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Indirect sliding mode control based on gray-box identification method for pneumatic artificial muscle

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ABSTRACT

We present an indirect robust nonlinear controller for position-tracking control of a pneumatic artificial muscle (PAMs) testing system. The system modeling is reviewed, for which the existence of uncertain, unknown, and nonlinear terms in the internal dynamics is presented. From the obtained results, an online identification method is proposed for estimation of the internal functions with learning rules designed via a Lyapunov derivative function. A robust nonlinear controller is then designed based on the approximated functions to satisfy the control objective under the sliding mode technique. Appropriate selection of the smooth robust gain and the sliding surface ensures convergence of the tracking error to a desired level of performance. Stability of the closed-loop system is proven through another Lyapunov function. The proposed approach is verified and compared with a conventional proportional–integral–differential (PID) controller, adaptive recurrent neural network (ARNN) controller, and robust nonlinear controller in a real-time system with three different kinds of trajectories and loading. From the comparative experimental results, the effectiveness of the proposed method is confirmed with respect to transient response, steady-state behavior, and loading effect.

1. Introduction

Pneumatic artificial muscles (PAMs) have become increasingly popular in industrial automation and robot applications, especially for rehabilitation robots. Some remarkable achievements include the development of single joint therapy machines [1–3], parallel manipulators [4], and humanoid robots [5]. The original device was developed by McKibben in the 1950s for prosthetic and orthotic applications. A PAM usually consists of a contraction system that is formed by an inside inflatable rubber hose covered with loose-weave fiber, and fitting connections. When pressurized, the actuator shortens, generating a contraction force along the axial direction. Fig. 1 shows the basic structure of the device. Despite many advantages such as safety, low cost, cleanness, light weight, high force/weight ratio, and high force/volume ratio, modeling and control of the actuator have posed major challenges due to the existence of uncertain, unknown, and highly nonlinear terms. The following presents a survey of related works on the device in the literature.

Many approaches have been developed for the modeling of actuator dynamics in recent decades. Concerning mathematical approaches, the static and dynamic characteristics of the PAM were derived from physical analysis by Chou et al. and Tondu et al. [6–8]. Some general aspects were deeply considered in such studies; for example, the relationship between pressure and force, changes in the geometric structure, the contraction ratio, the elastic characteristics, and viscous and Coulomb friction. However, validating the obtained results shows that it is difficult to describe an accurate model of the actuator. Thus, several experimental approaches have been developed to provide a more exact explanation of the actuator dynamics [9–12]. Although the actuator dynamics have been estimated from empirical data and then successfully applied in real applications, these methods have limited popularity. Another category of intelligent modeling was developed in recent years [13,14]: basic and modified genetic algorithms have been used to approximate the parameters of system models that are considered to be nonlinear auto-regressive exogenous (NARX) fuzzy configurations. The black-box model was obtained from offline input/output data acquisition. Unlike the aforementioned approaches, our study proposes a new online identification method for the estimation of the internal dynamics of a PAM system based on current input/output data. First, the system model

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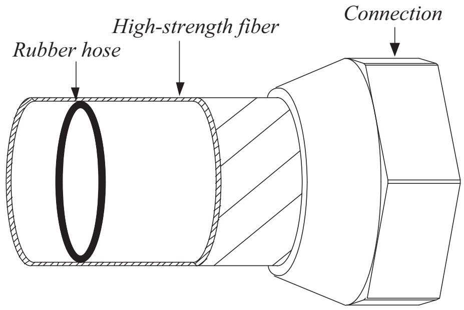

Fig. 1. Typical structure of the PAM actuator.

is derived with the presence of the uncertain, unknown, and nonlinear terms, (the exact details are difficult to obtain) [6–8]. The inputs of the internal functions are known. Proper neural networks are then considered to be estimates of these functions. The learning laws of the networks are developed from a special Lyapunov function. Hence, through this method, the terms influencing the system are updated and fed to a position controller simultaneously.

