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Robust control with unknown dynamic estimation for multi-axial piezoelectric actuators with coupled dynamics

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A R T I C L E   I N F O

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A B S T R A C T

Piezoelectric actuators are widely used for precise micro-positioning. The ability of fine positioning is strictly under the effect of hysteresis nonlinear behavior. Simultaneous micro-positioning in multi-dimensions has also attracted much attention in recent years. In addition to hysteresis behavior, a nonlinear dynamic coupling exists between the different degrees of freedom in multi-axis piezoelectric actuators. The nonlinear coupling phenomenon is called the *Axes Coupling Effect* (ACE). A modified Prandtl–Ishlinskii (PI) operator and its inverse are utilized for both the identification and real time compensation of the hysteresis effect in this article. Considering the PI estimation error and probable un-modeled dynamics, a variable structure controller coupled with the neural network is proposed for position tracking. Due to the model-based structure of the proposed controller, the dynamic model of actuator should be identified. Coupling between nonlinear hysteresis behavior and the linear dynamic model causes a complicated identification. The ACE has also an unknown trend. Eliminating the necessity of dynamic parameters and ACE identification, a Radial Basis Function (RBF) neural network approach would estimate the unknown dynamics of the designed controller. Stability of the controller in the presence of estimated unknown dynamics is demonstrated analytically. Experimental results depict that the proposed approach can achieve precise tracking of multi-frequency trajectories and appropriate estimation of unknown dynamics.

1. Introduction

Piezoelectric actuators are widely used for fine positioning and vibration control. This is due to properties such as high resolution, natural frequency and frequency response [1]. However, precise control of smart actuators, such as piezoelectric ones, is a challenging problem, caused by nonlinear hysteresis behavior.

Micro-positioning in multi-dimensions has also become attractive in recent years. Therefore general piezoelectric actuators with multi-Degrees Of Freedom (DOF) have been designed and manufactured by various producers.

In addition to nonlinear hysteresis effect, a nonlinear dynamic coupling also exists between different degrees of freedom in multi-axes piezoelectric actuators. This means actuating the stage in one direction can cause undesired position drift in other directions. This nonlinear coupling phenomenon is called *Axes Coupling Effect* (ACE).

The major part of research work reported has been concentrated on hysteresis nonlinearity effect. Models of Preisach, Krasnoselskii–Pokrovskii, Prandtl–Ishlinskii, Duhem and Bouc–Wen have been proposed for the identification of the

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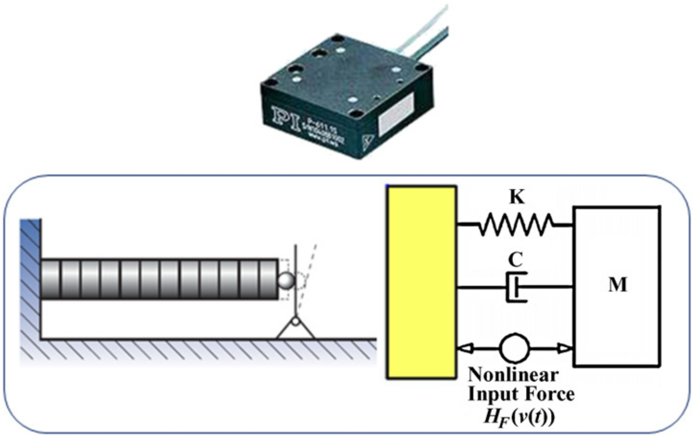

Fig. 1. Second-order nonlinear dynamic model of a 1 DOF piezoelectric actuator.

hysteresis effect [2–6]. By applying the inverse hysteresis models as a compensator, hysteresis behavior could be eliminated and feedforward position control of such actuators can be carried out.

This open loop approach is limited to only quasi-static trajectories. Several methods have also been suggested for closed loop micro-positioning control.

Impedance control [7], sliding mode control [8] and robust control coupled with adaptive approaches [8–10] have been used in such a case. An observer-based robust control has also been proposed with restricted access to all states of the actuator [11].

The main drawback of above mentioned control structures is the model dependency. In other words, system dynamic parameters should be identified before implementing control approaches. The identification of piezoelectric actuators is a tedious problem due to coupling between the hysteresis nonlinearity effect and linear dynamic model. Unknown nonlinear structure of ACE would also have to be considered. As a result, control approaches with non-parameter dependency would be an alternative for these mechanical systems. Neural networks are an appropriate solution. In fact, a neural network structure could estimate the unknown dynamic part of the controller. A common approach is the overall inverse model identification by neural networks. In such a case, Zhang et al. [12] have introduced a neural based control approach, but experimental results did not depict an appropriate trajectory tracking. In addition, solo neural network based controls are not robust to the inevitable sensor noises problem. Therefore, Yu et al. represented a robust neural network control [13].

The rate dependent hysteresis effect was compensated by a neural network based inverse dynamic identification. There is not any analytical proof for the represented approach. Liaw et al. proposed a robust control coupled with a neural network [14]. All actuator hysteresis effects have been modeled as a perturbation. The designed controller should be robust to these perturbations. Therefore it would increase the controller chattering effect. Eliminating this problem, the hysteresis behavior has been assumed as a function of desired position and velocity [15]. In a hysteretic system such as a piezoelectric actuator, the current position depends on the current input voltage and the last step time position. It means that the output is related with the input and the history of the output. Although in a closed loop system the input is a function of the desired output, the assumption mentioned in [15] would not be appropriate alone. It means that the hysteresis would also be a function of actual output.

