sliding surface has the capacity of restraining the steady-state error. Meanwhile, we take advantage of the global sliding mode manifold to overcome shortcomings of the conventional sliding mode controller, obtaining the fast response and overall robustness. Furthermore, faced with the unknown dynamic characteristic of the MEMS system, an RBF neural approximator is employed to estimate it. Besides, a fuzzy controller is put forward to suppress the chattering phenomenon caused by the sliding mode controller. The globally asymptotic stability of the closed loop system is guaranteed by the selected adaptive laws and Lyapunov theory. The simulation results demonstrate satisfactory effects of the proposed advanced controller. The comparison studies verify the better properties of the suggested control approach.

INDEX TERMS Micro electromechanical systems gyroscope, PID global sliding mode control, RBF neural network control, backstepping control, fuzzy control.

I. INTRODUCTION

A MEMS gyroscope has the merits of low price, small size, low energy consumption and so on, it is commonly used in many fields widely (e.g. automotive, aviation, consumer electronics, navigation…). However, owing to the capabilities are influenced by external disturbances, time varying parameters and manufacture errors, MEMS gyroscope also has several shortcomings. Thus, many progressive strategies have been proposed to solve these issues in MEMS gyroscope and improve the robustness and performance. For instance, a new active disturbance rejection scheme is designed for a gyroscope to regulate the output amplitude of the axis in [1]. Asad *et al.* [2] designed a new fuzzy sliding mode strategy with nonlinear part in fuzzy rules for control of MEMS gyroscope. Chu *et al.* [3] derived an adaptive proportional integral derivative global sliding mode controller using neural estimator for a MEMS gyroscope to obtain better robust performance. Sung and Lee [4] introduced a mode-matched controller through phase-domain analysis for a MEMS gyroscope. John and Vinay [5] designed a novel concept for a triaxial angular velocity sensor device. Chang *et al*. [6] presented a scheme to improve the accuracy of MEMS gyroscopes with combining numerous gyroscopes. Fei and Xin [7] developed a fuzzy adaptive sliding mode method which combined the advantages of adaptive fuzzy control and sliding mode control.

Global sliding mode control (GSMC) is a valid approach which can overcome the shortcoming of the conventional sliding mode control and ensure the global robustness all the response process fast. An adaptive backstepping global proportional, integral and differential sliding mode fuzzy control method based on radial basis function neural network estimation was realized by Chu and Fei [8]. Hu *et al.* [9] introduced a novel global sliding mode control with IPF compensation for matrix rectifiers using a hyperbolic tangent function. A control approach was presented by combining the neural network method with the global sliding mode

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control which was adaptively implemented by Men *et al.* [10]. Chu and Fei [11] learnt a global sliding mode control approach on the basis of RBF NN, which eliminated the arrival time of the sliding mode level and reduced chattering.

It is sensible to lead PID (Proportional Integral Derivative) sliding mode controller to the conventional one due to the large steady-state error which is caused by external disturbance and uncertainty, inhibiting the steady-state error and enhancing the robustness. For example, to obtain the stability of the robot motion, Jafarov *et al.* [12] proposed a novel PID variable structure control for tracking. A discrete Proportional Integral Derivative sliding mode scheme for a MIMO system based on output tracking was investigated by Singh *et al.* [13]. Aiming at the second order nonlinear inverted pendulum system, a PID sliding mode model along with robust control law was realized by utilizing the improved particle swarm intelligence optimization method by Cao and Chen [14]. Li *et al.* [15] adopted a neural adaptive backstepping hybrid controller based on a dynamic PID sliding mode manifold.

For the past few years, backstepping technique has drawn a lot of attention by its recursive and systematic designing step for feedback nonlinear system [16]. The backstepping technique has a most significant step to choose several recursively state variable function which are utilized as the virtual control input of the whole system's low-dimensional subsystem [17].

Wai *et al.* [18] proposed a backstepping sliding mode approach adaptively that combines the advantages of adaptive backstepping methodology and sliding mode method for the control of motor motion position driven by linear induction motor. Chiang *et al.* [19] resolved the uncertainty of the magnetic ball suspension system by introducing the backstepping sliding mode scheme. A neural backstepping global sliding mode strategy using fuzzy approximator for an active power filter was studied by Fei *et al.* [20].

Intelligent control methods include neural network control, fuzzy control and so on, which could approximate nonlinear function or reduce chattering. In addition, neural network can also estimate the uncertainty of parameters and the external interference, which greatly alleviates chattering phenomenon. Li and Cheah [21] focused on an original adaptive neural control formula which was aimed at solving the problem of fixed-point control, trajectory tracking control, etc.

Wai *et al.* [22] realized an adaptive sensorless speed controller on the basis of fuzzy neural network to acquire position tracking with high accuracy for n-link robot manipulator. Wu and Liu [23] derived a fuzzy control combined with sliding mode method with inherent robustness. A stable tracking method of fuzzy neural network was designed by Wu and Tam [24] for a class of nonlinear unknown systems. Chen *et al.* [25] studied the robust control scheme for nonlinear systems, which could be approximated or expressed in non-affine form. Regardless of external disturbances, to realize superior property of H ∞ tracking for servo drives, a direct adaptive fuzzy technology was presented by Rubaai [26]. Chang and Wang [27] developed a proportional integral fuzzy method for the sake of maintaining the signal power of all users received by the base station meanwhile which is almost equal so as to obtain better control performance. Chu *et al.* [28] designed a dynamic neural global PID sliding mode approach for an active power filter.

In this paper, a strategy of neural backstepping PID global sliding mode fuzzy technology for a MEMS gyroscope was studied which contains a backstepping PID global sliding surface, a fuzzy estimator and a neural network approximator. The proposed method possesses the following merits:

(1) The robustness and instantaneous characteristics of the designed controlled system could be ameliorated by selecting suitable sliding mode coefficient. Adaptive laws of the fuzzy estimator and the neural network approximator ensure stability of the whole closed loop system by Lyapunov theorem.

