An extended state observer-based full-order sliding mode control for robotic joint actuated by antagonistic pneumatic artificial muscles

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Abstract
Pneumatic artificial muscles (PAMs) are expected to play an important role in endowing the advanced robot with the compliant manipulation, which is very important for a robot to coexist and cooperate with humans. However, the strong nonlinear characteristics of PAMs hinder its wide application in robots, and therefore, advanced control algorithms are urgently needed for making the best use of the advantages and bypassing the disadvantages of PAMs. In this article, we propose a full-order sliding mode control extended state observer (fSMC-ESO) algorithm that combines the ESO and the fSMC for a robotic joint actuated by a pair of antagonistic PAMs. The fSMC is employed to eliminate the chattering and to guarantee the finite-time convergence, and the ESO is adopted to observe both the total disturbance and the states of the robot system, so that we can inhibit the disturbance and compensate the nonlinearity efficiently. Both simulations and physical experiments are conducted to validate the proposed method. We suggest that the proposed method can be applied to the robotic systems actuated by PAMs and remarkably improve the performance of the robot system.

Keywords
Pneumatic artificial muscles, sliding mode control, extended state observer, robot

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Introduction
Advanced robots are expected to be able to coexist and collaborate with human natural as well as interact with the environment and other robots safely and efficiently.¹,² Human-like motion compliance and flexibility are critically important for a robot to carry out a task in the human-centered, complex, unstructured, dynamic daily-living environment.³,⁴ Sadrfaripour and Wang have experimentally proven that the anthropomorphic features of the robot and the human trust motion pattern of the robot are very important for performing human–robot collaboration tasks, which may reduce the human burdens and increase the utilization of robot significantly.⁵ Kato et al. reported that the unexpected speed variation of an industrial robot arm will increase the “surprise” subjective rate, which will cause the mental strain of human cooperators.⁶ Bortot et al. emphasize that the human cooperator

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will feel comfortable when he finds the robot’s behavior is predictable, otherwise, it will pose him a mental burden, which will reduce the efficiency of human–robot cooperation.\textsuperscript{7} It is crucial for effective human–robot collaboration that the robot’s motion patterns are natural and predictable for the human cooperator.\textsuperscript{8}

Studies in physiology, anatomy, biomechanics, and neuroscience have revealed that human motion has its own special characteristics.\textsuperscript{9} The motion of human arm in the free space is assured satisfying the minimal jerk model, namely, the motion of the human arm conforms to the logistic equation and shows a bell-shaped velocity profile.\textsuperscript{10–12} Researchers have been endowing both an autonomous robot and a teleoperate robot with human-like motion patterns. This is to say when a human master operator or a higher-level decision-making module issued an order, the slave robot or an autonomous robot is able to perform the expected motion in a human-like manner.

A human-like motion pattern of a robot needs to be realized via a human-muscle-like actuator. The pneumatic artificial muscles (PAMs) are exactly a kind of actuators that possess the similar actuating properties of human muscles.\textsuperscript{9,13} Moreover, it possesses a lot of other advantages, such as natural elasticity (compliance), low cost, high power/weight, and power/volume ratios. Therefore, PAMs are regarded as the ideal actuator for cooperative robots and usually be configured as antagonistic pairs to mimic human muscle organization. However, PAMs also possess some unfavorable characteristics, such as nonlinearities, hysteresis effects (the output characteristic curve of the inflation process is noticeable different from those of the deflation process), as well as temperature and humidity drift, which severely impede the modeling and control of PAMs.

Extensive studies have been conducted by researchers to improve the control performance of PAM systems, including the PAM model based on machine learning\textsuperscript{13} and artificial neural networks,\textsuperscript{14} as well as the control algorithms based on learning vector quantization neural network,\textsuperscript{15} fuzzy control,\textsuperscript{16} and nonparametric control algorithms,\textsuperscript{17} and all of them have demonstrated some exciting results.

The sliding mode control (SMC) is widely regarded as a kind of powerful nonlinear control scheme, therefore, a variety of SMCs have been adopted to control PAM systems. Kang studied the compliance characteristics and force control of the antagonistic pair of PAMs;\textsuperscript{18} Lilly and Liang studied the SMC tracking control of an antagonistic pair of PAMs;\textsuperscript{19} Estrada and Plestan applied second-order SMC sliding mode to control a PAM system;\textsuperscript{20} Shi and Shen proposed a hybrid controller, which combines the SMC and adaptive fuzzy CMAC\textsuperscript{21} to control a PAM system; Amar et al. studied the nonsingular terminal SMC\textsuperscript{22}, and Rezoug et al. studied the fuzzy terminal sliding mode controller for a PAM-actuated robot arm,\textsuperscript{23} respectively. These studies have shown a vast potential for the application of SMC in the PAM system.

In this article, we propose a control scheme based on both the full-order SMC (fSMC) and the extended state observer (ESO) for achieving a human-like motion pattern on a robotic joint actuated by a pair of antagonistic PAMs. We adopt fSMC because it is chattering free and especially suits for higher-order nonlinear systems with both uncertainty parameters and external disturbance.\textsuperscript{24,25} We adopt the ESO because it is widely used in the active disturbance rejection control\textsuperscript{26,27} scheme, and it is suited for observing both the total disturbance and the states of the robot system so as to inhibit the disturbance and compensate the nonlinearity of the PAM system.

This article is organized as follows: The mathematical model of a robotic joint actuated by a pair of antagonistic PAMs is introduced in the second section. The control algorithm that combines ESO with fSMC is presented in the third section. Simulation and physical experiments are conducted in the fourth section to validate the proposed control scheme. Finally, the advantages and some potential applications of the proposed scheme for the robotic system actuated by antagonistic PAMs are summarized in the fifth section.

### Mathematical model of robotic joint actuated by antagonistic pneumatic artificial muscles

The antagonistic structure is a typical actuating configuration of the human arm. Therefore, it is widely adopted as the bionic robot arm actuating solution (Figure 1).

Though the dynamic properties of PAM are very complicated, Martens and Boblan have proved that accurate and effective control can be achieved via a delicate control algorithm based on the static mathematical models of PAM.\textsuperscript{28}

Yu has proposed a static mathematical model of PAM,\textsuperscript{29} which consists of two parts, that is, the model of the inflation process and those of the deflation process. There is an obvious hysteresis between the inflation and deflation processes. The deflation part of the model is more difficult than those of the inflation part for taking the derivative in modeling the antagonistic robot joint of PAMs, therefore, we only adopt the inflation part of the Yu’s model to modeling the robotic system. As regard to the inaccuracy of the system model caused by the incompleteness of the model of PAM, we count on the robustness of the control scheme.

The Yu’s static mathematical model of PAM is as follows

\[
F(\varepsilon, p) = k_1(p) - k_2(p)\varepsilon + k_3(p)\exp(-\mu\varepsilon)
\]  

(1)

where \( F \) is the output force of PAM; \( \varepsilon = (L_0 - L)/L_0 \) is the contraction rate of PAM; \( L_0 \) and \( L \) are the original length and the actual length of PAM, respectively; \( p \) is the inner pressure of pneumatic muscles; \( k_1(p) = k_{11}p + k_{12} \) are
pending coefficients depended on \( p \), \( k_1 \), and \( k_2 \) are fitting coefficients, which are different in the inflation and the deflation processes; and \( \mu \) is the nonlinear attenuation coefficient of \( \varepsilon \).

Equation (1) can be rewritten as

\[
F(\varepsilon,p) = (k_{11}p + k_{12}) - (k_{21}p + k_{22})\varepsilon + (k_{31}p + k_{32})\exp\left(-\mu\varepsilon\right) + h(\varepsilon) + f_b(\varepsilon) + \frac{mgl\sin(\theta)}{J}
\]

where \( g(\varepsilon) = k_{11} - k_{21}\varepsilon + k_{31}\exp\left(-\mu\varepsilon\right) \) and \( h(\varepsilon) = k_{12} - k_{22}\varepsilon + k_{32}\exp\left(-\mu\varepsilon\right) \).