A generalized Prandtl–Ishlinskii model and its inverse are utilized for the identification and online feedforward compensation of hysteresis in this article. This leads to the elimination of the actuator hysteresis behavior. The ACE is also considered as a nonlinear dynamic model. Considering the PI estimation error and probably un-modeled dynamics, a variable structure controller is proposed for trajectory tracking. A neural network structure estimates unknown parameter dependent dynamics and unknown ACE all together. The stability of the controller in the presence of neural network output is demonstrated analytically. Experimental results demonstrate that the PI model is achieved in hysteresis identification and compensation. The proposed controller also tracks desired multi-frequency trajectories precisely. The results also validate the neural network essential role in the precise trajectory tracking. Finally, the controller performance is compared with alternative control schemes.

2. Full dynamic model of a 2-DOF piezoelectric actuators

A second-order dynamics has been utilized for piezoelectric actuators. The model was divided into two parts. The first part is a second-order linear dynamics that refers to the mass–spring–damper system. The second part describes the nonlinear portion of the dynamics, i.e. hysteresis nonlinearity effect.

Fig. 1 shows the linear second-order dynamics of a 1-DOF piezoelectric actuator that would be added by hysteresis nonlinearity effect in the input.

Governing equation in free motion is represented as follows:

$$m\ddot{x}(t) + c\dot{x}(t) + kx(t) = H_F\big(v(t)\big) \tag{1}$$

where $x(t)$ and $v(t)$ represent the actuator displacement and input voltage, respectively. m, c and k denote mass, damping and stiffness gains, respectively. $H_F(v(t))$ expresses the hysteretic relation between the input voltage and the excitation force.

Having high stiffness, piezoelectric actuators possess high natural frequency. Due to high natural frequency, in the low frequency operation the inertia and damping effects could be neglected. Hence (1) can be transformed to (2) in a free motion:

$$x(t) = \frac{1}{k} H_F\big(v(t)\big) = H_x\big(v(t)\big) \qquad \big\{m\ddot{x}(t) \ll c\dot{x}(t) \ll kx(t)\big\} \tag{2}$$

This equation relates the input voltage and actuator displacement to each other. By this facilitation, the constraint of identification of voltage–force nonlinear hysteretic relation is not necessary. As a result, the nonlinear relation of input voltage and displacement would be identified. This means that the necessity of an accurate force sensor can be converted to the usual actuator position sensor.

By the identification of the hysteresis mapping between the input voltage and the actuator displacement $(H_x(v(t)))$, can be scaled up with a factor to obtain $H_F(v(t))$.

Considering uncertainties, hysteresis estimation error and probably un-modeled dynamics, a perturbation term $P(t)$ would be added to the dynamic model. Finally, the dynamic model of the system is as follows:

$$m\ddot{x}(t) + c\dot{x}(t) + kx(t) = kH_x\big(v(t)\big) + P(t) \tag{3}$$

An extra nonlinear effect known as the *Axes Coupling Effect* (ACE) should be considered in multi-degrees of freedom micro-stages. Due to structural coupling of different axes, moving in a certain direction would cause a drift in others. As shown in Fig. 2, actuating the micro-stage in the direction of X would cause displacement in the other direction.

In closed loop applications this effect would be more considerable. To illustrate this fact, a closed loop control is utilized for the X trajectory tracking. The X tracking error with and without existence of Y actuation is shown in Fig. 3. The effect of ACE on the tracking error is clearly depicted.

The ACE relation is nonlinear and should be accounted in dynamic modeling. A 2-DOF micro-stage as shown in Fig. 4 is utilized as an experimental positioning setup in this article.

As a result, the piezoelectric dynamic model in any degree of freedom should be modified as follows:

$$m_i\ddot{x}_i(t) + c_i\dot{x}_i(t) + k_i x_i(t) = k_i H_{x_i}\big(v_i(t)\big) + P_i(t) + C_i\big(x_j(t)\big), \quad i, j = 1, 2 \tag{4}$$

where $C_i(x_j(t))$ hints the ACE in a certain direction. Finally the dynamic model of 2-DOF piezoelectric actuator is represented as follows:

$$\begin{aligned} m_1\ddot{x}_1(t) + c_1\dot{x}_1(t) + k_1 x_1(t) &= H_{F_1}\big(v_1(t)\big) + P_1(t) + C_1\big(x_2(t)\big) \\ m_2\ddot{x}_2(t) + c_2\dot{x}_2(t) + k_2 x_2(t) &= H_{F_2}\big(v_2(t)\big) + P_2(t) + C_2\big(x_1(t)\big) \end{aligned} \tag{5}$$

2.1. Generalized Prandtl–Ishlinskii (PI) hysteresis model

A generalized Prandtl–Ishlinskii model is used for both hysteresis identification and compensation [6]. The most important advantage of this model is its simplicity, and that its inverse could be calculated analytically. In addition, this approach could be utilized in open-loop systems where the feedback of signals is not accessible. A rate independent backlash operator, as shown in Fig. 5, is the primary operator in the PI hysteresis model.

$$\begin{aligned} &y(t) = w_h H_r[x, y_0](t) \\ &H_r = \max\big[x(t) - r, \min\big\{x(t) + r, y(t - T)\big\}\big] \\ &y(0) = \max\big[x(0) - r, \min\big\{x(0) + r, y_0\big\}\big] \end{aligned} \tag{6}$$

The Prandtl–Ishlinskii method expresses that the hysteresis loop could be identified as the summation of a number of backlash operators with different thresholds (r) and weights (w_h).

$$y(t) = \sum_{i=0}^{n} w_h^{T^i} H_r^i[x, y_0](t) \tag{7}$$

The key idea of an inverse feedforward compensation of hysteresis is to cascade the inverse hysteresis operator H_x^{-1} with the actual hysteresis. As a result, an identity mapping between the desired actuator output $x_d(t)$ and the actuator response $x(t)$ would be obtained. The structure of inverse feedforward hysteresis compensation is shown in Fig. 6.