In order to cover the challenges in control performance, a number of approaches have been developed to overcome the modeling drawbacks of the actuator. Among the approaches, Kawashima et al. [15] proposed a proportional–integral–differential (PID) controller for a six degree-of-freedom (DOF) robotic arm driven by PAM actuators. The mathematical model of the device was analyzed, and the controller was then constructed based on the modeling results. Since the actuator is very nonlinear and sensitive to working conditions (including the supplied pressure and temperature), the controller only works well in a specific region. Another major category of intelligent approaches to improving control performance includes neural network-based controllers [16,17], the fuzzy PD+I learning control method [18], advanced nonlinear PID control using a neural network [19,20], enhanced state network controllers [21], and combinations of fuzzy and neural approaches [22,23]. The uncertain, unknown, and nonlinear terms of the system can be compensated by these methods. Thus, control results can be enhanced significantly. However, the robustness and stability of the closed-loop system have not been proven. In addition, other possible advanced approaches have been found, such as adaptive pole-placement controllers based on system estimation [24], nonlinear model-based robust adaptive controllers [25–32], model-based hysteresis compensation [33–35], and T-S fuzzy model-based tracking controllers [36]. Although such methods maintain robustness and adaptation, they have the drawback of dependence on the accuracy of system dynamics. Hence, a number of intelligent nonlinear methods have been introduced based on the integration of fuzzy and nonlinear control [37–40], and on the switching predictive approach [41]. The dependence on system modeling has been resolved by these control laws; however, the self-learning characteristics are still a limitation.

In the present study, the problem of dependence on system modeling is addressed by the proposed identification method. In addition, to satisfy the control objective and handle the identification errors, we propose a robust nonlinear controller for the studied system under the sliding mode scheme. An integral term of control error is added to the sliding surface to improve the steady-state tracking error, and a smooth robust term is used to avoid the chattering problem. An appropriate choice of robust gain and the sliding surface ensures that the tracking error will converge to a desired bound. The stability of the closed-loop system is proven through another Lyapunov function. The robustness provided by the control method, and the adaptation from the identification technique of the proposed approach, are presented. To verify the designed controller, experiments are carried out in a real-time system with three different kinds of trajectories and loadings. A conventional PID controller, an adaptive recurrent neural network (ARNN) controller [17], and a conventional sliding mode (CSM) controller are employed in the same system and under the same conditions to provide a more concrete validation of the controller. From the obtained comparative experimental results, the effectiveness and feasibility of the proposed approach are strongly confirmed with respect to transient response, steady-state behavior, and loading effect.

The remainder of the paper is organized as follows: the identification idea is derived in Section 2, an overview of the studied system is given in Section 3, an application of the identification method to the system and the robust nonlinear control design are shown in Section 4, the experimental results are discussed in Section 5, and our conclusions are presented in Section 6.

2. Identification of system dynamics

In this section, an identification method is proposed for the approximation of the internal dynamics of a bounded system. The method considers not only the parametric uncertainties, the uncertain nonlinearities, and the hard-to-model dynamics, but also the unknown terms.

Consider a nonlinear system expressed in the following state-space form:

$$\dot{x} = f(x) + g(x)u \tag{1}$$

where $x = [x_1; x_2; \ldots x_n]^T$ is the state variable vector on a compact region $D \in R^n$, u is the input signal of the system, and $f(x)$, $g(x)$ are the unknown internal functions that will be identified through the following idea.

Assumption 1. The input signal u and the state vector x can be measured and bounded. The internal functions $f(x)$, $g(x)$ are also bounded. $f(x)$ is called the offset function and $g(x)$ is called the activation function. Consequently, system (1) is a stable open loop.

Define a positive value ∂_u as the boundary of the signal u:

$$|u| \le \partial_u \tag{2}$$

Assumption 2. With any function $z = h(x)$, there exists a neural network to approximate the z function, or

$$z^* = W^{*T}\xi(x) \tag{3}$$

where $\xi(x) = [\xi_1; \xi_2; \ldots \xi_l]^T$ is the hidden neural matrix, and $W^* = [W_1^*; W_2^*; \ldots W_l^*]^T$ is the constant weight matrix of the output layer, which satisfies the following condition:

$$\sup|z - W^{*T}\xi(x)| \le \sigma_0, \quad (\sigma_0 \ge 0) \tag{4}$$

in which σ_0 is a bounded value. Note that if the functions z and $\xi(x)$ are bounded, W^* is also bounded. This assumption was introduced in [42].

Based on this assumption, $f(x)$, $g(x)$ can be expressed in the following forms:

$$f(x) = W_f^{*T}\xi_f(x) + \sigma_f, \quad \sup|\sigma_f| \le \sigma_{f0} \;\&\; \sigma_{f0} \ge 0 \tag{5}$$

$$g(x) = W_g^{*T}\xi_g(x) + \sigma_g, \quad \sup|\sigma_g| \le \sigma_{g0} \;\&\; \sigma_{g0} \ge 0 \tag{6}$$

where σ_f, σ_g, σ_{f0}, and σ_{g0} are bounded values, and σ_{f0}, σ_{g0} are the boundaries of σ_f and σ_g, respectively. Thus, model (1) has the following equivalent form: