Research Article

Actor Critic Neural Network-Based Adaptive Control for MEMS Gyroscopes Suffering from Multiresource Disturbances

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In this paper, an actor critic neural network-based adaptive control scheme for micro-electro-mechanical system (MEMS) gyroscopes suffering from multiresource disturbances is proposed. Faced with multiresource interferences consisting of parametric uncertainties, strong couplings between axes, Coriolis forces, and variable external disturbances, an actor critic neural network is introduced, where the actor neural network is employed to estimate the packaged disturbances and the critic neural network is utilized to supervise the system performance. Hence, strong robustness against uncertainties and better tracking properties can be derived for MEMS gyroscopes. Aiming at handling the nonlinearities inherent in gyroscopes without analytically differentiating the virtual control signals, dynamic surface control (DSC) rather than backstepping control method is employed to divide the 2nd order system into two 1st order systems and design the actual control policy. Moreover, theoretical analyses along with simulation experiments are conducted with a view to validate the effectiveness of the proposed control approach.

1. Introduction

Owing to the microvolume, easy integration, and mass production, micro-electro-mechanical system (MEMS) gyroscopes are indispensable angular rate sensors in a myriad of areas including inertial guidance, aerospace, and national defense industry [1–5]. Typically, the accurate detection of angular rates is highly dependent on the high-precision control of drive axis and sense axis. However, MEMS gyroscopes are inherently accounted for strong uncertainties and nonlinearities, rendering the high-precision control a challenging issue.

Ideally, the parameters of MEMS gyroscopes are naturally fixed, including mass, damping parameters, and spring parameters, and mechanical motion of two axes are uncoupled. While in real word applications, manufacturing defects and unpredictable operation environments undesirably result in multiresource interferences, i.e., parametric uncertainties, mechanical coupling between axes, and external disturbances, which inevitably reduce the tracking accuracy of both axes and even lead to system instability.

Aiming at reducing the effects of uncertainties and enhancing system behaviours, several advanced schemes have been devised, such as neural networks (NNs) [6–8], extended state observers (ESOs) [9], and fuzzy logic systems (FLSs) [10], where the packaged disturbances are online estimated and compensated in the control policy. In [11], on the basis of universal approximation theorem, the RBFNN is employed to online estimate unknown system dynamics, effectively enhancing system robustness against uncertainties. In [7–10, 12], the tracking errors as well as estimation errors are bounded, while the tracking performance is usually neglected, which plays a central role in the high-accuracy measurement of angular rates. Hence, it is meaningful to devise a control scheme capable of recovering unknown interferences and supervising system tracking properties at the same time.

On the contrary, an appropriate stabilizing control policy is crucial to driving the output of MEMS gyroscopes to track the reference signals. In real-world applications, proportional integral derivative (PID) approaches [13, 14] are ubiquitous deployed to control nonlinear systems due to

its theoretical simplicity and easy implementation. However, in the existence of both system and external uncertainties, the PID-based methods cannot fulfil some high-accuracy tracking requirements, which is a fatal weakness of PID controllers. To simultaneously stabilize high-order nonlinear systems and compensate for the lumped disturbances, backstepping control schemes [15–18] are proposed, where the overall system is divided into several first-order systems and virtual control signals are developed to link up each subsystem. Nevertheless, the repeated analytical differentiations of virtual control signals may result in differentiating explosions, threatening the normal operations of nonlinear systems. Hence, it is urgent and necessary to modify existing backstepping control approaches for MEMS gyroscopes without inducing such issues.

Oriented by the previous investigations, an actor critic NN-based adaptive control scheme for MEMS gyroscopes suffering from multiresource disturbances is proposed in this paper, the striking features of which can be summarized as follows:

Unlike the existing PID controller [13, 14], where the system uncertainties are neglected, the proposed control scheme can reduce the effects of lumped disturbances and stabilize the overall system. And, differing from previous backstepping control approaches [15–18] for MEMS gyroscopes that suffer from differentiating explosions, a low-pass filter is embedded to modify the controller design and avoid the analytical differentiations of virtual control signals.

Different from most NN or FLS-based control schemes [7–10, 12], which can only ensure the ultimately uniformly bounded (UUB) properties of tracking errors, the proposed ACNN-based control scheme can simultaneously recover unknown dynamics and supervise tracking properties of MEMS gyroscope, resulting better robustness against uncertainties.