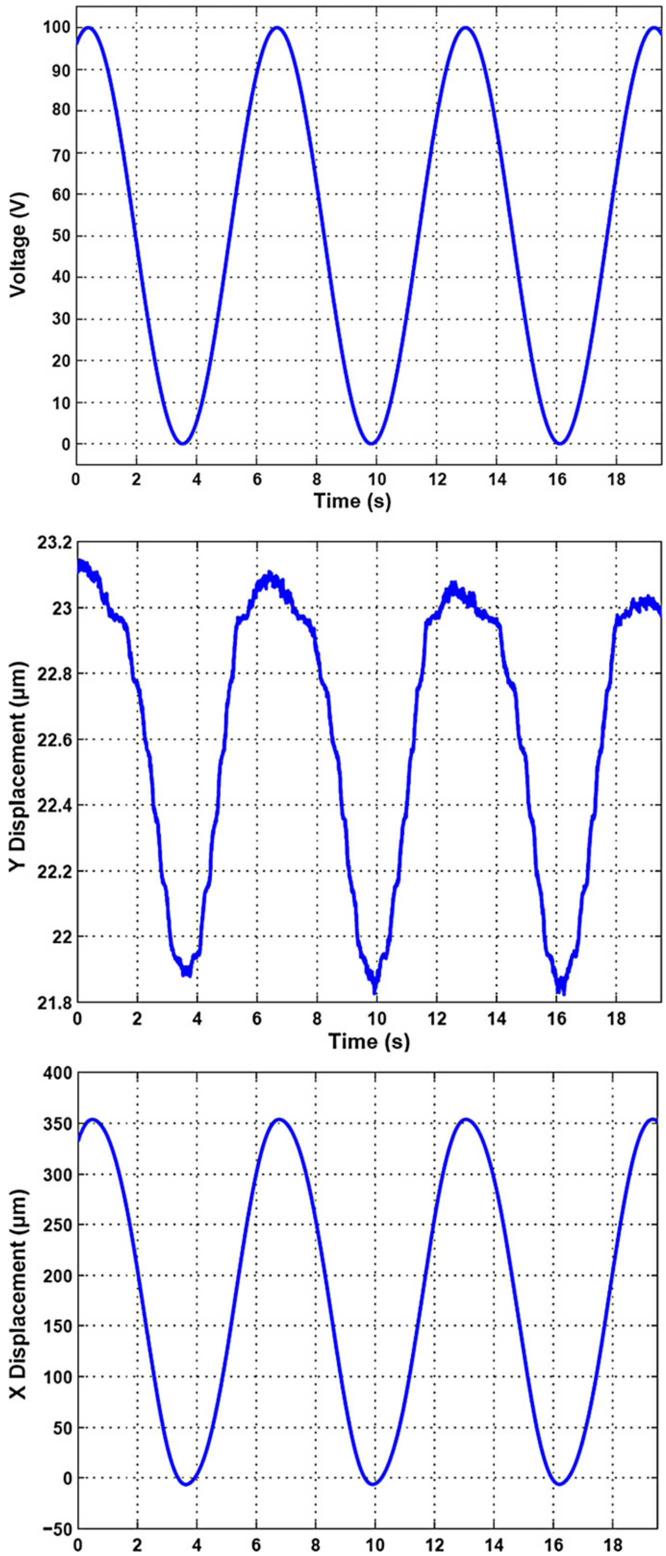

Fig. 2. ACE due to actuating in the X axis direction.

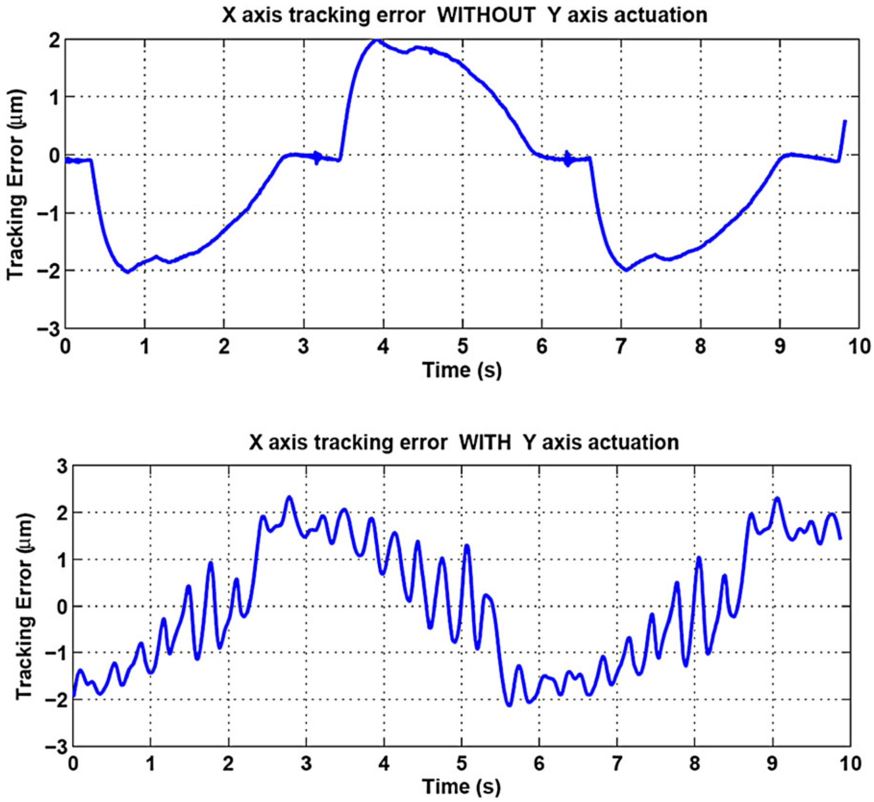

Fig. 3. The effect of axis coupling on the tracking error.

