A Composite Controller for Piezoelectric Actuators with Model Predictive Control and Hysteresis Compensation

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Abstract. Piezoelectric actuators (PEAs) are ubiquitous in nanopositioning applications due to their high precision, rapid response and large mechanical force. However, precise control of PEAs is a challenging task because of the existence of hysteresis, an inherent strong nonlinear property. To minimize its influence, various control methods have been proposed in the literature, which can be roughly classified into three categories: feedforward control, feedback control and feedforward-feedback control. Feedforward-feedback control combines the advantages of feedforward control and feedback control and turns into a better control scheme. Inspired by this strategy, a composite controller is proposed for the tracking control of PEAs in this paper. Specifically, the model of PEAs is constructed by a multilayer feedforward neural network (MFNN). This model is then instantaneously linearized, which leads to an explicit model predictive control law. Then, an inverse Duhem hysteresis model is adopted as a feedforward compensator to mitigate the hysteresis nonlinearity. Experiments are designed to validate the effectiveness of the proposed method on a piezoelectric nanopositioning stage (P-753.1CD, Physik Instrumente). Comparative experiments are also conducted between the proposed method and some existing control methods. Experimental results demonstrate that the root mean square tracking error of the proposed method is reduced to 16% of that under the previously proposed model predictive controller [16].

Keywords: Feedforward-feedback control · Hysteresis compensation · Model predictive control (MPC) · Instantaneous linearization · Piezoelectric actuators (PEAs)

1 Introduction

Recent decades have witnessed the explosive development of nanotechnology which has been recognized as the fundamental requirement of modern manufacturing and process industry. To fulfill this requirement, piezoelectric actuators (PEAs) have been widely applied in nanopositioning applications such as

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micromanipulators [1], nanopositioning stages [2] and atomic force microscopes [3] because of their predominant capabilities of rapid response, high resolution, large mechanical force and wide operating bandwidth. However, the intrinsic nonlinear hysteresis of PEAs has the potential of degrading the control accuracy and system stability. Hysteresis is a memory effect that the current output of PEAs depends on the historical operations and the current control input. Moreover, it is also rate-dependent, which means the dynamic behavior of PEAs changes with the frequency of the control input. Therefore, how to deal with these difficulties has been drawing considerable attention.

Various control methods have been proposed for accurate tracking control of PEAs. These approaches are generally divided into feedforward control, feedback control and feedforward-feedback control. Feedforward control methods are naturally exploited to compensate the hysteresis nonlinearity with the inverse model of hysteresis. Before constructing the inversion, the feedforward hysteresis model needs to be obtained, which is usually described by Duhem model [4], Preisach model [5], Prandtl-Ishlinskii model [6] and Bouc-Wen model [7]. Then, a feedforward controller is constructed by cascading the inversion of these models for canceling the hysteresis effect [8]. However, the dependency on the accuracy of the inverse hysteresis model and the vulnerability to external disturbances may degrade the control performance of feedforward control methods. Feedback control methods treat the hysteresis nonlinearity as bounded nonlinear disturbances, and a feedback controller is designed based on control strategies like proportional-integral-derivative (PID) control, adaptive control [9] and sliding-mode control [10] to suppress the disturbances. However, the main drawbacks of feedback control are the difficulty of obtaining robust stable results and the performance maintenance when operating at high-frequency situation [2]. Furthermore, feedforward-feedback control methods have been developed with the idea of combining feedforward and feedback control schemes, where feedforward control mitigates the hysteresis nonlinearity and feedback control compensates the inaccuracy of the hysteresis model and unknown disturbances. It is noted that adding feedforward terms to feedback control systems can improve the tracking performance even in the presence of modelling error [11]. Inspired by this strategy, extensive studies have been conducted by combining different inverse hysteresis models and different feedback control approaches [12,13]. It is noted that the tracking error of these control methods is more than 20 nm when tracking low-frequency references. However, extreme high precision is required in some nanopositioning and nanomanipulation applications. For instance, the required accuracy of atom manipulation is less than 10 nm [14]. Therefore, more advanced control methods should be exploited for the precise control of PEAs in order to satisfy the extreme demand.