The dynamic function of the bionic robotic joint actuated by antagonistic PAMs, as shown in Figure 1, is as follows

\[
\begin{align*}
J\ddot{\theta} + f_b\dot{\theta} & = (F_1 - F_2)r - mgl\sin(\theta) + d \\
\dot{x}_1 & = x_2 \\
\dot{x}_2 & = \frac{(h(\varepsilon_1) - h(\varepsilon_2))}{}r - mgl\sin(x_1) - f_bx_2 + \frac{(g(\varepsilon_1)p_1 - g(\varepsilon_2)p_2)r}{J} + \frac{d}{J}
\end{align*}
\]

Let \( f(x) = [(h(\varepsilon_1) - h(\varepsilon_2))r - mgl\sin(x_1) - f_bx_2]/J \), \( b = r/J \), \( d_j = d/J \), and describe the control input as \( u = g(\varepsilon_1)p_1 - g(\varepsilon_2)p_2 \), then we have

\[
\begin{align*}
\dot{x}_1 & = x_2 \\
\dot{x}_2 & = f(x) + bu + d_j
\end{align*}
\]

This is a second-order nonlinear system with its control inputs \( u \) decided by the inner pressures of the pair of PAMs: \( p_1 \) and \( p_2 \). By controlling the pressure difference between the two antagonistic PAMs, we may exert the desired actuate force on the studied joint to achieve the expected motion.

**Control algorithm combines extended state observer and full-order sliding mode control**

As mentioned before, it is very difficult to model the robotic joint actuated by antagonistic PAMs accurately because of the strong nonlinearity of PAM. Therefore, we view the model inaccuracy as a kind of internal disturbance and propose an FSMC-ESO scheme that combines the ESO
and the fSMC for a robotic joint actuated by a pair of antagonistic PAMs. The fSMC is employed to eliminate the chattering and guarantee the finite-time convergence, and the ESO is adopted to observe both the total disturbance and the states of the robot system, so that we can inhibit the disturbance and compensate the nonlinearity efficiently. In this way, we try to achieve the robust human-like motion control in the studied bionic robotic joint system.

**Human-like motion pattern**

Assuming that the free human motion is optimal and corresponds to the minimal jerk model, Flash and Hogan verified that the free motion trajectory of the human hand satisfies the logistic function, which can be described as follows

\[
\frac{\partial}{\partial t} x = \frac{\partial}{\partial s} \left( \frac{\partial}{\partial t} \left( \frac{\partial}{\partial s} \left( \frac{\partial}{\partial s} x \right) \right) \right) = \alpha_1 \frac{\partial}{\partial s} x + \alpha_2 \frac{\partial^2}{\partial s^2} x + \alpha_3 \frac{\partial^3}{\partial s^3} x
\]

where \( \alpha_1, \alpha_2, \alpha_3 \) are constants. The control function (15) can serve as a low-pass filter to inhibit the high-frequency disturbance and enhance the robustness of the system, where \( T = 0.01 \text{ Hz} \) is the bandwidth of the low-pass filter.

The control performance of both cSMC and fSMC controller on the robotic joint system via simulations. The parameters of the mathematical model of PAM are given in Table 1. Sinusoidal disturbance as a kind of external disturbance often occurs in the control of nonlinear systems. Therefore, we take \( d = 0.1 \sin (2\pi t) \) as the disturbance. The tracking performance of cSMC and ISMC is shown in Figure 2, from which we can learn that both the cSMC and the fSMC can almost track the desired trajectory but fSMC outperforms cSMC with much less both error and derivative of the error. Therefore, both the tracking error and the approaching time of the system need to be further improved for better performance of human-like motion control.

**Full-order sliding mode control extended state observer approach**

The ESO is able to estimate both the state variable and the total disturbance so as to make the whole control system more robust. Therefore, we combine ESO and ISMC to control the aforementioned robotic joint actuated by PAMs.

### Table 1. Parameters of mathematical model of PAMs.

| Parameter |  \( k_{11} \) |  \( k_{12} \) |  \( k_{21} \) |  \( k_{22} \) |  \( k_{31} \) |  \( k_{32} \) |  \( L_0 \) (m) |
|-----------|----------------|----------------|----------------|----------------|----------------|----------------|---------------|
| Value     | 2.573          | -222.7         | 6.389          | 1347.3         | 0.296          | 141.5          | 0.2           |

PAM: pneumatic artificial muscle.
As mentioned in the second section, when we model the robotic joint system, we only adopt the inflation part of Yu’s static model of PAM for the convenience of calculation. As for the inaccuracy of the system model caused by the incompleteness of the model of PAM, we count on the robustness of the control scheme. We view the uncertainties caused by the model imprecision as a kind of internal disturbance and apply the ESO to estimate the total disturbances (including both the external and the internal disturbances) and eliminate them via fSMC.

Besides the states of $x_1$ and $x_2$, as defined in equation (7), we define an extended state $x_3 = f(x) + d_f$ as the total disturbance in the system, and consequently, we get a new model of the studied robotic joint system described with the new set of state variables

\[
\begin{align*}
\dot{x}_1 &= x_2 \\
\dot{x}_2 &= x_3 + bu \\
\dot{x}_3 &= f(x) + d_f \\
y &= x_1
\end{align*}
\]

(16)

Define $z_1$, $z_2$, and $z_3$ as the estimated value of the state variables $x_1$, $x_2$, and $x_3$, respectively, then we have the following system model of the tracking control system

\[
\begin{align*}
e_1 &= z_1 - y \\
\dot{z}_1 &= z_2 - \beta_{01} e_1 \\
\dot{z}_2 &= z_3 - \beta_{02} e_1 + bu \\
\dot{z}_3 &= -\beta_{03} e_1
\end{align*}
\]

(17)
which are positive constants and we set it as $\omega = 150 \text{ rad/s}$ according to reference.\textsuperscript{35}

The structure of the tracking control system of the studied robotic joint is shown in Figure 3. It estimates both the internal disturbances (model uncertainty) and the external disturbances with ESO and eliminates these disturbances via fSMC. Consequently, it achieves the expected tracking control performance with the control input as follows

$$u = -b^{-1} \left( -\dot{x}_d + z_3 - c_2 \text{sign} (\dot{e}) |\dot{e}|^{\alpha_2} \\
- c_1 \text{sign} (e) |e|^{\alpha_1} + u_n \right)$$

where $c_1 = 16, c_2 = 6$, and $\alpha_i (i = 1, 2)$ are the same as the values in fSMC.

Again, we validate the performance of the fSMC-ESO approach via simulation by tracking the desired trajectory with a sinusoidal disturbance signal $d = 0.1 \sin (2\pi t)$. The tracking performances of both fSMC and fSMC-ESO are shown in Figure 4, from which we can learn that the fSMC-ESO approach outperforms fSMC with much fewer fluctuations of both the joint angle tracking error and the derivative of joint angle. The joint angle error of fSMC-ESO almost converges to zero.

Both the phase trajectory and the manifold are shown in Figure 5, where $e$ is the tracking error of the robotic joint, $de$ is the derivative of error, and $dde$ is the second derivative of error, and they constitute a three-dimensional sliding manifold. The phase trajectory of the system starts from the beginning point because the initial state of the bionic joint system is zero joint angle, zero angular velocity, and zero angular acceleration. Figure 5 validated that the designed controller will drive the state of the system approaching to
and sliding along the manifold, and eventually wrapping around the zero point.

**Simulation and physical experiments**

We validate the proposed approach via physical experiments on a robotic joint actuated by a pair of antagonistic PAMs, as shown in Figure 1(b). The PAMs are FESTO DMSF-20-200 with pretension of 40 N, and the parameters of the robotic joint are presented in Table 2.

We keep the antagonistic tension as a fixed value of $F_2 \equiv 40$ N, then $p_2$ can be obtained according to equation (2), and $p_1$ can be calculated via $u = g(e_1)p_1 - g(e_2)p_2$, as presented in equation (6). In the physical experiments, we set sampling time is 0.01 s, $x_f = 90^\circ$, and $t_f = 2$ s.

We firstly validate the performance of the proposed fSMC-ESO approach on the bionic joint model without external disturbance ($d = 0$) with constant external disturbance ($d = 2$ rad) and with variable external disturbances (sinusoidal signal, $d = 2 \sin (2\pi t)$, and $d = 2 \sin (\pi t)$). The simulation results (the output of the control system and the result of state observation) are shown in Figures 6 and 7, respectively. Figure 6 shows that under different disturbances, the bionic joint can track the desired curve well. In the case of sinusoidal disturbances ($d = 2 \sin (2\pi t)$ and $d = 2 \sin (\pi t)$), the bionic robotic joint can closely track the desired trajectory with a small error (the amplitude is 0.006 and 0.001, respectively) with the same frequency of the external disturbances signal, which is acceptable. Figure 7 validates that the ESO can accurately observe the state variation (including the external disturbances) of the system. The observation will improve the control performance of the fSMC as a result.

Then, when the external disturbance is zero, we change the payload of the physical robotic arm to validate the robustness of the proposed fSMC-ESO approach to the load variation. Figure 8 shows the changing process of tension, pressure, and length of the antagonistic PAMs in the course of human-like motion of the robotic joint with a payload of 1, 3, and 5 kg, respectively. From Figure 8, we can learn

| Parameter | $m_{pulley}$ (kg) | $r$ (m) | $m$ (kg) | $l$ (m) | $f_b$ (N·s/m) |
|-----------|------------------|---------|---------|---------|---------------|
| Value     | 0.2              | 0.016   | 3       | 0.2     | 0.2           |

Figure 5. The sliding surface and the phase portrait of sliding motion.

Figure 6. Simulation result of joint angle response under different disturbances.
that the proposed approach can adjust the air pressure of PAMs according to load variation. As a result, the proposed fSMC-ESO approach possesses good performance of robustness to the payload variation as well as the good performance of human-like motion patterns.

Figures 9 and 10 show two physical experiment results of the robotic joint, from which we can see that the studied approach can achieve the expected human-like motion pattern with a small overshoot (less than 1.2%, i.e. 1.1° angle). An estimated initial value of the total disturbance, which can be approximately determined via simulations and experiments, is helpful for suppressing the fluctuations at the initial period of the rise time, and as a result, improving the performance of the control system. We can estimate this initial value according to the wave amplitude (about 60) of the initial phase of Figure 7 and accordingly adjust it in the experiment. From the experimental results ($z_I(0) = 70$ and $130$, as shown in Figures 9 and 10, respectively), we can learn that the latter is better because of smaller fluctuations. At the time of 6.5 s, an external disturbance is exerted on the robotic arm, and the control system is able to suppress the disturbance and drive the platform back to its primary position within the settling time of 1 s. From both Figures 9 and 10, we can note that the ESO can exactly observe the states of the control system whether in the normal human-like motion course or under an unexpected external disturbance. We reasonably attribute the aforementioned good performances of trajectory tracking and robustness of the robotic joint to
both the powerful state observing ability of ESO and the powerful nonlinear control ability of fSMC.

**Conclusions**

PAM prominently possesses desirable compliant actuating properties that are similar to those of human muscles. Therefore, it is expected to play an important role in endowing the advanced robot with the ability of coexisting and cooperating with human beings. However, PAMs also possess strong nonlinearities, hysteresis effects as well as the uncertainty of parameters. These unfavorable characteristics severely impede the application of PAMs. To address this issue, we proposed an fSMC-ESO approach that combines the ESO and the fSMC to achieve human-like motions on a bionic joint system actuated by a pair of antagonistic PAMs and validated that the proposed scheme outperforms both cSMC and fSMC via comparative studies of simulations and physical experiments.

The advantages of the fSMC-ESO approach include the following:

Firstly, the approach can compensate for the imprecision of the plant model. As mentioned, it is very difficult to model a PAM actuator precisely, and the imprecision of the model will seriously impact the performance of the control system. Though hysteresis is a typical feature of the PAM, we achieve good control performance of the robotic joint system by only taking the inflation part of Yu’s static model of PAM in our control algorithm design. These results validated that the proposed approach can observe the imprecision of the system model via ESO, and then view the model imprecision as a kind of internal disturbance and compensate it via fSMC.

Secondly, the approach can effectively inhibit the external disturbances of the robotic system. As mentioned, the PAM is a kind of flexible actuator, which has the advantages of natural compliance for the safety of human–robot interaction but also has the disadvantages of oscillation under disturbance, which will bring adverse impacts on the stability and accuracy of the control system. Again, we validated that the studied approach can achieve good performance by observing the external disturbance (whether constant or variable) via ESO and inhibiting it via fSMC.

Thirdly, the approach can achieve good performance of the human-like motion, which is critical for safe and effective human–robot cooperation. Because of the good (internal and external) disturbance observing and compensating ability of the fSMC-ESO approach, it endows the robotic joint system good performance of robustness and tracking accuracy for the human-like motion pattern of logistic function. We suggested that the proposed method can be applied to the robotic systems actuated by PAMs and consequently improve their performance of human–robot cooperation.

In future studies, we will develop the application of the proposed fSMC-ESO approach on a homogeneous humanoid robotic arm, with which its joints actuated by pair of antagonistic PAMs, to achieve the human-like logistic pattern of arm motion, and finally realize the safe and friendly human–robot interaction/cooperation.

**Declaration of conflicting interests**

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