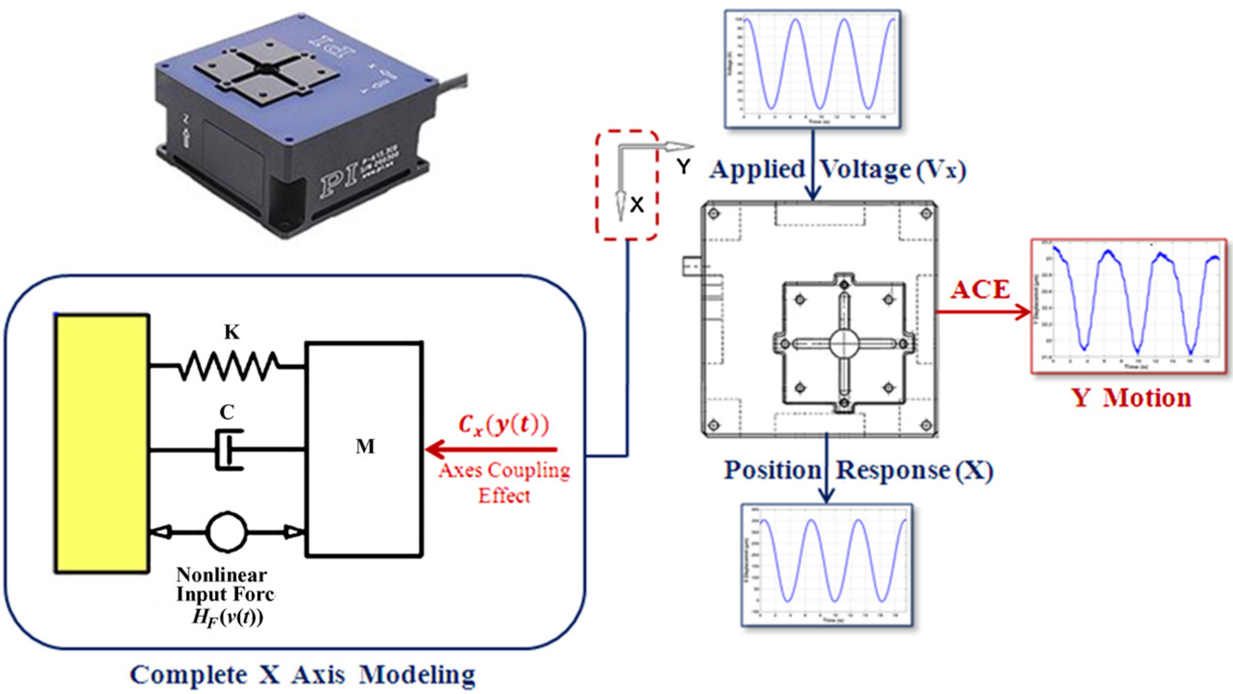

Fig. 4. 2-DOF piezoelectric actuator as an experimental setup.

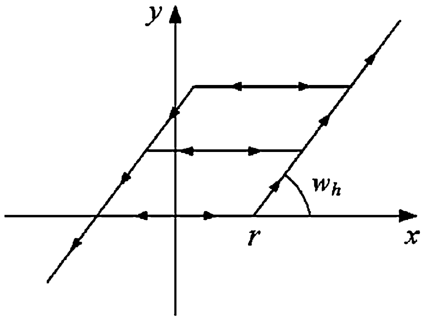

Fig. 5. Backlash operator.

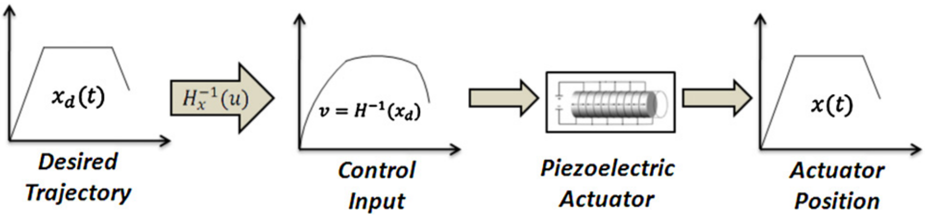

Fig. 6. Inverse feedforward compensation of hysteresis effect.

As shown in Fig. 6, the inverse PI operator H_x^{-1}, uses $x_d(t)$ as an input and transforms it into a control input $v = H^{-1}(x_d)$ which produces $x(t)$ in the hysteretic system that closely tracks $x_d(t)$ [16].

As a result, the feedforward positioning of the actuator for low frequency trajectories is achieved as follows:

$$x(t) = H_x\big[H_x^{-1}\big[x_d(t)\big]\big] \tag{8}$$

3. Unknown dynamic estimation based robust control

Utilizing the inverse PI hysteresis model and choosing the input voltage as:

$$v_i = H_{F_i}^{-1}\big(u_i(t)\big) \tag{9}$$

apparently, the dynamic of actuator would be linearized as follows:

$$m_i\ddot{x}_i(t) + c_i\dot{x}_i(t) + k_i x_i(t) = u_i + P_i(t) + C_i\big(x_j(t)\big), \quad i, j = 1, 2 \tag{10}$$

where u would be the control input.

Eq. (10) implies the linear structure of the actuator due to using the inverse PI model. The total perturbation $P(t)$, would contain model uncertainties such as the hysteresis estimation error and un-modeled dynamics. Sliding mode control, because of its natural robustness, would be appropriate. Such a controller is absolutely dynamic parameter dependent. Relaxing this dependency, a neural network structure would be designed for estimation of unknown parameter dependent functions.

3.1. Sliding mode robust control design

Sliding mode control designs asymptotically stable hyperplanes such that all system trajectories converge to these hyperplanes and slide along their path until approach the desired destination [8].

The objective is accurate trajectory tracking of the actuator position. Designing the control system, it is assumed that the dynamic parameters are unknown and all disturbances are bounded. Tracking errors and sliding surfaces are defined as:

$$\begin{aligned} e_i &= x_i(t) - x_{d_i}(t) \\ \dot{e}_i &= \dot{x}_i(t) - \dot{x}_{d_i}(t) \\ S_i &= \dot{e}_i + \lambda_i e_i \end{aligned} \tag{11}$$

where λ_i is a positive constant. The robust controller for trajectory tracking is proposed as:

$$v_i(t) = H_{x_i}^{-1}\left[\frac{1}{k_i}\big(m_i(\ddot{x}_{d_i} - \lambda_i\dot{e}_i) + c_i\dot{x}_i + k_i x_i + C_i\big(x_j(t)\big) - \eta_{1_i}S_i - \eta_{2_i}Sgn(S_i)\big)\right] \tag{12}$$

η_{1_i} and η_{2_i} are positive coefficients and $Sgn(\cdot)$ is the signum function. Substituting the control input (12) in the dynamic model (1), the closed loop dynamic would be obtained.

$$m_i \dot{S}_i + \eta_{1_i} S_i + \eta_{2_i} Sgn(S_i) = P_i(t) \tag{13}$$

Satisfying the overall stability and sliding condition, η_2 should be more than all disturbances as $\eta_{2_i} > |P_i(t)|$.

The designed controller is contained the unknown dynamic parameters. Therefore, unknown parts could be assumed as a function G_i.

$$\begin{aligned} v_i(t) &= H_{x_i}^{-1}\left[\frac{1}{k_i}\big(G_i - \eta_{1_i} S_i - \eta_{2_i} Sgn(S_i)\big)\right] \\ G_i &= m_i(\ddot{x}_{d_i} - \lambda_i \dot{e}_i) + c_i \dot{x}_i + k_i x_i + C_i\big(x_j(t)\big) \end{aligned} \tag{14}$$

In such a case, a neural network approach would estimate the unknown function G_i. The function G_i is assumed as follows:

$$G_i \equiv G_i(z_i) \tag{15}$$

z_i is the neural network input vector.

Therefore the control input would be as follows:

$$v_i(t) = H_{x_i}^{-1}\left[\frac{1}{k_i}\big(\hat{G}_i(z) - \eta_{1_i} S_i - \eta_{2_i} Sgn(S_i)\big)\right] \tag{16}$$

$\hat{G}_i(z)$ is the neural network estimation.

3.2. Unknown dynamic estimation approach

Estimating an unknown vector function $f(z)$, an RBF neural network is utilized [15]. RBF networks are special kind of 2 layer Multi-Layer Perceptron (MLP) networks with the fixed layer weights. In this approach, the activation function should be radial basis.

Considering the Universal Approximation Theorem, the vector function $f(z)$ with m outputs could be assumed as

$$\begin{aligned} f(z) &= W^T \sigma(z) + \varepsilon(z) \\ W^T &= \begin{bmatrix} w_{10} & \cdots & w_{1L} \\ \vdots & \ddots & \vdots \\ w_{m0} & \cdots & w_{mL} \end{bmatrix} \\ \sigma(z) &= \begin{bmatrix} 1 & \sigma_1(z) & \sigma_2(z) & \cdots & \sigma_L(z) \end{bmatrix}^T \end{aligned} \tag{17}$$

where $w_{ij}, \sigma(z)$ and $\varepsilon(z)$ are the weights and biases, activation function and network estimation error respectively. The estimation error would be bounded as follows:

$$\big\|\varepsilon(z)\big\| \leqslant \delta\varepsilon \quad \forall z \tag{18}$$

Activation functions would be Gaussian as follows:

$$\sigma_i(z) = \exp\left[-\frac{1}{2\eta_i^2}\|z - \mu_i\|^2\right] \tag{19}$$

μ_i and η_i are the center of function and its width, respectively.

Estimating the function $G_i(z_i)$, the input vector is introduced as:

$$z_i = \begin{bmatrix} x_i & \dot{x}_i & (\ddot{x}_{d_i} - \lambda_i \dot{e}_i) & x_j \end{bmatrix}^T \tag{20}$$

Neural network would estimate the function

$$\hat{G}_i(z_i) = \hat{W}^T \sigma(z) \tag{21}$$

$\hat{W}_i$ are the estimated weights. As a result, the control input would be as follows:

$$v_i(t) = H_{x_i}^{-1}\left[\frac{1}{k_i}\big(\hat{W}_i^T \sigma_i(z_i) - \eta_{1_i} S_i - \eta_{2_i} Sgn(S_i)\big)\right] \tag{22}$$

Fig. 7 depicts the overall block diagram of the proposed approach.

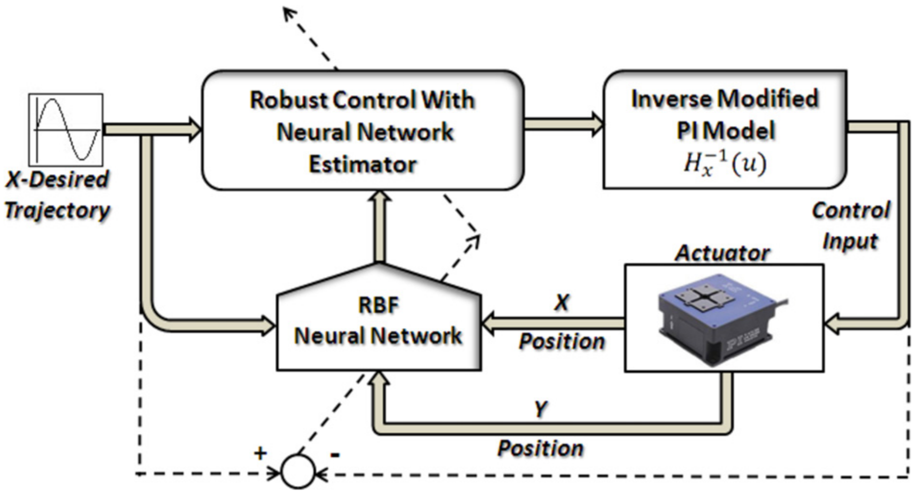

Fig. 7. Block diagram of the proposed control approach.

3.3. Stability analysis and updating rule

Substituting the control input in the dynamic model, the closed loop dynamic would be achieved.

$$m_i \dot{S}_i + \eta_{1_i} S_i + \eta_{2_i} Sgn(S_i) = \tilde{G}_i(z_i) + P_i(t) \tag{23}$$

$\tilde{G}_i(z_i) = \hat{G}_i(z_i) - G_i(z_i)$ is the function estimation error.

$$\tilde{G}_i(z_i) = \tilde{W}_i^T \sigma_i(z_i) - \varepsilon_i(z_i) \tag{24}$$

$\tilde{W}_i$ is the weight estimation error and is defined as $\tilde{W}_i = \hat{W}_i - W_i$. As a result, the closed loop dynamic system would be as follows:

$$m_i \dot{S}_i + \eta_{1_i} S_i + \eta_{2_i} Sgn(S_i) = \tilde{W}_i^T \sigma_i(z_i) - \varepsilon_i(z_i) + P_i(t) \tag{25}$$

The positive definite Lyapunov candidate function (26) is considered.

$$V_i = \frac{1}{2} m_i S_i^2 + \frac{1}{2} \tilde{W}_i^T \Gamma_i^{-1} \tilde{W}_i \tag{26}$$

Differentiating V_i and substituting the closed loop dynamic (23), $\dot{V}_i$ would be derived.

$$\dot{V}_i = -\eta_{1_i} S_i^2 - \eta_{2_i} |S_i| + \big(\tilde{W}_i^T \sigma_i(z_i) - \varepsilon_i(z_i) - P_i(t)\big) S_i + \tilde{W}_i^T \Gamma_i^{-1} \dot{\tilde{W}}_i \tag{27}$$

Considering fixed desired weights $\dot{\tilde{W}}_i = \dot{\hat{W}}_i$, the weight updating rule is proposed as follows:

$$\dot{\hat{W}}_i = -\Gamma_i \sigma_i(z_i) S_i \tag{28}$$

Γ_i is the symmetric, positive definite diagonal gain matrix. Therefore $\dot{V}_i$ would be negative semidefinite by a lower bounded gain η_{2_i}.

$$\begin{aligned} \dot{V}_i &< -\eta_{1_i} S_i^2 - \eta_{2_i} |S_i| - \big(\varepsilon_i(z_i) + P_i(t)\big) S_i \\ &< -\eta_{1_i} S_i^2 - \eta_{2_i} |S_i| + \big|\varepsilon_i(z_i)\big||S_i| + \big|P_i(t)\big||S_i| \\ &< -\eta_{1_i} S_i^2 - \eta_{2_i} |S_i| \end{aligned} \tag{29}$$

if

$$\begin{aligned} \eta_{2_i} &> \big|P_i(t)\big| + \big|\varepsilon_i(z_i)\big| \\ &> \big|P_i(t)\big| + \delta\varepsilon_i \end{aligned}$$

Utilizing the Barbalat lemma, asymptotic tracking of the desired trajectory could apparently be achieved.

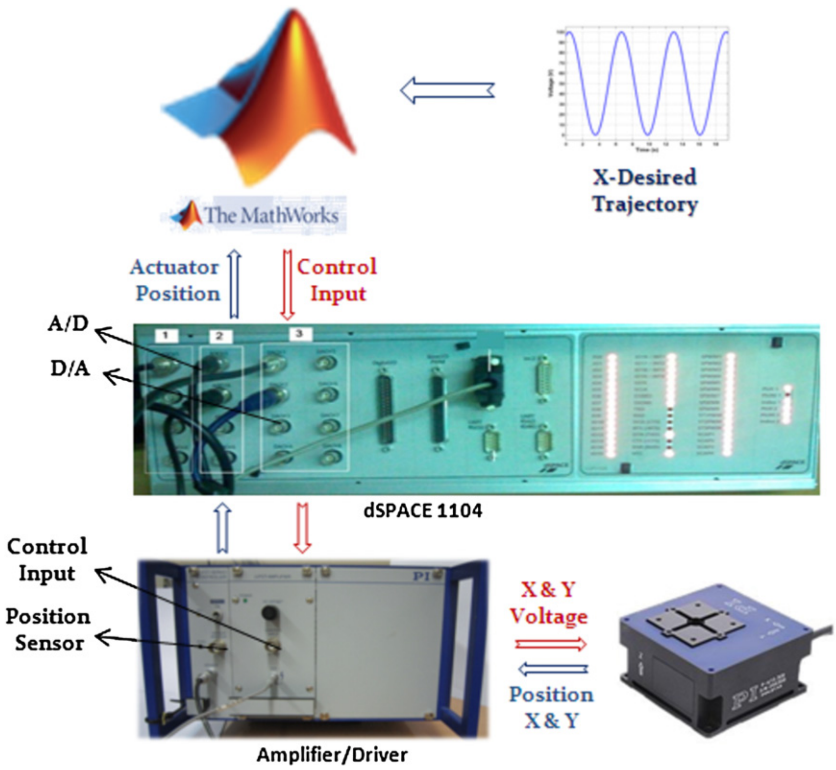

Fig. 8. The experimental setup.

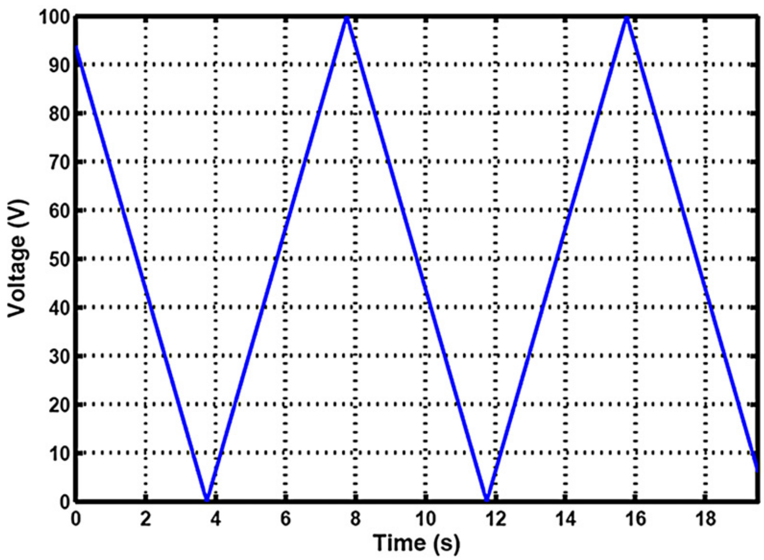

Fig. 9. The triangular quasi-static input voltage for hysteretic estimation.

4. Experimental results

The proposed controller was implemented experimentally. The experimental setup is shown in Fig. 8. The setup contains a P-615 Nano Cube piezoelectric actuator with 420 μm maximum displacement in X and Y directions. A DS1104 dSPACE data acquisition and controller board are used for data capturing. Matlab/Simulink software is utilized for implementation of the control approach. Two capacitive sensors would feed back the position of the actuator.

The modified PI model could estimate the actuator hysteresis behavior. Eliminating the dynamic hysteresis effect, a low frequency quasi-static input is utilized for hysteresis identification as shown in Fig. 9.

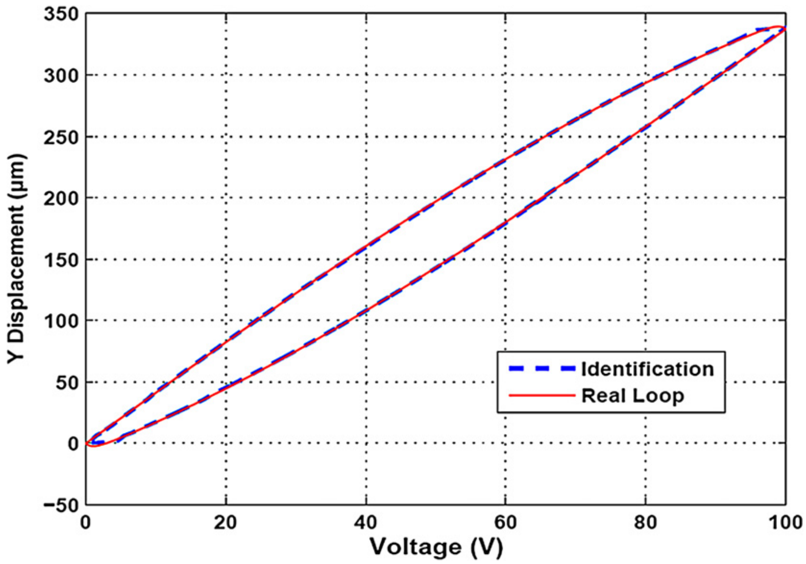

Fig. 10. The modified PI hysteresis identification.

Table 1
Controller parameters and network gains.

Parameter	Value	Parameter	Value
K_{1x}	100	λ	300
K_{2x}	500	η_1	200
K_{3x}	2000	η_2	20
K_{4x}	500		

The domain and frequency of the input voltage are 100 V and 0.125 Hz respectively. As a result, Fig. 10 shows the precise hysteresis identification.

The proposed controller was tested on the actuator. Initial network weights were set at zero. Increasing the network convergence, $G_i(z_i)$ is divided to four subfunctions. Each one would be identified by a network including 30 activation functions.

$$\begin{aligned} G_i(z_i) &= m_i(\ddot{x}_{d_i} - \lambda_i \dot{e}_i) + c_i \dot{x}_i + k_i x_i + C_i\big(x_j(t)\big) \\ &= G_{m_i} + G_{c_i} + G_{k_i} + G_{CO_i} \end{aligned} \tag{30}$$

Updating gain matrices is proposed as follows:

$$\begin{aligned} \Gamma_{m_i} &= K_1\, Diag\{1/K_1, 1, 1, \ldots, 1\} \\ \Gamma_{c_i} &= K_2\, Diag\{1/K_2, 1, 1, \ldots, 1\} \\ \Gamma_{k_i} &= K_3\, Diag\{1/K_3, 1, 1, \ldots, 1\} \\ \Gamma_{CO_i} &= K_4\, Diag\{1/K_4, 1, 1, \ldots, 1\} \end{aligned} \tag{31}$$

4.1. One axis control simultaneous with the other's actuation

For the first trial, the Y axis is actuated by a harmonic voltage as $V_y = 50 + 30\sin(10t)$. Simultaneously, the desired trajectory in the X direction would be $x_d = 40 + 30\sin(t)$. Table 1 shows controller gains and network parameters.

Fig. 11 depicts clearly that the actuator has a precise tracking.

Validating the effect of neural network estimation, it has been eliminated in the control input structure. The tracking result is seen in Fig. 12. The actuator response does not absolutely converge to the desired trajectory by the robust control alone.

Validating the controller performance, a multi-frequency desired trajectory $x_d = 70 + 10.5[\sin(5t) + \sin(7t) + \sin(10t)]$ is considered. The tracking is achieved as shown in Fig. 13. The control input would also be bounded as seen in Fig. 14.