Recently, model predictive control (MPC) is developed for the tracking problem of PEAs, which has demonstrated a great performance in industrial applications due to its robustness and disturbance rejection properties. In [15], a nonlinear model predictive control (NMPC) method is proposed for tracking control of PEAs based on an MFNN model, where the control law is obtained by solving a complicated nonlinear optimization problem. The dynamic linearization is carried out to the MFNN model of PEAs in [16], then an explicit predictive control law can be obtained, which leads to a faster computational rate. In order to solve the off-line training accuracy problem, a predictive controller based on an adaptive Takagi-Sugeno (T-S) fuzzy model is designed for PEAs, where the model parameters can be on-line adjusted to achieve a better control performance [17]. All these control approaches belong to the feedback control method. It is known that the tracking performance can be improved by adding feedforward terms to feedback control systems. It is natural to ask whether the control performance can be improved if the feedforward compensator is added to the model predictive control.

In this paper, a composite controller with model predictive control and hysteresis compensation is proposed to achieve high-precision tracking control of PEAs. First, the complicated nonlinear mapping between the driving voltage and the output displacement of PEAs is modeled by the MFNN because of its strong approximation capability. In order to accelerate the on-line calculation, the MFNN model is linearized in each sample interval, and a predictive controller is designed based on the instantaneously linearized MFNN model, which yields an explicit control law and enables PEAs to track high-frequency references. Then, the inverse Duhem hysteresis model is adopted as a feedforward compensator to mitigate the hysteresis nonlinearity. To validate the effectiveness of the proposed method, extensive experiments are performed on a piezoelectric nanopositioning stage (P-753.1CD, Physik Instrumente). Comparisons are conducted between the proposed method and some existing control methods. Experimental results and comparisons demonstrate that the control accuracy of the proposed control method is superior to the majority of control approaches mentioned in the literature.

2 Composite Controller for PEAs with MPC and Hysteresis Compensation

First, the model of PEAs is approximated by an MFNN, which is further linearized instantaneously to mitigate the computational burden. A model predictive controller is designed based on this instantaneously linearized MFNN model. Then, the hysteresis model is constructed by the Duhem model, which is used to derive the inverse hysteresis model as a feedforward compensator. Synthesizing the predictive controller and the hysteresis compensator yields the proposed composite controller.

2.1 Instantaneously Linearized MFNN Model of PEAs

According to [16], a three-layer MFNN is utilized to approximate the complex nonlinear mapping between the driving voltage and the output displacement of PEAs. The input vector of the MFNN is defined as $X(k) = [y(k-1), \cdots, y(k-n), u(k), \cdots, u(k-m)]$, where $y(k)$ is the output displacement of PEAs, $u(k)$ is the driving voltage, and nonnegative integers n and m are the maximum time delays for $y(k)$ and $u(k)$, respectively. The nonlinear relation between the input and output of the MFNN is described as

$$y(k) = \sum_{h=1}^{q} w_h^2 \mathscr{F}(\sum_{i=1}^{p} w_{ji}^1 x_i(k) + w_{j0}^1) + w_0^2, \tag{1}$$

where $p = n + m + 1$ is the length of the input vector, q is the number of the hidden-layer neurons, and the output layer only has one neuron. w_h^2 is the weight between the output neuron and the hth hidden-layer neuron, and w_{ji}^1 denotes the weight between the jth hidden-layer neuron and the ith input-layer neuron, which can be obtained by the off-line training. $x_i(k)$ is the ith element of input vector $X(k)$. The input-layer and output-layer neurons possess linear unit activation function, while the tangent sigmoid function $\mathscr{F}(x) = (e^x - e^{-x})/(e^x + e^{-x})$ is chosen for the hidden-layer neurons.