(2) Backstepping technology is a good way to realize the schematized and structurized designing process of Lyapunov function via reverse designing. The property of global sliding maniflod is better than the conventional ones because of its fast response and global robustness. In view of the problem of large steady-state error of traditional sliding mode scheme under external disturbances, it is advisable to introduce PID sliding mode approach to suppress this phenomenon, enhancing global robustness.

(3) Regardless of the influence of various unknown factors, the controller of RBFNN is usually used to approximate the unknown dynamic features in the absence of accurate model with strong robustness and good approximation effects. Further, the adding of fuzzy system effectively eliminates the chattering phenomenon where the PID global sliding controller force is converted to continuous output.

The components of this paper is as follows. In section 2, mathematical model of gyroscope is described. In section 3, the backstepping PID global sliding mode controller, the neural backstepping PID global sliding mode controller, the neural backstepping PID global sliding mode fuzzy control are discussed respectively and the globally asymptotic stabilities of the focused controlling system are demonstrated by Lyapunov stability theory. Section 4 shows the simulation results of the developed controllers. Conclusions are given in the last section.

II. MATHEMATICAL MODEL OF MEMS GYROSCOPE

The dynamic model of a MEMS gyroscope is constructed in the following section. The schematic model of the gyroscope is shown in Fig.1. The model could be simplified as a damped oscillation system which composed of mass and spring. The motion is divided into two directions by ignoring the linear acceleration of the gyro frame. Thus the vibratory equation could be received as:

$$\begin{aligned} m\ddot{x} + d_{xx}\dot{x} + d_{xy}\dot{y} + k_{xx}x + k_{xy}y &= u_x + d_x + 2m\Omega_z\dot{y} \\ m\ddot{y} + d_{xy}\dot{x} + d_{yy}\dot{y} + k_{xy}x + k_{yy}y &= u_y + d_y - 2m\Omega_z\dot{x} \end{aligned} \quad (1)$$

where m is the mass; d_{xx}, d_{yy} and k_{xx}, k_{yy} are the damping and spring constants respectively; k_{xy}, d_{xy} are damping coefficients and coupling elastic; u_x, u_y are the control inputs of two axes; d_x, d_y are mechanical noise and environmental interference. Ω_z is the z direction angular velocity.

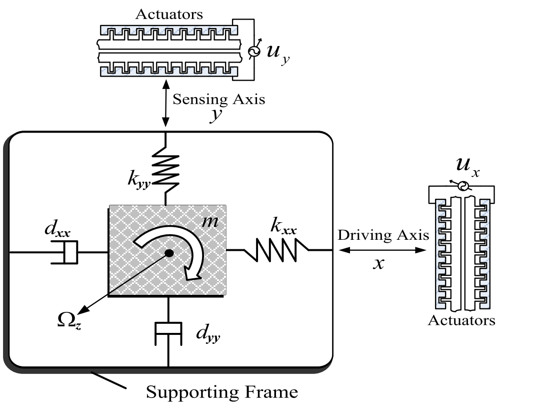

FIGURE 1. The block diagram of a z-axis gyroscope.

We replace q^* by $q^* = \frac{q}{q_0}$ and t^* by $t^* = \omega_0 t$. Eq. (1) can be divided by ω_0 (the square of the resonant frequency), m and q_0 (the reference length) on both sides. As a result, the dimensionless kinetic equation of the gyroscope is:

$$\ddot{q}^* + D^*\dot{q}^* + K^*q^* = u^* - 2\Omega^*\dot{q}^* \tag{2}$$

where

$$q = \begin{bmatrix} x \\ y \end{bmatrix}, \quad D^* = \frac{D}{m\omega_0}, \quad D = \begin{bmatrix} d_{xx} & d_{xy} \\ d_{xy} & d_{yy} \end{bmatrix},$$
$$K^* = \begin{bmatrix} \omega_x^2 & \omega_{xy} \\ \omega_{xy} & \omega_y^2 \end{bmatrix}, \quad u^* = \frac{u}{m\omega_0^2 q_0}, \quad \omega_x = \sqrt{\frac{k_{xx}}{m\omega_0^2}},$$
$$\omega_y = \sqrt{\frac{k_{yy}}{m\omega_0^2}}, \quad \omega_{xy} = \frac{k_{xy}}{m\omega_0^2}, \quad u = \begin{bmatrix} u_x \\ u_y \end{bmatrix},$$
$$\Omega^* = \frac{\Omega}{\omega_0}, \quad \Omega = \begin{bmatrix} 0 & -\Omega_z \\ \Omega_z & 0 \end{bmatrix}$$

Then substitute t^* with t, q^* with q, K^* with K, D^* with D, Ω^* with Ω, u^* with u, and the eventual dimensionless model could be depicted:

$$\ddot{q} + D\dot{q} + Kq = u - 2\Omega\dot{q} \tag{3}$$

Take the external disturbance into consideration, the above equation will be changed into:

$$\ddot{q} + M\dot{q} + Kq = u + d \tag{4}$$

where d is the external disturbance, $M = D + 2\Omega$, and E(which is a constant) is the upper bound of d ($\|d\| \leq E$).

III. PID GLOBAL SLIDING MODE FUZZY CONTROL USING NEURAL NETWORK

Backstepping is a useful technique of designing stable controllers for several special nonlinear dynamical systems in control theory. A known stable system could be selected to start the designing process, which can gradually stabilize each external subsystem due to this recursive structure.

Compare with conventional sliding mode control, global sliding surface could achieve whole robustness and faster response. Owing to the steady-state error caused by external disturbances, PID sliding controller is introduced to restraining steady state error and enhancing system global robustness.

Moreover, owing to the unknown dynamic characteristic, a neural network is good at approaching it. On the other hand, faced with chattering caused by variable structure control, a fuzzy estimator is utilized to eliminate the chattering and to obtain strong ability of adaptive tracking. As a consequence an adaptive neural backstepping PID global sliding mode fuzzy control (NBPIDGSMFC) is designed and investigated.