By resorting Lyapunov analyses, all the existing signals are proven to be UUB and a series of simulation verifications are presented to further validate the effectiveness of our proposed control approach.

2. Problem Statements

2.1. Kinetic Model of MEMS Gyroscopes. By resorting to [19–22], the kinetic model of MEMS gyroscopes is typically expressed as

$$\begin{aligned} m\ddot{x} + d_{xx}\dot{x} + (d_{xy} - 2m\Omega_Z)\dot{y} + (k_{xx} - m\Omega_Z^2)x + k_{xy}y \\ + \tilde{\lambda}_x = u_x, \\ m\ddot{y} + d_{yy}\dot{y} + (d_{xy} + 2m\Omega_Z)\dot{x} + (k_{yy} - m\Omega_Z^2)y + k_{xy}x \\ + \tilde{\lambda}_y = u_y, \end{aligned} \quad (1)$$

where m denotes the mass of internal moving mass, Ω_Z represents the rotation velocity, x and y are, respectively, the displacements of drive and sensitive modes, k_{xx} and k_{yy}

represent linear spring terms, d_{xx} and d_{yy} refer to damping terms, k_{xy} and d_{xy} are the coupling coefficients, and u_x and u_y denote the input forces of drive and sensitive modes. Additionally, $\tilde{\lambda}_x$ and $\tilde{\lambda}_y$ describe the external disturbances. An overall structure of MEMS gyroscope is depicted in Figure 1.

Dividing both side of (1) by $m\omega_0^2 l_0$, the following non-dimensional model can be derived:

$$\begin{aligned} \ddot{x}^* + \frac{d_{xx}}{m\omega_0} \dot{x}^* + \frac{(d_{xy} - 2m\Omega_Z)}{m\omega_0} \dot{y}^* + \frac{(k_{xx} - m\Omega_Z^2)}{m\omega_0^2} x^* + \frac{k_{xy}}{m\omega_0^2} y^* \\ + \frac{\tilde{\lambda}_x}{m\omega_0^2 l_0} = \frac{u_x}{m\omega_0^2 l_0}, \\ \ddot{y}^* + \frac{d_{yy}}{m\omega_0} \dot{y}^* + \frac{(d_{xy} + 2m\Omega_Z)}{m\omega_0} \dot{x}^* + \frac{(k_{yy} - m\Omega_Z^2)}{m\omega_0^2} y^* + \frac{k_{xy}}{m\omega_0^2} x^* \\ + \frac{\tilde{\lambda}_y}{m\omega_0^2 l_0} = \frac{u_y}{m\omega_0^2 l_0}, \end{aligned} \quad (2)$$

with

$$\begin{aligned} \mathbf{x}_p &= \begin{bmatrix} x_{p1} \\ x_{p2} \end{bmatrix} = \begin{bmatrix} x^* \\ y^* \end{bmatrix}, \\ \mathbf{x}_v &= \begin{bmatrix} x_{v1} \\ x_{v2} \end{bmatrix} = \begin{bmatrix} \dot{x}^* \\ \dot{y}^* \end{bmatrix}, \\ \mathbf{u} &= \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} \frac{u_x}{m\omega_0^2 l_0} \\ \frac{u_y}{m\omega_0^2 l_0} \end{bmatrix}, \\ \mathbf{\Omega} &= \begin{bmatrix} 0 & \frac{\Omega_Z}{\omega_0} \\ \frac{\Omega_Z}{\omega_0} & 0 \end{bmatrix}, \\ \mathbf{D} &= \begin{bmatrix} \frac{d_{xx}}{m\omega_0} & \frac{d_{xy}}{m\omega_0} \\ \frac{d_{xy}}{m\omega_0} & \frac{d_{yy}}{m\omega_0} \end{bmatrix}, \\ \mathbf{K} &= \begin{bmatrix} \frac{k_{xx}}{m\omega_0^2} & \frac{k_{xy}}{m\omega_0^2} \\ \frac{k_{xy}}{m\omega_0^2} & \frac{k_{yy}}{m\omega_0^2} \end{bmatrix}, \\ \tilde{\lambda} &= \begin{bmatrix} \frac{\tilde{\lambda}_x}{m\omega_0^2 l_0} \\ \frac{\tilde{\lambda}_y}{m\omega_0^2 l_0} \end{bmatrix}. \end{aligned} \quad (3)$$

FIGURE 1: Overall structure of MEMS gyroscope.

