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Research paper

Hysteresis modeling and trajectory tracking control of the pneumatic muscle actuator using modified Prandtl–Ishlinskii model

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ABSTRACT

The pneumatic muscle actuator (PMA) has attracted extensive attentions from both industrial and academic fields due to its high power/weight ratio and significant compliance. However, on the one hand the inherent hysteresis nonlinearity has high influence on the accuracy of trajectory tracking control of PMA, and on the other hand a system actuated by PMAs is at a high cost. This paper presents a modified Prandtl–Ishlinskii (MPI) model for the asymmetric hysteresis characterization and compensation of the PMA using fast switching valves. By using the Levenberg–Marquardt (L-M) method, the parameters in the MPI model are identified. To compensate the nonlinear length/pressure hysteresis and reduce the cost, a cascade control scheme using fast switching valves based on the inverse MPI model is developed to realize the trajectory tracking control. The experimental result shows the effectiveness of the proposed control scheme on compensating the asymmetric length/pressure hysteresis of the PMA.

1. Introduction

In the last few decades, great efforts have been made to develop robots possessing the characteristics of human-friendly [1] and high mechanical impedance [2]. The applications include but not limited to rehabilitation, service and surgery [3], where compliant actuators are absolutely essential to avoid accidental injury to humans. As a classical compliant actuator, the pneumatic muscle actuator (PMA) possess several unique advantages, such as compactness, low cost, high power-to-weight ratio and significantly similar compliance as muscles [4,5]. These characteristics make it widely used in medical nursing [6], elbow exoskeleton [7], lower-limb rehabilitation [8] and arm/ankle orthotics [9]. However, the accurate trajectory tracking control of a PMA is by no means an easy task and usually at a high cost, due to the inherent hysteretic behavior and nonlinearity during its working process.

To achieve the accurate trajectory tracking control of PMAs, two approaches are utilized in the state of the art [10], i.e. the model-based advanced control algorithms and the feed-forward hysteresis compensation. Along the first track, the hysteresis is considered as the disturbance or unmodeled dynamics, which is tackled by using advanced nonlinear control algorithms [11], such as the adaptive robust control [12], the slide mode control [13], the artificial neural network [14] However, the inherent chattering property of sliding mode strategy caused by the discontinuous switching may lead to unmodeled high-frequency and even make system instable [15]. The feedback linearization method is rigorously dependent on the accuracy

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of the mathematical model, resulting in large linearization errors. Thus, it may degrade the control performance, and even cause instability [15]. The artificial neural network is only valid for the description of single-loop hysteresis, which cannot be directly used for the modeling of the multi-valued hysteresis loops [16]. Although these algorithms can be used to improve the performance of trajectory tracking *via* compensating the model errors and uncertainties, they are highly dependent on the accuracy and stability of the controlled system. Therefore, great efforts have been made to characterize the hysteresis phenomenon amongst the length, pressure and pulling force of the PMA to improve its dynamic response. For example, the force/length or length/pressure hysteresis loop is modeled precisely to characterize the complex hysteresis nonlinearity, and its inverse is used to linearize the response of the PMA [17]. The hysteresis models can be roughly divided into two classes [18]: (1) operator-based models, utilizing different kinds of mathematical operators to characterize the hysteresis loops, such as Preisach model [19], Prandtl–Ishlinskii (PI) model [20], Maxwell-Slip model [21] and its modified version [22]; (2) differential-based models, adopting nonlinear differential equations to characterize the hysteresis dynamics [23], such as Duhem model [24], Bouc–Wen model [23,25] and its variations [26]. Among these investigations, the PI model is the most widely used model due to its simple expression and analytical inversion, which makes it efficient for real-time applications. It has to be pointed out that the classical PI model is unable to describe asymmetric hysteresis loops [27], thanks to the symmetric property of linear play operators. Therefore, asymmetric hysteresis modeling approaches, especially for smart materials, ferromagnetic materials and smart actuators, are intensively studied. Kuhen [28] proposed a modified PI (MPI) model that combines the linear play operators with the dead-zone operators, which is capable of describing the asymmetric hysteresis of magnetostrictive actuators. Gu [17] combined a classical PI model with a nonlinear non-hysteretic function of the input to capture the asymmetric hysteresis of piezoceramic actuators. Al Janaideh [29] proposed a generalized PI (GPI) model to characterize the saturated symmetric hysteresis loops of smart actuators. However, few researches show the effectiveness of these variations of the PI model on PMAs except for the investigation carried out in [10,30], where a modified PI model utilizing two independent operators to describe the ascending and descending branches of hysteresis loops was presented.

Moreover, the control of a PMA is usually at a high cost due to the employment of expensive pressure sensor and proportional valve. One way to reduce the cost is utilizing a globally stable pressure observer instead of the necessary pressure sensor [3]. An alternative approach is replacing the proportional valve by inexpensive fast switching valve [3,15,31,32]. However, few studies show the effectiveness of fast switching valve on the length/pressure hysteresis compensation of a PMA except for the investigation carried out in [20], where the PI model was used to describe the length/pressure hysteresis of a PMA, but this approach was only testified by simulation. Mainly drawing on the MPI model proposed by Kuhen [28], this paper deals with the length/pressure hysteresis modeling and compensation of the PMA using fast switching valves. The rest of this paper is organized as follows. In Section 2, the analytical formulation of the MPI model and its inverse is presented. Then, the length/pressure hysteresis characteristic is discussed in Section 3, followed by the parameter identification of the model using the Levenberg–Marquardt method. Section 4 presents a cascade control scheme based on the compensator of the inverse MPI model using fast switching valves for the trajectory tracking control. Finally, conclusions are drawn in Section 5.

2. Mathematical formulation of MPI model

In this section, the PI model and the DZ model are briefly reviewed. In order to characterize asymmetric hysteresis loops of a PMA, a modified PI (MPI) model is proposed by making a combination of the PI and DZ models.

2.1. PI model

The elementary operator of the PI model is a linear play operator (LPO), which can be mathematically illustrated as shown in Fig. 1. The expression of the ith LPO can be formulated as [20]

$$y_i(k) = \max\{x(k) - r_i, \min\{x(k) + r_i, y_i(k-1)\}\} \tag{1}$$

while the initial condition is

$$y_i(0) = \max\{x(0) - r_i, \min\{x(0) + r_i, y_{i0}\}\} \tag{2}$$

The output of the PI model can be derived as

$$y_P(k) = \sum_{i=1}^{n} \omega_i y_i(k) = \boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{H}_r[x(k), \boldsymbol{y}_0] \tag{3}$$

where $\boldsymbol{H}_r$ denotes the vector of LPOs; $\boldsymbol{\omega} = [\omega_1, \ldots, \omega_n]^{\mathrm{T}}$ is the weighting vector; $\boldsymbol{r} = [r_1, \ldots, r_n]^{\mathrm{T}}$ is the threshold vector; x and y_P are the input and output of the PI model, respectively; $\boldsymbol{y}_0$ is the initial state; n is the number of play operators. From Eq. (1), the inverse PI model can be formulated as [20]

$$x_i'(k) = \max\{y(k) - r_i', \min\{y(k) + r_i', x_i'(k-1)\}\} \tag{4}$$