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Improved EHM-based NN hysteresis model

Lianwei Ma [a,*], Yonghong Tan [a,b], Ya Chu [c]

[a] A0203091, Department of Automatic Control, Shanghai Jiaotong University, Shanghai 200240, China
[b] Laboratory of Intelligent Systems and Control Engineering, Guilin University of Electronic Technology, Guilin 541004, China
[c] SGS-CSTC Standards Technical Services Co. Ltd., Gzhou Lab, Guangzhou 510660, China

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Abstract

An improved EHM-based hysteresis model is proposed in this paper. In this scheme, neural networks are employed to implement the mapping between the input and output of hysteresis. The so-called elementary hysteresis model (EHM) is introduced to construct the transformation to transform the multi-valued mapping of hysteresis into a one-to-one mapping. In order to construct the EHM, parabolas are chosen as monotone curves in the EHM-based NN model. In this paper, a new method for determining the coefficients of the parabolas is proposed. The coefficients of the parabolas are different from each other in the improved EHM-based NN model. Finally, both the numerical and experimental examples of using the proposed modeling scheme are presented.

Keywords: Hysteresis; EHM; Neural network

1. Introduction

It is well known that hysteresis is a type of non-differentiable nonlinearity, and is usually complex and poorly understood. Hysteresis often exists in control systems, magnetic suspensions and bearings contain the typical systems with hysteresis in their input. There is hysteresis presented in air disk brakes and piezoelectric positioning systems. The existence of hysteresis severely limits system performance, giving rise to undesirable inaccuracy, oscillations, or even leading to instability.

The existing control methods mainly implement their inverse models to compensate for the effects of hysteresis. Those control methods often require accurate models and inverse models as well. Thus, it is necessary to construct accuracy hysteresis models and its inverse models.

In past decade, neural networks (NN) have been widely and successfully used in many fields, including the modeling of hysteresis. However, the relationship between the input and the output of hysteresis is a kind of multi-valued mapping. Both theory [1] and practice have proven that the traditional modeling schemes of NN can only approximate one-to-one or multiple-to-one mapping. Wei and Sun [1] proposed a novel neural network cell as the propulsive neural unit. Hwang et al. [2] utilized two neural networks to approximate the descending and ascending parts of hysteresis loops, respectively. Nafalski et al. [3] used a NN to replace hysteresis models. Taga et al. [4] developed a network containing six-coupled oscillators, as neurons, to control a two-wheeled locomotive. The locomotive exhibits hysteresis when a change in movement occurs. It can be seen that the approaches mentioned above are basically limited to some simple cases, such as single loop or first-order reserve curve. It is seldom to find the reports in literature on the dynamic hysteresis model, which can be adapted to any input signal. Thus, it would be useful to find a method to transform the multi-valued mapping of hysteresis into a one-to-one mapping. Tong et al. proposed the EHM-based NN model in Ref. [5]. The EHM constructs a one-to-one mapping relation between the input space and the output space of NN. But the proof was not sufficient in Ref. [5]. At the same time, the coefficients of the monotone curves are equal in EHM-based NN model. In fact, the precision

* Corresponding author.
E-mail address: chris5257@163.com (L. Ma).

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is not guaranteed if the coefficients are equal in each modeling procedure. Therefore, it is necessary to look for a new method to calculate the coefficients.

2. EHM-based NN hysteresis model

EHM-based NN hysteresis model [5] adopts the continuous transformation approach to construct one-to-one mapping between the input signal and output of the hysteresis. Its basic idea is that when an extremum of input occurs, move a motion point along a regular curve that is a part of a monotone conic, so as to produce a branch of minor or main loop. By continuously transforming, an arbitrary number of hysteresis minor loops can be obtained so that an elementary hysteresis model (EHM) can be constructed. The EHM extracts the elementary information of hysteresis so that the expanded input space can be constructed. Based on the constructed expanded input space, a neural network can be used to approximate hysteresis.

A plane of Cartesian coordinate system (e.g. point o, x–y, see Fig. 1) that is called major coordinate system (x–y) is constructed. When an input extremum occurs, another coordinate system (e.g. point i, x_i–y_i, see Fig. 1) is constructed, the ith minor coordinate system. Let the motion point move along a monotone curve under the minor coordinate to produce a branch of minor loop, so does each extremum point. A monotone curve replaces each branch of the minor and the major loops. The equation of coordinate transformation [6] is as follows:

$$\begin{bmatrix} x(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} \cos\theta_i & -\sin\theta_i \\ \sin\theta_i & \cos\theta_i \end{bmatrix} \begin{bmatrix} x'(t) \\ y'(t) \end{bmatrix} + \begin{bmatrix} x_i(t) \\ y_i(t) \end{bmatrix} \tag{1}$$

where $x_i(t)$ and $y_i(t)$ are respectively the ith input extremum and the calculated output corresponding to the original point of the ith minor coordinate system. $x'(t)$ and $y'(t)$ are respectively the input and the calculated output under the ith minor coordinate system. $x(t)$ and $y(t)$ are respectively the actual input and the calculated output under the major coordinate system. θ_i is the transformation angle of the ith minor coordinate system to the major coordinate system. Notice that the above calculated output values are computed via suitably selected curve equations.

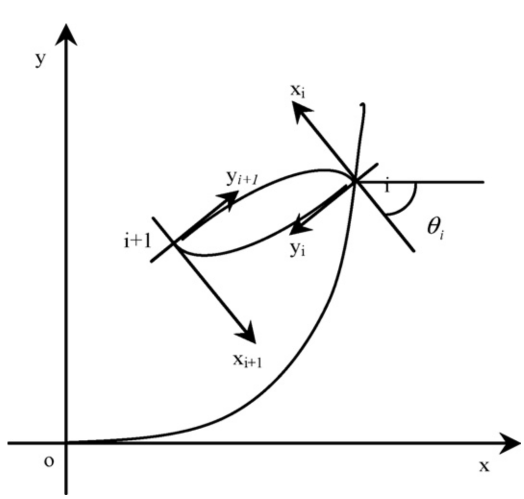

Fig. 1. Coordinate transformation.

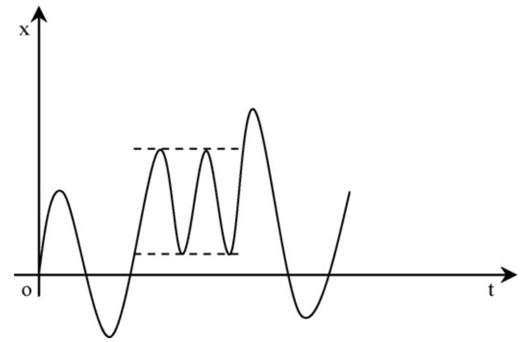

Fig. 2. Excluded time-varying input signal.

Assumption 1. The input is assumed to be a smoothly periodical signal. Moreover there are not any continuously uniformed maxima and minima pairs in a cycle.

Fig. 2 shows the situation excluded by Assumption 1. The mapping of the two continuously uniformed maxima and minima pairs of the hysteresis are completely superposed into two minor loops.

The proposed EHM $f(x)$ is defined as

$$f(x) = \begin{cases} f(x_e) + [x - x_e]^2 & \dot{x} > 0 \\ f(x_e) - [x_e - x]^2 & \dot{x} < 0 \end{cases} \tag{2}$$

where x is the current input, $f(x)$ is the current output and x_e is the dominant extremum adjacent to the current input x. $f(x_e)$ is the output of the EHM when the input is x_e.

Lemma 1. *Let $x(t) \in C(R)$, where $R = \{t \mid -\infty < t < \infty\}$ and $C(R)$ is the sets of continuous functions on R. For the different time instances t_1 and t_2 ($t_1 \neq t_2$), $x(t_1) = x(t_2)$, but it leads to $f[x(t_1)] \neq f[x(t_2)]$, where $x(t_1)$ and $x(t_2)$ are not the extrema.*

Proof. Considering the segment $x(t)$ decreases monotonically, (2) becomes

$$f(x) = f_{de}(x) = f(x_e) - [x_e - x]^2 \tag{3}$$

where $f_{de}(x)$ is the decreasing segment of the function, x_e is the maximum extremum of the input, whilst

$$f(x) = f_{in}(x) = f(x_e) + [x - x_e]^2 \tag{4}$$

denotes the increasing segment of the function. In this case, x_e is the minimum extremum of the input. Since

$$\frac{d f_{in}(x)}{dx} = 2(x - x_e) > 0 \tag{5}$$

$$\frac{d f_{de}(x)}{dx} = 2(x_e - x) > 0 \tag{6}$$

Therefore, $f_{in}(x)$ and $f_{de}(x)$ are monotonic.

It is noted that $t_1 \neq t_2$ and $x(t_1) = x(t_2)$ in Fig. 3. x_{e1} and x_{e2} are respectively the dominant extrema of $x(t_1)$ and $x(t_2)$. Fig. 4 is the corresponding input-output curve of EHM. According to (3):

$$f[x(t_1)] = f(x_{e1}) - [x_{e1} - x(t_1)]^2 \tag{7}$$