In pursuit of description conciseness, (2) is further re-written into the following strict-feedback vector form:

$$\begin{cases} \dot{\mathbf{x}}_p = \mathbf{x}_v, \\ \dot{\mathbf{x}}_v = \mathbf{u} + \mathbf{F}, \end{cases} \quad (4)$$

with $\mathbf{F} = [F_1, F_2]^T = -(\mathbf{D} - 2\Omega)\mathbf{x}_v - (\mathbf{K} - \Omega^2)\mathbf{x}_p - \dot{\mathbf{A}}$ defined as the packaged disturbances.

2.2. Control Objective. Our objective is to devise a control policy $\mathbf{u}$ based on ACNNs and DSC schemes, which is capable of driving the output states of MEMS gyroscopes $\mathbf{x}_p$ to track the reference signal $\mathbf{y}_r = [y_{r1}, y_{r2}]^T$ as accurately as possible, in the existence of multisource interferences, i.e., $\mathbf{F}$.

3. Main Results

3.1. AC Neural Networks. In what follows, the actor neural network is employed to reconstruct the packaged disturbance $\mathbf{F}$, which is formulated as

$$F_i(\bar{\mathbf{x}}) = \mathbf{W}_{ai}\boldsymbol{\theta}_{ai}(\bar{\mathbf{x}}) + \delta_{ai}(\bar{\mathbf{x}}). \quad (5)$$

where $\mathbf{W}_{ai} = [W_{ai,1}, W_{ai,2}, \dots, W_{ai,l}]^T \in \mathbf{R}^l$ denotes the weight vector and $\delta_{ai}(\bar{\mathbf{x}})$ describes the reconstruction errors satisfying $\delta_{ai}(\bar{\mathbf{x}}) \leq \bar{\delta}_{ai}$ with $\bar{\delta}_{ai}$ being a positive finite constant. Define that $\hat{\mathbf{W}}_{ai} = [\hat{W}_{ai,1}, \hat{W}_{ai,2}, \dots, \hat{W}_{ai,l}]^T \in \mathbf{R}^l$ is estimation of $\mathbf{W}_{ai}$ and $\tilde{\mathbf{W}}_{ai} = \hat{\mathbf{W}}_{ai} - \mathbf{W}_{ai}$ denotes the estimation error. $\boldsymbol{\theta}_{ai}(\bar{\mathbf{x}})$ is the active function vector, which is chosen as the commonly used sigmoid function.

Herein, in order to supervise the tracking properties in real time, a reinforcement function is devised in the following form similar to [23]

$$S_i = \frac{\bar{S}_i}{1 + \exp(-\tau_i e_{pi})} - \frac{\bar{S}_i}{1 + \exp(\tau_i e_{pi})}, \quad (6)$$

where τ_i and $\bar{S}_i$ are positive design parameters.

Subsequently, the critic function is defined as

$$S_{ci} = \varphi_i S_i + \varphi_i S_i \mathbf{W}_{ci} \boldsymbol{\theta}_{ci}(\bar{\mathbf{x}}), \quad (7)$$

where $\mathbf{W}_{ci} = [W_{ci,1}, W_{ci,2}, \dots, W_{ci,l}]^T \in \mathbf{R}^l$ denotes the weight vector. Define that $\hat{\mathbf{W}}_{ci} = [\hat{W}_{ci,1}, \hat{W}_{ci,2}, \dots, \hat{W}_{ci,l}]^T \in \mathbf{R}^l$ is estimation of $\mathbf{W}_{ci}$ and $\tilde{\mathbf{W}}_{ci} = \hat{\mathbf{W}}_{ci} - \mathbf{W}_{ci}$ denotes the estimation error. $\boldsymbol{\theta}_{ci}(\bar{\mathbf{x}})$ is the active function vector, which can be calculated in the following form:

Apparently, S_i is always bounded within $[-\bar{S}_i, \bar{S}_i]$, and the smaller $|e_{pi}|$ is, the closer S_i is to zero. Hence, the control objective of driving $\mathbf{x}_p$ to track $\mathbf{y}_r$ boils down to ensuring that S_c is as close to zero as possible. The actual critic signal is formulated as follows:

$$\hat{S}_{ci} = \varphi_i S_i + \|\varphi_i S_i\| \hat{\mathbf{W}}_{ci} \boldsymbol{\theta}_{ci}(\bar{\mathbf{x}}), \quad (8)$$

where $\hat{\mathbf{W}}_{ci}$ is the estimation of $\mathbf{W}_{ci}$.

3.2. Controller Design. The following error dynamics are defined in advance, aiming at promoting the controller design and stability analysis:

$$\begin{aligned} e_{pi} &\triangleq x_{pi} - y_{ri}, \\ e_{vi} &\triangleq x_{vi} - \bar{v}_i, \\ \varphi_i &\triangleq \bar{v}_i - v_i, \end{aligned} \quad (9)$$

with v_i being the virtual control policy and $\bar{v}_i$ is its low-pass filtered signal, which are formulated as

$$\begin{aligned} \chi_i \dot{\bar{v}}_i + \bar{v}_i &= v_i, \\ \bar{v}_i(0) &= \bar{v}_i(0), \end{aligned} \quad (10)$$

with χ_i being a positive time-delay parameter.

Taking the time derivative of $\varphi_i \triangleq \bar{v}_i - v_i$ and utilizing (10), the following equation can be guaranteed:

$$\dot{\varphi}_i + \frac{\varphi_i}{\chi_i} = -\dot{v}_i. \quad (11)$$

Note that $\dot{v}_i$ is a continuous and bounded function satisfying $|\dot{v}_i| \leq \dot{v}_0$ and $\dot{v}_0$ is a positive constant.

Step 1. at this point, devise the Lyapunov candidate of displacement loop as $V_p = \sum_{i=1}^2 (e_{pi}^2 + \varphi_i^2)/2$. Differentiating it along with time and recalling the kinetic model of MEMS gyroscope (4), one has

$$\begin{aligned} \dot{V}_p &= \sum_{i=1}^2 (\dot{e}_{pi} e_{pi} + \dot{\varphi}_i \varphi_i) \\ &= \sum_{i=1}^2 ((e_{vi} + v_i + \varphi_i - \dot{y}_{ri}) e_{pi} + \dot{\varphi}_i \varphi_i). \end{aligned} \quad (12)$$

In order to stabilize V_p , the virtual control policy is developed as

$$v_i = -k_{pi} e_{pi} + \dot{y}_{ri}. \quad (13)$$

According to Young's inequality, the following inequalities hold:

$$e_{vi}e_{pi} \leq \frac{1}{2}e_{vi}^2 + \frac{1}{2}e_{pi}^2, \varphi_i e_{pi} \leq \frac{1}{2}\varphi_i^2 + \frac{1}{2}e_{pi}^2, \varphi_i \dot{\gamma}_i \leq \frac{1}{2}\varphi_i^2 + \frac{1}{2}\dot{\gamma}_i^2. \quad (14)$$

Subsequently, inserting (13) and (14) into (12), it follows that

$$\dot{V}_p \leq \sum_{i=1}^2 \left(-k_{pi}e_{pi}^2 + \frac{1}{2}e_{vi}^2 + e_{pi}^2 + \varphi_i^2 - \frac{1}{\chi_i}\varphi_i^2 + \frac{1}{2}\dot{\gamma}_i^2 \right). \quad (15)$$

Step 2. construct the Lyapunov candidate of velocity loop as

$V_v = \sum_{i=1}^2 (\bar{S}_i (\ln(1 + \exp(-\tau_i e_{pi})) + \ln(1 + \exp(\tau_i e_{pi}))) / \tau_i + \dot{\tilde{W}}_{ai}^T \tilde{W}_{ai} / 2\sigma_{ai} + \dot{\tilde{W}}_{ci}^T \tilde{W}_{ci} / 2\sigma_{ci})$. Differentiating it along with time and recollecting the kinetic dynamics of MEMS gyroscope (4), it follows

$$\begin{aligned} \dot{V}_i &= \sum_{i=1}^2 \left(S_i \dot{e}_{vi} + \frac{\dot{\tilde{W}}_{ai}^T \tilde{W}_{ai}}{\sigma_{ai}} + \frac{\dot{\tilde{W}}_{ci}^T \tilde{W}_{ci}}{\sigma_{ci}} \right), \\ &= \sum_{i=1}^2 \left(S_i (u_i + F_i - \dot{\gamma}_i) + \frac{\dot{\tilde{W}}_{ai}^T \tilde{W}_{ai}}{\sigma_{ai}} + \frac{\dot{\tilde{W}}_{ci}^T \tilde{W}_{ci}}{\sigma_{ci}} \right). \end{aligned} \quad (16)$$

$$\begin{aligned} \dot{V}_i &= \sum_{i=1}^2 \left((-\tilde{W}_{ai} \boldsymbol{\theta}_{ai} + \delta_{ai} - k_{vi} S_i) \varphi_i S_i - k_{vi} S_i^2 + (\hat{S}_{ci} \boldsymbol{\theta}_{ci}^T - \kappa_{ai} \tilde{W}_{ai}^T) \tilde{W}_{ai} - (\varphi_i S_i \boldsymbol{\theta}_{ci}^T (\tilde{W}_{ai} \boldsymbol{\theta}_{ai})^T + \kappa_{ci} \tilde{W}_{ci}^T) \tilde{W}_{ci} \right), \\ &= \sum_{i=1}^2 \left((-\tilde{W}_{ai} \boldsymbol{\theta}_{ai} + \delta_{ai} - k_{vi} S_i) \varphi_i S_i - k_{vi} S_i^2 - \kappa_{ai} \tilde{W}_{ai}^T \tilde{W}_{ai} + (\varphi_i S_i + \varphi_i S_i \hat{W}_{ci} \boldsymbol{\theta}_{ci}) \boldsymbol{\theta}_{ai}^T \tilde{W}_{ai} - \kappa_{ci} \tilde{W}_{ci}^T \tilde{W}_{ci} - (\varphi_i S_i \boldsymbol{\theta}_{ci}^T) \tilde{W}_{ci} (\tilde{W}_{ai} \boldsymbol{\theta}_{ai})^T \right). \end{aligned} \quad (20)$$

4. Stability Analyses

Herein, the main theorem of our paper is presented as, on the basis of the virtual control policy, the actual control policy and the adaptive updating policy; all the error dynamics involved in the closed-loop MEMS gyroscope system are UUB.

In order to stabilize the velocity loop and supervise the tracking performance in real time for MEMS gyroscopes, the actual control policy as well as adaptive updating policy are presented in (18)–(20):

$$u_i = -k_{vi} S_i - \hat{W}_{ai} \boldsymbol{\theta}_{ai} + \dot{\gamma}_i, \quad (17)$$

$$\dot{\tilde{W}}_{ai}^T = \sigma_{ai} (\hat{S}_{ci} \boldsymbol{\theta}_{ci}^T - \kappa_{ai} \tilde{W}_{ai}^T), \quad (18)$$

$$\dot{\tilde{W}}_{ci}^T = -\sigma_{ci} (\varphi_i S_i \boldsymbol{\theta}_{ci}^T (\tilde{W}_{ai} \boldsymbol{\theta}_{ai})^T + \kappa_{ci} \tilde{W}_{ci}^T), \quad (19)$$

with u_{mi} being the modification control term, which can be derived from (19) and (20). σ_{ai} , σ_{ci} , κ_{ai} , and κ_{ci} are commonly positive constants.

Via inserting (17)–(19) into (16) and recalling (5) as well as (7), the following inequality can be ensured:

Proof. In the first place, constructing the general Lyapunov function as $V = V_p + V_v$, differentiating it along with time and employing (15), (20), it can be derived that

$$\begin{aligned} \dot{V} &= \dot{V}_p + \dot{V}_v \leq \sum_{i=1}^2 \left(-k_{pi}e_{pi}^2 + \frac{1}{2}e_{vi}^2 + e_{pi}^2 + \varphi_i^2 - \frac{1}{\chi_i}\varphi_i^2 + \frac{1}{2}\dot{\gamma}_i^2 \right) + \sum_{i=1}^2 \left((-\tilde{W}_{ai} \boldsymbol{\theta}_{ai} + \delta_{ai} - u_{mi}) \varphi_i S_i - k_{vi} S_i^2 - \kappa_{ai} \tilde{W}_{ai}^T \tilde{W}_{ai} \right. \\ &\quad \left. + (\varphi_i S_i + \varphi_i S_i \hat{W}_{ci} \boldsymbol{\theta}_{ci}) \boldsymbol{\theta}_{ai}^T \tilde{W}_{ai} - \kappa_{ci} \tilde{W}_{ci}^T \tilde{W}_{ci} - (\varphi_i S_i \boldsymbol{\theta}_{ci}^T) \tilde{W}_{ci} (\tilde{W}_{ai} \boldsymbol{\theta}_{ai})^T \right). \end{aligned} \quad (21)$$

Due to Young's inequality and the fact that $\|\boldsymbol{\theta}_{ci}\| \leq \bar{\theta}_{ci}$, the following inequalities hold:

TABLE 1: Design parameters of this simulation.

Section	Parameters
ACNN	$\sigma_{a1} = 1200, \sigma_{a2} = 1100, \kappa_{a1} = 15, \kappa_{a2} = 12$ $\sigma_{c1} = 670, \sigma_{c2} = 840, \kappa_{c1} = 8, \kappa_{c2} = 7, \tau_1 = \tau_2 = 0.5$
Controller	$k_{p1} = 5, k_{p2} = 5, \chi_1 = \chi_2 = 0.05, k_{v1} = 10, k_{v2} = 10$

FIGURE 2: Tracking performance of both displacement and velocity loops.

$$\begin{aligned}
& (-\tilde{W}_{ai}\theta_{ai} + \delta_{ai})\varphi_i S_i + (\varphi_i S_i + \varphi_i S_i \tilde{W}_{ci}\theta_{ci})\theta_{ai}^T \tilde{W}_{ai} - \varphi_i S_i \theta_{ci}^T \tilde{W}_{ci} (\tilde{W}_{ai}\theta_{ai})^T \leq \varphi_i S_i (\|\tilde{W}_{ai}\| \|\tilde{\theta}_{ai}\| \|\mathbf{W}_{ci}\| + \|\mathbf{W}_{ai}^T\| \|\tilde{\theta}_{ai}\| \|\tilde{W}_{ci}\| + \bar{\delta}_{ai}), \\
& -\tilde{W}_{ci}^T \tilde{W}_{ci} \leq \frac{1}{2} (\|\mathbf{W}_{ci}\|^2 - \|\tilde{W}_{ci}\|^2), -\tilde{W}_{ai}^T \tilde{W}_{ai} \leq \frac{1}{2} (\|\mathbf{W}_{ai}\|^2 - \|\tilde{W}_{ai}\|^2).
\end{aligned} \tag{22}$$

Hence, (21) can be further rewritten as

$$\dot{V} \leq \sum_{i=1}^2 \left(-(k_{pi} - 1)e_{pi}^2 - \left(\frac{1}{\chi_i} - 1\right)\varphi_i^2 - k_{vi}S_i^2 - \frac{1}{2}\kappa_{ci}\|\tilde{W}_{ci}\|^2 - \frac{1}{2}\kappa_{ai}\|\tilde{W}_{ai}\|^2 + \delta_{ai}\varphi_i S_i + \varphi_i S_i G_i + \frac{1}{2}\nu_0^2 + \frac{1}{2}\|\mathbf{W}_{ci}\|^2 + \frac{1}{2}\|\mathbf{W}_{ai}\|^2 \right), \tag{23}$$

with $G_i = \|\tilde{W}_{ai}\| \|\tilde{\theta}_{ai}\| \|\mathbf{W}_{ci}\| + \|\mathbf{W}_{ai}^T\| \|\tilde{\theta}_{ai}\| \|\tilde{W}_{ci}\| + \bar{\delta}_{ai}$.

Moreover, employing Young's inequality, it can be achieved that

$$\delta_{ai}\varphi_i S_i \leq \frac{1}{2}\varphi_i S_i^2 + \frac{1}{2}\varphi_i \bar{\delta}_{ai}^2, \varphi_i S_i G_i \leq \frac{1}{2}\varphi_i S_i^2 + \frac{1}{2}\varphi_i G_i^2. \tag{24}$$

Substituting (24) into (23) further produces

$$\dot{V} \leq \sum_{i=1}^2 \left(-(k_{pi} - 1)e_{pi}^2 - \left(\frac{1}{\chi_i} - 1\right)\varphi_i^2 - (k_{vi} - 1)S_i^2 - \frac{1}{2}\kappa_{ci}\|\tilde{W}_{ci}\|^2 - \frac{1}{2}\kappa_{ai}\|\tilde{W}_{ai}\|^2 + \frac{1}{2}\nu_0^2 + \frac{1}{2}\|\mathbf{W}_{ci}\|^2 + \frac{1}{2}\|\mathbf{W}_{ai}\|^2 + \frac{1}{2}\varphi_i \bar{\delta}_{ai}^2 + \frac{1}{2}\varphi_i G_i^2 \right). \tag{25}$$