Then, the MFNN model is instantaneously linearized [16]. The instantaneously linearized model is able to express the behaviors of PEAs around the current operation point with a reasonable error. Taylor expansion is carried out for instantaneously linearizing the MFNN model,

$$\begin{aligned} y(k) - y(l) = a_1(l)(y(k-1) - y(l-1)) + \cdots + a_n(l)(y(k-n) - y(l-n)) \\ + b_0(l)(u(k) - u(l)) + \cdots + b_m(l)(u(k-m) - u(l-m)), \end{aligned} \tag{2}$$

where l is the current operating time, $a_i(l)$ $(i = 1, \cdots, n)$ and $b_i(l)$ $(i = n+1, j = 0, \cdots, m)$ are the partial derivative terms. Rewrite (2) as

$$\begin{aligned} y(k) = a_1(l)y(k-1) + \cdots + a_n(l)y(k-n) \\ + b_0(l)u(k) + \cdots + b_m(l)u(k-m) + \varepsilon(l), \end{aligned} \tag{3}$$

where the bias term

$$\begin{aligned} \varepsilon(l) = y(l) - a_1(l)y(l-1) - \cdots - a_n(l)y(l-n) \\ - b_0(l)u(l) - \cdots - b_m(l)u(l-m) \end{aligned} \tag{4}$$

can be regarded as the comprehensive effect of the hysteresis nonlinearity and external disturbances.

2.2 Inversion of the Duhem Hysteresis Model

The Duhem model is used to describe the hysteresis nonlinearity of PEAs, which can be expressed as [18]

$$\dot{f} = |\dot{u}| (\alpha u + \gamma f) + \beta \dot{u}, \tag{5}$$

where u and f are the input and output of the Duhen model, respectively. α, β and γ are model parameters which need to be identified in practice. For experimental implementation, the discrete-time form of (5) is required.

If $\dot{u} > 0$ (the input voltage is monotonically increasing), the discrete-time hysteresis model can be derived with the trapezoid estimation [18], which is given by

$$f(k+1) = \alpha\frac{\lambda(k+1)}{2-\gamma\phi(k+1)} + \frac{2+\gamma\phi(k+1)}{2-\gamma\phi(k+1)}f(k) + \beta\frac{2\phi(k+1)}{2-\gamma\phi(k+1)}, \tag{6}$$

where $\lambda(k+1) = u^2(k+1) - u^2(k)$, $\phi(k+1) = u(k+1) - u(k)$. Rewrite (6) as a quadratic function of $u(k+1)$, and the discrete-time inverse Duhem model can be obtained by solving the equation

$$\alpha u^2(k+1) + \delta_1 u(k+1) - \tau_1 = 0, \tag{7}$$

where $\delta_1 = \gamma f(k+1) + \gamma f(k) + 2\beta$, $\tau_1 = \alpha u^2(k) + \delta_1 u(k) + 2\left[f(k+1) - f(k)\right]$. The solution of (7) is (see [19] for details)

$$u(k+1) = \frac{-\delta_1 + \sqrt{\delta_1^2 + 4\alpha\tau_1}}{2\alpha}. \tag{8}$$

If $\dot{u} < 0$ (the input voltage is monotonically decreasing), similarly, the discrete-time inverse Duhem model is derived as

$$u(k+1) = \frac{\delta_2 - \sqrt{\delta_2^2 - 4\alpha\tau_2}}{2\alpha}, \tag{9}$$

where $\delta_2 = -\gamma f(k+1) - \gamma f(k) + 2\beta$, $\tau_2 = -\alpha u^2(k) + \delta_2 u(k) + 2\left[f(k+1) - f(k)\right]$. Therefore, the inversion of the Duhem hysteresis model is described by (8) and (9).

2.3 MPC with Hysteresis Compensation

The principle of the proposed composite controller is shown in Fig. 1, which consists of a dynamic linearized MFNN model predictive controller and a hysteresis compensator. The feedforward compensator is directly constructed by the inversion of the Duhem hysteresis model, which has been derived in Sect. 2.2. Next, the predictive controller based on the instantaneously linearized MFNN model is designed to suppress the model uncertainties and other unknown disturbances.

In the predictive controller of PEAs, the control signal is generated by minimizing the differences between reference signal and predicted displacement. The instantaneously linearized MFNN model is adopted to predict the output displacement of PEAs, which is described by (3). The bias term $\varepsilon(l)$ only depends on the current operating point and can be modelled as integrated white noise. Therefore, it can be eliminated by transforming this equation to an adjacent difference form [20], and the displacement of the ith step is predicted as

$$\begin{aligned} y_p(k+i) =& (1+a_1(l))y_p(k+i-1) + (a_2(l) - a_1(l))y(k+i-2) + \cdots \\ &- a_n(l)y_p(k+i-n-1) + b_0(l)\Delta u(k+i) + \cdots \\ &+ b_m(l)\Delta u(k+i-m). \end{aligned} \tag{10}$$

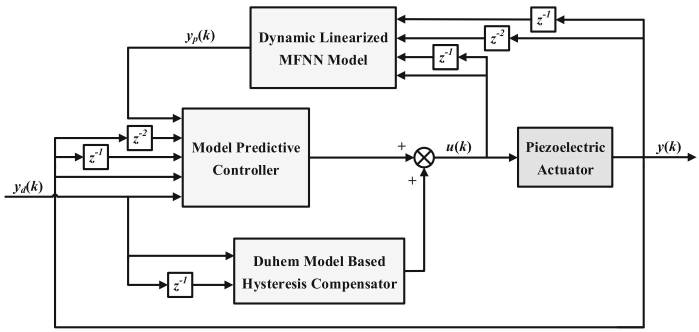

Fig. 1. Schematic diagram of the composite controller with MPC and hysteresis compensation.

Define P as the prediction horizon and the control horizon (for accuracy, P shouldn't be too large), the predicted displacements up to the Pth step are expressed as

$$Y_p(k) = G\Delta U(k) + H\Delta W(k) + SZ(k), \tag{11}$$

where $\Delta U(k) = [\Delta u(k+1), \Delta u(k+2), \cdots, \Delta u(k+P)]^T$, $\Delta W(k) = [\Delta u(k), \Delta u(k-1), \cdots, \Delta u(k-m+1)]^T$, $Z(k) = [y(k), y(k-1), \cdots, y(k-n)]^T$, and the definitions of G, H and S can be found in [16], which are matrices consisting of the coefficients of (3).

When the predicted displacement is available, a performance index is required to derive the control law of the predictive controller. Taking the error minimization and input voltage changing rate into account, the performance index is selected as [16]

$$V = [Y_d(k) - Y_p(k)]^T[Y_d(k) - Y_p(k)] + \rho\Delta U^T(k)\Delta U(k), \tag{12}$$

where $Y_d(k) = [y_d(k), \cdots, y_d(k+P)]^T$ is the reference signal, and penalty parameter $\rho > 0$ is used to limit $\Delta U(k)$. The predictive control law is obtained by solving the convex quadratic programming problem $\partial V/\partial\Delta U(k) = 0$, and the solution is

$$\Delta U(k) = (G^TG + \rho I)^{-1}G^T(Y_p(k) - H\Delta W(k) - SZ(k)). \tag{13}$$

Then, the control signal is

$$u(k+1) = u(k) + \Delta u(k+1), \tag{14}$$

where $\Delta u(k+1)$ is the increment of control signal for the next sampling interval.

3 Experiments and Comparisons

To validate the effectiveness of the proposed composite controller, extensive experiments have been conducted on a commercial piezoelectric nanopositioning stage (Physik Instrumente P-753.1CD). In this setup, a host computer (with

MATLAB/SIMULINK environment) transmits the control signal to a voltage amplifier (Physik Instrumente E-665.CR) with a fixed gain of 10, where the Real-Time Windows Target Toolbox in SIMULINK and Advantech PCI-1716 data acquisition card are needed. Under the amplified voltage, the travel range of the PEA is up to 12 µm. The displacement of the PEA is obtained from the integrated capacitive sensor (with a high resolution of 0.05 nm), and the PCI-1716 data acquisition card collects data at a sampling frequence of 200 kHz.

3.1 Model Identification

According to [16], the MFNN model can be determined with the parameters $n = 2$, $m = 1$, and $q = 5$. Before constructing the inversion of the Duhem hysteresis model as a feedforward compensator, parameters of Duhem model are required. Since the hysteresis nonlinearity is the dominant factor of the performance of PEAs under low-frequency activated voltage, a 80 V sinusoidal voltage of 1 Hz is used to activate the PEA. The forgetting factor recursive least squares algorithm is utilized to identify the parameters α, β, and γ with the input-output data, and the results are $\alpha = 0.7016$, $\beta = 1.0346$, and $\gamma = -0.4821$. Then, the hysteresis compensator is obtained by (8) and (9).

3.2 Verification of the Predictive Controller with Hysteresis Compensation

After the model parameters are determined, a set of experiments are conducted to test the proposed controller with the penalty parameter $\rho = 30$ and prediction horizon $P = 7$. The sinusoidal references ($4\sin(2\pi ft - \pi/2) + 5$ (µm)) with different frequencies are adopted as fixed-frequency references, and the tracking performances are provided in Figs. 2(a) and (b). For the 10 Hz reference signal, the steady-state tracking error is within the range of $[-0.0075, 0.0069]$ µm, and slightly increases to $[-0.0200, 0.0217]$ µm under 50 Hz reference signal.

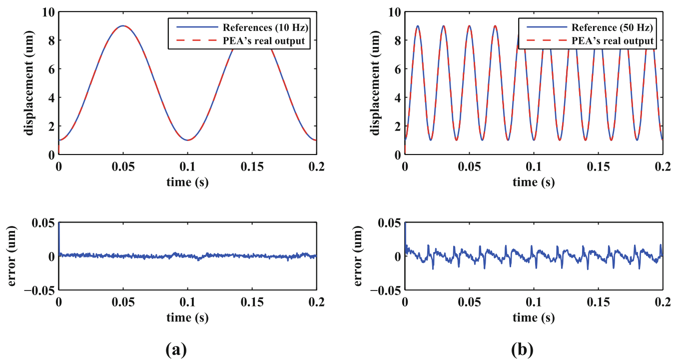

Fig. 2. Tracking performance of the PEA under different references: (a) 10 Hz; (b) 50 Hz.

Table 1. Comparison between the proposed method and the inversion-based MPC in [19]: the RMSE.

Reference frequency	The inversion-based MPC (RMSE, μm)	The proposed method (RMSE, μm)
$f = 1$ Hz	0.0083 µm	0.0014 µm
$f = 10$ Hz	0.0201 µm	0.0018 µm
$f = 50$ Hz	0.1669 µm	0.0060 µm

When tracking high-frequency trajectories, the proposed controller also has an acceptable performance. For instance, even for the reference of 200 Hz, the steady-state tracking error is only between −0.0549 and 0.1113 µm, which is still suitable for some nanopositioning applications like the DNA manipulation [14].

3.3 Comparisons with Other Methods

To further illustrate the effectiveness and superiority of the proposed method, comparisons are also conducted between the proposed control method and several other control methods mentioned in the literature.

Comparison with Inversion-Based MPC. In [19], an inversion-based MPC method with an integral-of-error state variable was developed, where an inverse Duhem hysteresis model was applied as a feedforward term to compensate the hysteresis nonlinearity. However, the MPC approach is only used for a global linear model of PEAs. This control method is considered for the performance comparison because the model predictive control and the inversion of the hysteresis model are utilized in both this method and the control method proposed in this paper. Comparison of the tracking performance is listed in Table 1, where the reference signal in [19] is $4\sin(2\pi ft - \pi/2) + 5$ (µm). It can be found that the RMSE of the proposed method is reduced to 4% of that of the inversion-based MPC in [19] under 50 Hz reference.

Comparison with Inversion-Free MPC. The inversion-free model predictive control proposed in [16] is a kind of feedback control schemes without using the feedforward compensator. It is noted that the use of feedforward terms can improve the tracking performance compared to the one using the feedback control alone [11]. It is likely that the proposed method has a better tracking performance than the inversion-free model predictive control proposed in [16]. This point has been validated by experiments under a sinusoidal reference $4\sin(2\pi ft - \pi/2) + 5$ (µm). The tracking performances of both methods are summarized in Table 2, which demonstrates that the RMSE of the proposed method is less than one sixth of that of the inversion-free MPC proposed in [16].

Comparison with Adaptive Fuzzy Internal Model Control [21]**.** The last comparison is conducted with the adaptive fuzzy internal model control [21],

Table 2. Comparison between the proposed method and the inversion-free MPC in [16]: the RMSE and the MAXE.

References frequency	The method in [16] (RMSE/MAXE, μm)	The proposed method (RMSE/MAXE, μm)
$f = 1\,\mathrm{Hz}$	0.0022/0.0094	0.0014/0.0058
$f = 5\,\mathrm{Hz}$	0.0042/0.0125	0.0015/0.0064
$f = 10\,\mathrm{Hz}$	0.0080/0.0184	0.0018/0.0075
$f = 50\,\mathrm{Hz}$	0.0395/0.0618	0.0060/0.0217
$f = 100\,\mathrm{Hz}$	0.0794/0.1189	0.0122/0.0460
$f = 150\,\mathrm{Hz}$	0.1182/0.1771	0.0194/0.0741

which belongs to the feedforward-feedback control scheme. A fixed-frequency signal $y_{d3}(t) = 0.8sin(100\pi t) + 1$ and a mixed-frequency signal $y_{d4}(t) = 0.5sin(100\pi t) + 0.35sin(50\pi t) + 1.1$ are set as references. Table 3 gives the tracking performances of the adaptive fuzzy internal model control and the proposed method. The control accuracy is quite close when tracking the fixed-frequency signal, however, for the mixed-frequency reference, the RMSE and MAXE of the proposed method are significantly lower than those of the approach proposed in [21].

Table 3. Comparison between the proposed method and the adaptive fuzzy internal model control in [21]: the RMSE and the MAXE.

References	The method in [21] (RMSE/MAXE, μm)	The proposed method (RMSE/MAXE, μm)
$y_{d3}(t)$	0.0033/0.0058	0.0018/0.0069
$y_{d4}(t)$	0.0085/0.0290	0.0016/0.0064

4 Conclusion

In this paper, a composite controller with the model predictive control and hysteresis compensation is proposed to achieve high-precision tracking control of PEAs. The overall feedforward-feedback control scheme consists of a feedforward compensator and a feedback predictive controller. First, the inverse Duhem model of PEAs is used to construct the feedforward compensator, aiming at mitigating the hysteresis nonlinearity of PEAs. Then, an MFNN model is adopted to approximate the dynamic behavior of PEAs, and the instantaneous linearization is implemented to this model. Based on the instantaneously linearized MFNN model, an explicit model predictive controller is designed to suppress the model inaccuracy and other unknown disturbances. Extensive experiments are conducted to verify the effectiveness of the proposed method on the P-753.1CD nanopositioning stage. Comparisons are also made with some existing control approaches in the literature. The experimental results demonstrate the superior of the proposed method for tracking control of PEAs.

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