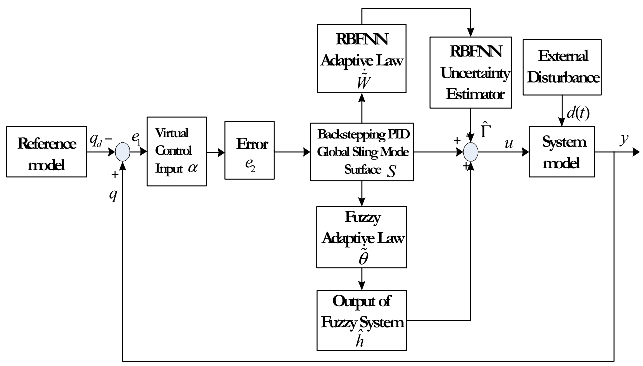

FIGURE 2. Block diagram of NBPIDGSMFC for a MEMS gyroscope.

The block diagram of the developed control is shown in Fig.2, the tracking error of gyroscope enters into the neural backstepping PID global sliding mode fuzzy controller. The NBPIDGSMFC could not only guarantee the stability of the closed loop system, but also make the whole system has strong robustness.

A. BACKSTEPPING PID GLOBAL SLIDING MODE CONTROLLER DESIGN (BPIDGSMC)

A backstepping method will be used to design a controller for two-axis vibratory gyroscope in the following part. The control target is to track an ideal trajectory q_d quickly and make all the signals which in closed-loop system be uniformly bounded.

Firstly, define the state variables as follows:

$$X_1 = q, \quad X_2 = \dot{q} \tag{5}$$

Then introduce a new variable named X.

$$X = \begin{bmatrix} X_1^T & X_2^T \end{bmatrix}^T \tag{6}$$

The system model Eq. (4) could be written in the following form

$$\begin{cases} \dot{X}_1 = X_2 \\ \dot{X}_2 = -MX_2 - KX_1 + u + d = \Gamma(X) + u + d \end{cases} \tag{7}$$

where $\Gamma(z)$ represents the unknown dynamic characteristic of the gyroscope.

$$\Gamma(X) = -MX_2 - KX_1 \tag{8}$$

The process of designing backstepping PID global sliding mode controller consists of two steps for this system. Construct a virtual control force via a Lyapunov function V_1 at first step. Then an actual control law is made up at the second step. In the following, we will give these two steps of the design procedure.

Step 1: Design a virtual control force for the aim of position tracking.

Define the position tracking error as:

$$e_1 = X_1 - q_d \tag{9}$$

Then

$$\dot{e}_1 = \dot{X}_1 - \dot{q}_d = X_2 - \dot{q}_d \tag{10}$$

Consider X_2 as the control input, then design a virtual control law α_1 so that $\lim_{t\to\infty} q = q_d$ (namely $\lim_{t\to\infty} e_1(t) = 0$). We select the virtual control force α_1 for X_2 gives

$$\alpha_1 = -c_1 e_1 + \dot{q}_d \tag{11}$$

where c_1 is a positive constant.

Define an error e_2 as

$$e_2 = X_2 - \alpha_1 \tag{12}$$

The first Lyapunov candidate function is selected in the following formula

$$V_1 = \frac{1}{2} e_1^T e_1 \tag{13}$$

and its derivative is

$$\begin{aligned}\dot{V}_1 &= e_1^T \dot{e}_1 = e_1^T (X_2 - \dot{q}_d)\\ &= e_1^T (e_2 + \alpha_1 - \dot{q}_d)\\ &= e_1^T (e_2 - c_1 e_1)\\ &= -c_1 e_1^T e_1 + e_1^T e_2\end{aligned} \tag{14}$$

If $e_2 = 0$, $S \neq 0$, we have

$$\dot{V}_1 = -c_1 e_1^T e_1 < 0 \tag{15}$$

Step 2: Differentiate Eq. (12) with respect to time, making use of Eq. (7), then

$$\begin{aligned}\dot{e}_2 &= \dot{X}_2 - \dot{\alpha}_1 = -MX_2 - KX_1 + u + d - \dot{\alpha}_1\\ &= \Gamma(X) + u + d - \dot{\alpha}_1\end{aligned} \tag{16}$$

In Eq. (16), the real control force u emerges at our disposal. For the target of satisfactory tracking performance for a MEMS gyroscope, we define the PID global sliding surface as:

$$S = e_2 + \dot{e}_1 + \lambda_1 e_1 + \lambda_2 \int_0^t e_1(\tau) d\tau - f(t) \tag{17}$$

where λ_1, λ_2 are positive constants, $f(t)$ is a function which is particularly introduced for arriving at the global sliding manifold, satisfying the following three conditions:

(1) $f(0) = \dot{e}_0 + ce_0$, (2) If $t \to \infty, f(t) \to 0$, (3) $f(t)$ has a first derivative.

where e_0 is a premier value of tracking error.

As a result, $f(t)$ could be designed as: $f(t) = f(0)\mathrm{e}^{-kt}$, where k is a constant.

The time derivative of S is as follows:

$$\begin{aligned}\dot{S} &= \dot{e}_2 + \ddot{e}_1 + \lambda_1 \dot{e}_1 + \lambda_2 e_1 - \dot{f}(t)\\ &= \Gamma(X) + u + d - \dot{\alpha}_1 + \ddot{e}_1 + \lambda_1 \dot{e}_1 + \lambda_2 e_1 - \dot{f}(t)\end{aligned} \tag{18}$$

After determining the PID global sliding surface, it is helpful to design a backstepping PID global sliding mode controller to ensure the presence of the global sliding mode stage.

Define the second Lyapunov function like

$$V_2 = V_1 + \frac{1}{2} S^T S \tag{19}$$

Meanwhile the derivative of V_2 is

$$\begin{aligned}\dot{V}_2 &= \dot{V}_1 + S^T \dot{S}\\ &= -c_1 e_1^T e_1 + e_1^T e_2 + S^T [\dot{e}_2 + \ddot{e}_1 + \lambda_1 \dot{e}_1 + \lambda_2 e_1 - \dot{f}(t)]\\ &= -c_1 e_1^T e_1 + e_1^T e_2 + S^T [\Gamma(X) + u\\ &\quad + d - \dot{\alpha}_1 + \ddot{e}_1 + \lambda_1 \dot{e}_1 + \lambda_2 e_1 - \dot{f}(t)]\end{aligned} \tag{20}$$

Based on Eq. (20), the control law of backstepping PID global sliding mode controller is designed as

$$\begin{aligned}u &= \dot{\alpha}_1 - \Gamma(X) - \ddot{e}_1 - \lambda_1 \dot{e}_1 - \lambda_2 e_1\\ &\quad + \dot{f}(t) - \frac{S}{\|S\|^2} e_1^T e_2 - \rho \frac{S}{\|S\|}\end{aligned} \tag{21}$$

where $\rho \geq E + \xi$, ξ is a positive arbitrary small constant.

When $S \neq 0$, substituting Eq. (21) into Eq. (20) gives

$$\begin{aligned}\dot{V}_2 &= -c_1 e_1^T e_1 + e_1^T e_2 + S^T (d - \frac{S}{\|S\|^2} e_1^T e_2 - \rho \frac{S}{\|S\|})\\ &= -c_1 e_1^T e_1 + e_1^T e_2 + S^T d - e_1^T e_2 - \|S\| \rho\\ &= -c_1 e_1^T e_1 + S^T d - \|S\| \rho\\ &\leq -c_1 e_1^T e_1 - \|S\| \rho + \|S\| E\\ &= -c_1 e_1^T e_1 - \|S\| (\rho - E)\\ &\leq -c_1 e_1^T e_1 - \xi \|S\|\\ &< 0\end{aligned} \tag{22}$$

In summary, we have the following result. Referring to the Lyapunov stability criterion, the developed global sliding mode manifold $S(t)$ in Eq. (17) converges to zero fast which verifies that the designed backstepping PID global sliding mode controller can ensure the global asymptotic stability of the gyroscope system. The error $e_1 = q - q_d$ also converges to zero quickly owing to S in Eq. (17). If the control law u (21) which is updated all the time, with the sliding surface S (17) is well applied to the uncertain nonlinear system which is defined in (4), the constructed PID global sliding mode manifold (19) converges to zero in short time, together with the tracking error of the system tending to zero.

B. BACKSTEPPING PID GLOBAL SLIDING MODE CONTROLLER BASED ON NEURAL NETWORK (NBPIDGSMC)

Through the above analysis, a conclusion can be drawn that the PID global sliding mode control scheme can ensure the state to converge to the origin quickly with global robustness, higher convergence speed and better trajectory tracking property. Nevertheless, the control law in Eq. (21) could not be carried out on account of the dynamic unknown characteristic ($\Gamma(X)$) of the gyroscope. An improved solution is applied to take advantage of the estimated value of neural network output to replace $\Gamma(X)$. So a neural approximator is presented to estimate $\Gamma(X)$.

Fig.3 shows the schematic diagram of the neural network. The desired output of the used neural network is

$$\Phi(z) = W^T \phi(z) \tag{23}$$

where $z = \begin{bmatrix} e & \dot{e} \end{bmatrix}$ and $\Phi(z)$ are the input and output of the neural network, respectively. $W = [W_1, W_2 \ldots W_L]^T$ is weight vector and $\phi(z) = [\phi_1(z), \phi_2(z) \ldots \phi_L(z)]^T$ is Gaussian function as

$$\phi_i(z) = \exp(-\left\| z - c_i \right\|^2 / \sigma_i^2), \quad i = 1, 2, \ldots, L \tag{24}$$

where L is number of the output node, c_i is the *ith* center vector, and σ_i is the *ith* standard deviation.

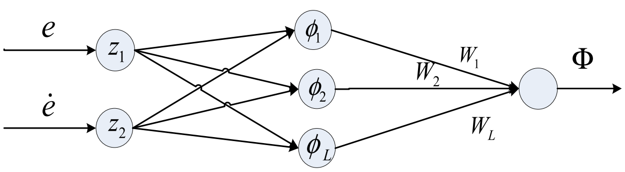

FIGURE 3. The structure of the RBF neural network.

The objective of the above neural network control is approaching to the nonlinear unknown function $\Gamma(X) = -MX_2 - KX_1$, which is dynamic characteristic of the gyroscope system. $\Gamma(X)$. The unknown function $\Gamma(X)$ can be represented as:

$$\Gamma(X) = W^T \phi(z) + \varepsilon \tag{25}$$

where W is the perfect weight vector and ε is the mapping error which can reach the minimum value when the network weights is optimal. Furthermore, ε is uniformly bounded as: $|\varepsilon| \le \varepsilon_b$, where ε_b is an arbitrary small positive constant.

The actual output of the neural network which is utilized for the estimation is:

$$\hat{\Phi}(z) = \hat{W}^T \phi(z) \tag{26}$$

where $\hat{W}$ is the real weight vector updated online all through.

Based on the above design step, for the global stability, the new control law can be designed as

$$u = \dot{\alpha}_1 - \hat{\Phi}(z) - \ddot{e}_1 - \lambda_1 \dot{e}_1 - \lambda_2 e_1 + \dot{f}(t) - \frac{S}{\|S\|^2} e_1^T e_2 - \rho \frac{S}{\|S\|} \tag{27}$$

where $\rho > E + \varepsilon_b$.

Substitute Eq. (26) into Eq. (27) yields:

$$u = \dot{\alpha}_1 - \hat{W}^T \phi(z) - \ddot{e}_1 - \lambda_1 \dot{e}_1 - \lambda_2 e_1 + \dot{f}(t) - \frac{S}{\|S\|^2} e_1^T e_2 - \rho \frac{S}{\|S\|} \tag{28}$$

Differentiating Eq. (17) and using u in Eq. (28) given

$$\begin{aligned} \dot{S} &= \dot{e}_2 + \ddot{e}_1 + \lambda_1 \dot{e}_1 + \lambda_2 e_1 - \dot{f}(t) \\ &= \Gamma(X) + u + d - \dot{\alpha}_1 + \ddot{e}_1 + \lambda_1 \dot{e}_1 + \lambda_2 e_1 - \dot{f}(t) \\ &= W^T \phi(z) + \varepsilon + \dot{\alpha}_1 - \hat{W}^T \phi(z) - \ddot{e}_1 - \lambda_1 \dot{e}_1 - \lambda_2 e_1 + \dot{f}(t) \\ &\quad - \frac{S}{\|S\|^2} e_1^T e_2 - \rho \frac{S}{\|S\|} + d - \dot{\alpha}_1 + \ddot{e}_1 + \lambda_1 \dot{e}_1 + \lambda_2 e_1 - \dot{f}(t) \end{aligned} \tag{29}$$

Let's consider the following function V_3 which is positive definite as a Lyapunov candidate function

$$V_3 = V_2 + \frac{1}{2} tr\{\tilde{W}^T F^{-1} \tilde{W}\} \tag{30}$$

where F is a positive constant and $\tilde{W}$ is the estimated error of weight vector described as

$$\tilde{W} = W - \hat{W} \tag{31}$$

Obviously, if the gyroscope system converges, we keep W a constant, as a result we obtain $\dot{W} = 0$ and $\dot{\tilde{W}} = -\dot{\hat{W}}$.

It is apparently that V_3 is positive and the derivative is

$$\begin{aligned} \dot{V}_3 &= -c_1 e_1^T e_1 + e_1^T e_2 + S^T [W^T \phi(z) + \varepsilon + u + d \\ &\quad - \dot{\alpha}_1 + \ddot{e}_1 + \lambda_1 \dot{e}_1 + \lambda_2 e_1 - \dot{f}(t)] + tr\{\tilde{W}^T F^{-1} \dot{\tilde{W}}\} \end{aligned} \tag{32}$$

By using Eq. (28) given:

$$\begin{aligned} \dot{V}_3 &= -c_1 e_1^T e_1 + e_1^T e_2 + S^T [W^T \phi(z) + \varepsilon + \dot{\alpha}_1 - \hat{W}^T \phi(z) \\ &\quad - \ddot{e}_1 - \lambda_1 \dot{e}_1 - \lambda_2 e_1 + \dot{f}(t) - \frac{S}{\|S\|^2} e_1^T e_2 - \rho \frac{S}{\|S\|} + d \\ &\quad - \dot{\alpha}_1 + \ddot{e}_1 + \lambda_1 \dot{e}_1 + \lambda_2 e_1 - \dot{f}(t)] + tr\{\tilde{W}^T F^{-1} \dot{\tilde{W}}\} \\ &= -c_1 e_1^T e_1 + e_1^T e_2 + S^T [\tilde{W}^T \phi(z) + \varepsilon \\ &\quad - \frac{S}{\|S\|^2} e_1^T e_2 - \rho \frac{S}{\|S\|} + d] + tr\{\tilde{W}^T F^{-1} \dot{\tilde{W}}\} \\ &= -c_1 e_1^T e_1 + e_1^T e_2 + S^T \tilde{W}^T \phi(z) + S^T \varepsilon - e_1^T e_2 \\ &\quad - \|S\| \rho + S^T d] + tr\{\tilde{W}^T F^{-1} \dot{\tilde{W}}\} \end{aligned} \tag{33}$$

Select an adaptive law as:

$$\dot{\tilde{W}} = -\dot{\hat{W}} = -F \phi(z) S^T \tag{34}$$

When $S \neq 0$, using $\dot{\tilde{W}}$ Eq. (34), it can be obtained that:

$$\begin{aligned} \dot{V}_3 &= -c_1 e_1^T e_1 + e_1^T e_2 + S^T \varepsilon - e_1^T e_2 - \|S\| \rho + S^T d \\ &= -c_1 e_1^T e_1 + S^T \varepsilon - \|S\| \rho + S^T d \\ &= -c_1 e_1^T e_1 + S^T (\varepsilon + d) - \|S\| \rho \\ &\le -c_1 e_1^T e_1 + \|S\| (\|\varepsilon\| + \|d\|) - \|S\| \rho \\ &= -c_1 e_1^T e_1 - \|S\| (\rho - \|d\| - \|\varepsilon\|) \\ &\le -c_1 e_1^T e_1 - \|S\| (\rho - E - \varepsilon_b) \\ &\le -\|S\| (\rho - E - \varepsilon_b) \\ &< 0 \end{aligned} \tag{35}$$

The negative definite of $\dot{V}_3$ ensures that V_3, S both are bounded. $\dot{S}$ is also bounded from Eq. (29). The inequality $\dot{V}_3 \le -\|S\|(\rho - E - \varepsilon_b)$ suggests that S is integrable as $\int_0^t \|S\|dt \le \frac{1}{(\rho-E-\varepsilon_b)}[V_3(0) - V_3(t)]$. On account of $V_3(0)$ is bounded and $V_3(t)$ is bounded and nonincreasing, then $\lim_{t\to\infty}\int_0^t \|S\|dt$ is bounded. According to Barbalat's lemma based on the boundedness of $\lim_{t\to\infty}\int_0^t \|S\|dt$ and $\dot{S}$, $S(t)$ will meet $\lim_{t\to\infty} S(t) = 0$. As a consequence, the developed controller could ensure the globally asymptotic stability and make the error of trajectory tracking converge to 0 fast.

C. NEURAL BACKSTEPPING PID GLOBAL SLIDING MODE FUZZY CONTROLLER (NBPIDGSMFC)

Considering the unknown external interference in practical applications, the switch gain ρ in Eq. (28) is too big to be put into effect. What is more, the satisfactory switching control is hard to achieve. As a consequence, a fuzzy controller is designed.

$\hat{h}(S)$ is an adaptive fuzzy control part which is utilized to approximate to $\rho\frac{S}{\|S\|}$. As a result, the output of switching controller is $u_{sw} = -\hat{h}(S)$.

Express the desired output of the fuzzy system as

$$h(S) = \theta^T\psi(S) + \sigma \tag{36}$$

where $\theta = [\theta_1, \theta_2, \ldots, \theta_m]^T$ is the parameter which can be adjusted, $\psi(S) = [\psi_1, \psi_2 \cdots \psi_m]^T$ is fuzzy vector, σ is the approximated error, σ could get to the minimum value if the adjustable parameter is optimal. Moreover, σ is uniformly bounded as: $\|\sigma\| \le \sigma_b$, where σ_b is a positive arbitrary small constant.

The actual output of the fuzzy system could be depicted as

$$\hat{h}(S) = \hat{\theta}^T\psi(S) \tag{37}$$

where $\hat{h}(S)$ is the estimation of $h(S)$, $\hat{\theta}$ represents real adjustable parameter updated online all through.

$$\hat{h}(S) = \begin{bmatrix}\hat{h}_1(S) & \hat{h}_2(S)\end{bmatrix}^T = \begin{bmatrix}\hat{\theta}_1^T\psi_1(S) & \hat{\theta}_2^T\psi_2(S)\end{bmatrix} \tag{38}$$

where $\hat{h}_i(S) = \hat{\theta}_i^T\psi_i(S), \hat{\theta}_i = [\theta_{i1}, \ \theta_{i2}\cdots\theta_{im}]^T$, $\psi_i = [\psi_{i1}, \psi_{i2}\cdots\psi_{im}]^T$, m is the number of membership functions.

To ensure stability of the gyroscope system, design the control force of NBPIDGSMFC as

$$u = \dot{\alpha}_1 - \hat{W}^T\phi(z) - \ddot{e}_1 - \lambda_1\dot{e}_1 - \lambda_2 e_1 + \dot{f}(t) - \frac{S}{\|S\|^2}e_1^Te_2 - \hat{h}(S) \tag{39}$$

where $\rho > E + \varepsilon_b + \sigma_b$, both ε_b and σ_b are positive arbitrary small constants.

Differentiating Eq. (17) and using u in Eq. (39), we obtain

$$\begin{aligned}\dot{S} &= \dot{e}_2 + \ddot{e}_1 + \lambda_1\dot{e}_1 + \lambda_2 e_1 - \dot{f}(t)\\ &= \Gamma(X) + u + d - \dot{\alpha}_1 + \ddot{e}_1 + \lambda_1\dot{e}_1 + \lambda_2 e_1 - \dot{f}(t)\\ &= W^T\phi(z) + \varepsilon + \dot{\alpha}_1 - \hat{W}^T\phi(z) - \ddot{e}_1\\ &\quad - \lambda_1\dot{e}_1 - \lambda_2 e_1 + \dot{f}(t) - \frac{S}{\|S\|^2}e_1^Te_2 - \hat{h}(S)\\ &\quad + d - \dot{\alpha}_1 + \ddot{e}_1 + \lambda_1\dot{e}_1 + \lambda_2 e_1 - \dot{f}(t)\end{aligned} \tag{40}$$

Let us consider a new Lyapunov function

$$V_4 = V_3 + \frac{1}{2\gamma}\sum_{i=1}^{2}\tilde{\theta}_i^T\tilde{\theta}_i \tag{41}$$

where γ is a positive constant, $\tilde{\theta}_i$ is the estimation error of θ_i as

$$\tilde{\theta}_i = \theta_i - \hat{\theta}_i \tag{42}$$

Distinctly, θ_i should be kept as a constant if the system converges together with $\dot{\theta}_i = 0$, $\dot{\tilde{\theta}} = -\dot{\hat{\theta}}$.

The derivative of V_4 is

$$\begin{aligned}\dot{V}_4 &= -c_1e_1^Te_1 + e_1^Te_2 + S^T[W^T\phi(z)\\ &\quad + \varepsilon + u + d - \dot{\alpha}_1 + \ddot{e}_1 + \lambda_1\dot{e}_1 + \lambda_2 e_1\\ &\quad - \dot{f}(t)] + tr\{\tilde{W}^TF^{-1}\dot{\tilde{W}}\} + \frac{1}{\gamma}\sum_{i=1}^{2}\tilde{\theta}_i^T\dot{\tilde{\theta}}_i\end{aligned} \tag{43}$$

Substituting u in Eq. (39) into Eq. (43) gives

$$\begin{aligned}\dot{V}_4 &= -c_1e_1^Te_1 + e_1^Te_2 + S^T[W^T\phi(z) + \varepsilon + \dot{\alpha}_1 - \hat{W}^T\phi(z)\\ &\quad - \ddot{e}_1 - \lambda_1\dot{e}_1 - \lambda_2 e_1 + \dot{f}(t) - \frac{S}{\|S\|^2}e_1^Te_2 - \hat{h}(S) + d\\ &\quad - \dot{\alpha}_1 + \ddot{e}_1 + \lambda_1\dot{e}_1 + \lambda_2 e_1 - \dot{f}(t)] + tr\{\tilde{W}^TF^{-1}\dot{\tilde{W}}\}\\ &\quad + \frac{1}{\gamma}\sum_{i=1}^{2}\tilde{\theta}_i^T\dot{\tilde{\theta}}_i\\ &= -c_1e_1^Te_1 + e_1^Te_2 + S^T[\tilde{W}^T\phi(z) + \varepsilon - \frac{S}{\|S\|^2}e_1^Te_2\\ &\quad - \hat{h}(S) + d] + tr\{\tilde{W}^TF^{-1}\dot{\tilde{W}}\} + \frac{1}{\gamma}\sum_{i=1}^{2}\tilde{\theta}_i^T\dot{\tilde{\theta}}_i\\ &= -c_1e_1^Te_1 + S^T\tilde{W}^T\phi(z) + S^T\varepsilon - S^T\hat{h}(S)\\ &\quad + S^Td + tr\{\tilde{W}^TF^{-1}\dot{\tilde{W}}\} + \frac{1}{\gamma}\sum_{i=1}^{2}\tilde{\theta}_i^T\dot{\tilde{\theta}}_i\\ &= -c_1e_1^Te_1 + S^T\varepsilon + S^T[d - \rho\frac{S}{\|S\|}] + S^T\tilde{\theta}_i^T\psi_i(S)\\ &\quad + S^T\sigma + S^T\tilde{W}^T\phi(z) + tr\{\tilde{W}^TF^{-1}\dot{\tilde{W}}\} + \frac{1}{\gamma}\sum_{i=1}^{2}\tilde{\theta}_i^T\dot{\tilde{\theta}}_i\end{aligned} \tag{44}$$

In order to achieve $\dot{V}_4 \le 0$, it is advisable to design adaptive laws as:

$$\dot{\tilde{W}} = -\dot{\hat{W}} = -F\phi(z)S^T \tag{45}$$

$$\dot{\tilde{\theta}}_i = -\dot{\hat{\theta}}_i = -\gamma\psi_i(S)S^T \tag{46}$$

When $S \ne 0$, then it can be obtained that

$$\begin{aligned}\dot{V}_4 &= -c_1e_1^Te_1 + S^T\varepsilon + S^Td - \|S\|\rho + S^T\sigma\\ &\le -c_1e_1^Te_1 + \|S\|\|\varepsilon\| + \|S\|\|d\| - \|S\|\rho + \|S\|\|\sigma\|\end{aligned}$$

$$\begin{aligned}&\le -c_1 e_1^T e_1 + \|S\|\,\varepsilon_b + \|S\|\,d - \|S\|\,\rho + \|S\|\,\sigma_b\\&\le -c_1 e_1^T e_1 - \|S\|\,(\rho - E - \varepsilon_b - \sigma_b)\\&\le -\|S\|\,(\rho - E - \varepsilon_b - \sigma_b)\\&< 0\end{aligned} \tag{47}$$

The negative definite of $\dot{V}_4$ guarantees that V_4, S both are bounded. It could draw a conclusion by Eq. (40) that $\dot{S}$ is bounded, too. The inequality $\dot{V}_4 \le -\|S\|\,(\rho - E - \varepsilon_b - \sigma_b)$ suggests that $\int_0^t \|S\|dt \le \frac{1}{(\rho-E-\varepsilon_b-\sigma_b)}[V_4(0) - V_4(t)]$. Due to $V_4(0)$ is bounded and $V_4(t)$ is bounded and nonincreasing, $\lim_{t\to\infty} \int_0^t \|S\|dt$ is also bounded. According to Barbalat's lemma, $S(t)$ will satisfy $\lim_{t\to\infty} S(t) = 0$ under the boundedness of $\lim_{t\to\infty} \int_0^t \|S\|\,dt$ and $\dot{S}$. Therefore, the presented controller ensures the globally asymptotic stability and makes the tracking error tend to 0 in quite short period of time.

IV. SIMULATION STUDY

To illustrate the effectiveness of the presented strategy of NBPIDGSMFC, the simulation is implemented based on Fig. 2. A set of gyroscope parameters are as follows:

$$\begin{aligned}&m = 1.8\times10^{-7}kg,\quad k_{xx} = 63.955N/m,\ k_{yy} = 95.92N/m,\\&k_{xy} = 12.779N/m,\quad d_{xx} = 1.8\times10^{-6}Ns/m,\ ,\\&d_{yy} = 1.8\times10^{-6}Ns/m,\quad d_{xy} = 3.6\times10^{-7}Ns/m\end{aligned}$$

We assume that input angular velocity of gyroscope system is $\Omega_Z = 100rad/s$, ideal length is $q_0 = 1\mu m$, resonance frequency is $\omega_0 = 1000Hz$. After dimensionless treatment, the parameters are listed as:

$$\begin{aligned}&\omega_x^2 = 355.3,\quad \omega_y^2 = 532.9,\ \omega_{xy} = 70.99,\\&d_{xx} = 0.01,\quad d_{yy} = 0.01,\ d_{xy} = 0.002,\ \Omega_Z = 0.1\end{aligned}$$

The optimal trajectory of the gyroscope is: $x_d = \sin(w_1 t), y_d = \sin(w_2 t), w_1 = 6.17rad/s, w_2 = 5.11rad/s$. The zero initial states are: $x(0) = [0, 0, 0, 0]^T$. Random signal $d(t) = [10 * randn(1); 10 * randn(1)]$ is regarded as external disturbances.

We take the parameters of PID global sliding manifold as $c(0) = 10, f(t) = s(0)e^{-100t}, \lambda_1 = 100, \lambda_2 = 10$. Moreover, the gains of adaptive laws are chosen as $F = 50, \gamma = 10$. The fixed gain is $\rho = 100$. In addition, select the membership functions of the fuzzy variable:

$$\begin{aligned}&\mu_{NM}(S) = \exp[-((S+10)/5)^2],\quad \mu_{ZO}(S) = \exp(-(S/5)^2),\\&\mu_{PM}(S) = \exp[-((S-10)/5)^2].\end{aligned}$$

The membership functions are shown in Fig.4.

The results of the simulation are displayed in Fig. 5∼ Fig.11. The trajectory tracking of this presented neural backstepping PID global sliding mode fuzzy control is of high accuracy, as what is shown in Fig.5. Meanwhile, the designed intelligent controller shows that there is little error between the ideal position tracking and the real one observed from Fig.6, suggesting the superior performance and globally stability of the control system.

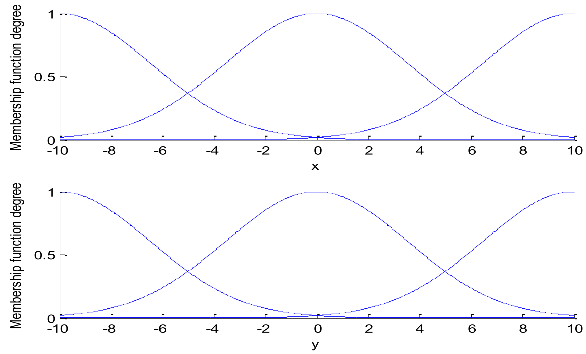

FIGURE 4. The membership functions.

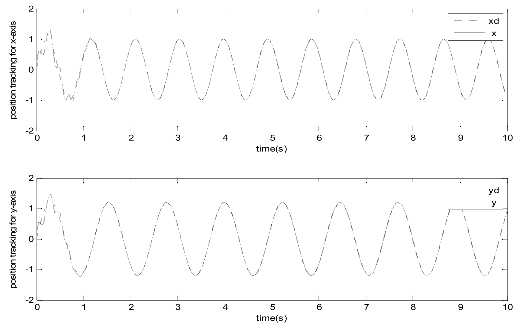

FIGURE 5. Position trackings of x-axis and y-axis.