From (25), it can be easily discovered that, as long as $(k_{pi} - 1) > p$, $(1/\chi_i - 1) > p$, $(k_{vi} - 1) > p$, $\kappa_{ci}/2 > p$, $\kappa_{ai}/2 > p$ and $\Gamma/V(0) < p$ hold with p being a positive constant and $\Gamma = \nu_0^2/2 + \|\mathbf{W}_{ci}\|^2/2 + 1/2\|\mathbf{W}_{ai}\|^2/2 + \varphi_i\bar{\delta}_{ai}^2/2 + \varphi_i G_i^2/2$, $\dot{V} \leq 0$ always holds for $\forall t \geq 0$. Hence, all the error signals considered in V are proven to be UUB, and the proof is completed. $\square$

$$\begin{aligned} m &= 1.8 \times 10^{-7} \text{ kg}, k_{xx} = 63.955 \text{ N/m}, k_{yy} = 95.92 \text{ N/m}, k_{xy} = 12.779 \text{ N/m}, \\ d_{xx} &= 1.8 \times 10^{-6} \text{ N s/m}, d_{yy} = 1.8 \times 10^{-6} \text{ N s/m}, d_{xy} = 3.6 \times 10^{-7} \text{ N s/m}, k_x^2 = 355.3, \\ k_y^2 &= 355.3, k_{xy} = 70.99, D_x = 0.01, D_y = 0.01, D_{xy} = 0.002, \Omega_z = 0.1. \end{aligned} \quad (26)$$

And, the following time-varying functions are utilized to simulate the unknown external disturbances:

$$\hat{\lambda}(t) = \begin{bmatrix} 6 \cos(3t) + 6 \sin(2t)\exp(-t) + 3 \\ 3 \cos(3t)\exp(-0.5t) + 4 \sin(2t) - 2 \end{bmatrix}, \quad t \geq 0. \quad (27)$$

Define the reference signal as $\mathbf{y}_r = [\sin(4.17t), 0]^T$. All the design parameters existing in the proposed control method are given in Table 1.

The tracking performance of displacement loop and velocity loop is presented in Figure 2, where satisfactory tracking accuracy can be discovered, which can be attributed to the effectiveness of DSC approach. Even in the presence of unknown dynamics, the tracking performance is rarely degraded, mainly due to the implementation of ACNN, which is able to recover system uncertainties and supervise system tracking performance at the same time.

Herein, it is notable that the issue of differentiation explosion is effectively avoided, mainly owing to the filtered signal is involved in the velocity loop controller design rather than the analytically differentiated signals. Moreover, although, in the existence of unknown multiresource interferences, the tracking performance is not degraded severely by resorting to the employed ACNN scheme and unlike most existing control schemes based on NN or FLS [7–10,12], which can only ensure the UUB behaviours of tracking errors, the proposed ACNN-based control scheme can recover unknown dynamics and supervise tracking properties of MEMS gyroscope at the same time, validating the robustness of our algorithm against uncertainties.

5. Conclusions

In this paper, an actor critic neural network-based adaptive control scheme for MEMS gyroscopes subject to multi-resource disturbances is proposed. By combining an actor NN with a critic NN, the packaged disturbances can be effectively suppressed and system performance can be supervised at the same time, such that better tracking properties and stronger robustness against unknown dynamics can be guaranteed. Through inserting a first-order filter between the displacement and velocity loops of MEMS

To verify the practicability of the proposed control scheme, a series of simulations are presented for MEMS gyroscopes in the proceeding section. By resorting to [20], the physical parameters of MEMS gyroscopes are typically chosen as

gyroscope, a DSC controller is constructed to ensure the stabilization for both displacement and velocity loops and avoid unexpected differentiation explosion. Moreover, all system dynamics are proven to be UUB via Lyapunov synthesis and a series of simulations through MATLAB/SIMULINK are presented in the end of this paper, validating the effectiveness of our algorithm. In the near future, we may modify the ACNN by combining the fuzzy logics with neural networks [24, 25], aiming at further enhancing its generalization ability. At the same time, prescribed performance of tracking error will be considered for MEMS gyroscope to improve transient and steady-state tracking accuracy.

Data Availability

The data used to support the findings of the study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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