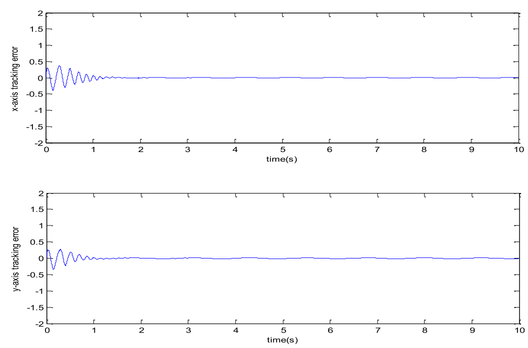

FIGURE 6. Position tracking errors of x-axis and y-axis.

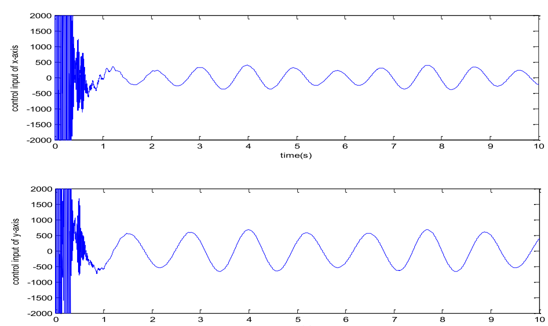

FIGURE 7. Control inputs utilizing backstepping PID global sliding mode.

Fig.7 draws the smooth control inputs which illustrates that the proposed fuzzy controller plays the effective role in eliminating the chattering phenomenon. Moreover, compared to the presented control, the method without fuzzy control leads to serious chattering phenomenon in Fig.8.

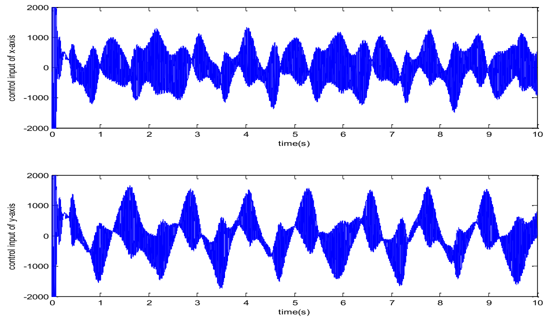

FIGURE 8. **Control inputs utilizing neural backstepping PID global sliding mode control with the fixed gain $\rho = 100$.**

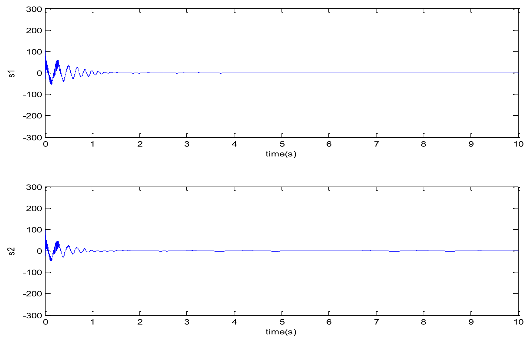

FIGURE 9. **Switch functions of x-axis and y-axis.**

Through figure 9, we could also see that the PID global sliding mode manifold arrives to zero in high speed accurately, which suggests that the system reach to the surface in such a short time with sliding along the switch surface, once again demonstrating the derived scheme of great effectiveness.

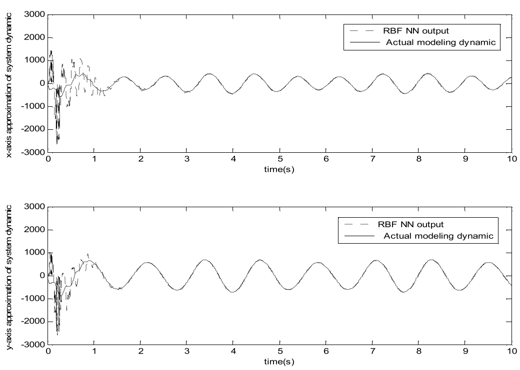

FIGURE 10. **Approximations of unknown dynamic characteristics by RBF neural network.**

Fig.10 exhibits approximation results to unknown characteristics of two-axis gyroscope system by RBF neural network. From which we can see that the output of the introduced neural network approach to the unknown dynamic feature quickly. Besides, as indicated in Fig.10, the neural estimator has a wonderful approaching property by the almost overlapped two curves.

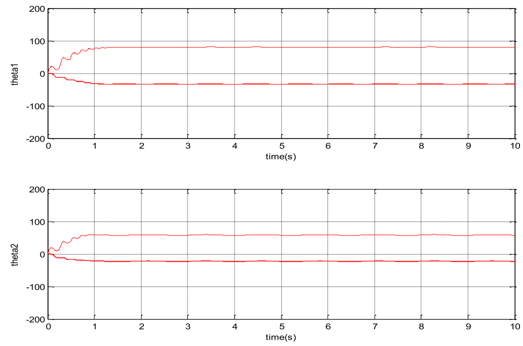

FIGURE 11. **Adaptive curves of the fuzzy parameters.**

Fig.11 describes the adaptation of $\hat{\theta}$. As we can see, the adjustable parameters $\hat{\theta}$ converge to constant values, implying the stability of the fuzzy control system.

All these simulation plots validate the superior property of the developed NBPIDGSMFC scheme from various aspects.

V. CONCLUSION

A new scheme of this neural PID global sliding mode fuzzy control utilizing backstepping technique for a MEMS gyroscope is developed in this paper. Firstly, the dynamic model of MEMS gyroscopes which have two axis is introduced. Secondly, in order to achieve global robustness by precise tracking performance in high speed, the controller on the basis of backstepping PID global sliding mode is presented. Then, the neural backstepping global sliding mode control strategy is employed for making the introduced neural network approach to system unknown dynamic feature. Moreover, a fuzzy controller is introduced to eliminate the chattering. Eventually, the availability of the suggested scheme is illustrated by the simulation results.

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