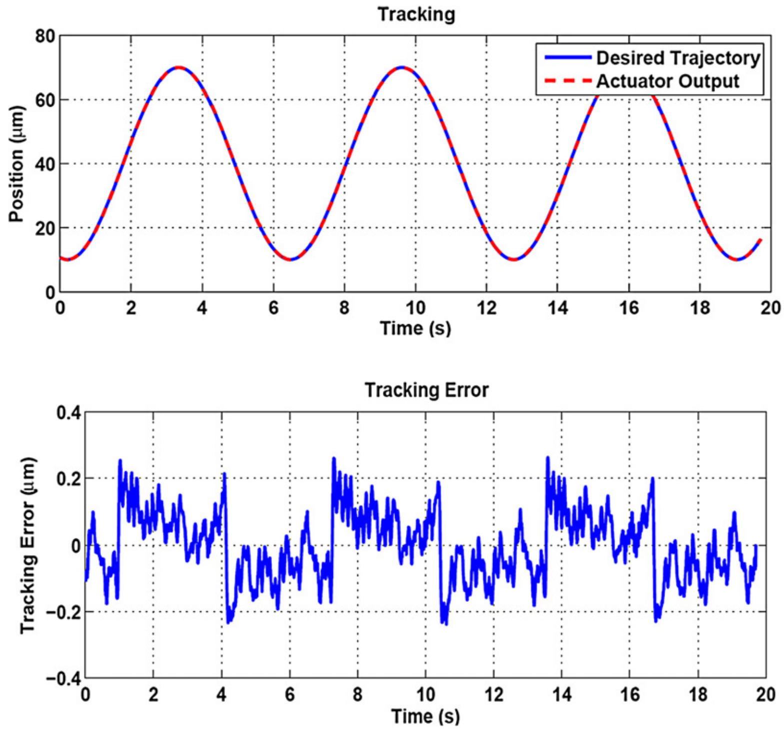

Fig. 11. Tracking and tracking error.

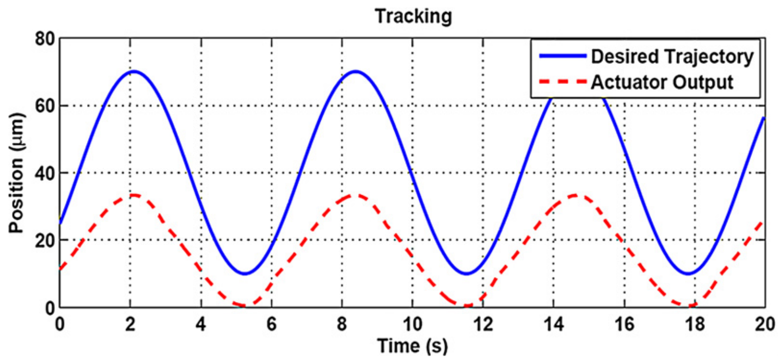

Fig. 12. The trajectory tracking without the neural network estimation.

4.2. Controller performance analysis

A comparative investigation has been done for evaluating the controller performance. Due to the non-model based structure of the proposed controller, the performance is compared with common non-model based control schemes. Therefore usual Proportional–Differential (PD) and Proportional–Integral (PI) controllers in the presence of hysteresis feedforward compensation are utilized. The overall block diagram of experiments is depicted in Fig. 15. The tracking result for the tuned PD controller with hysteresis compensation is shown in Fig. 16.

The performance is obviously poor and the tracking error is too large. The large tracking error is exactly caused by the high stiffness of the piezoelectric actuators. This specification leads to a large difference between the desired trajectory and the real output. Reducing the tracking error, a tuned PI controller with hysteresis compensation is utilized. The result is presented in Fig. 17.

The tracking error is considerably reduced. But the perfect tracking has not been achieved as yet. The main reason is the low controller robustness to the actuator output noises and ACE as shown in the focused part.

Finally, the tracking result for the proposed controller with the same trajectory is investigated as shown in Fig. 18.

The performance is absolutely improved due to the robust controller structure design.

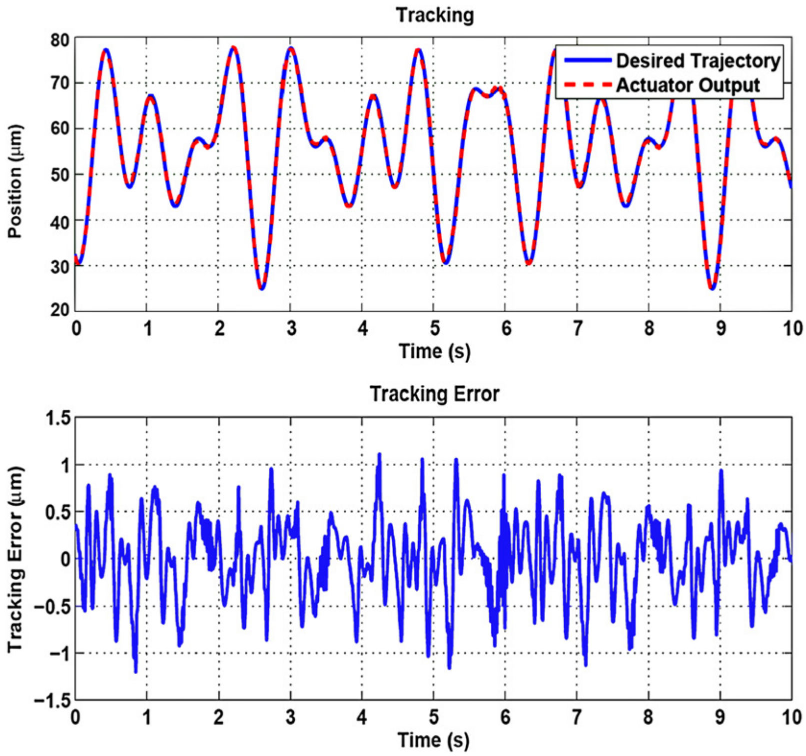

Fig. 13. Tracking and tracking error for a multi-frequency desired position.

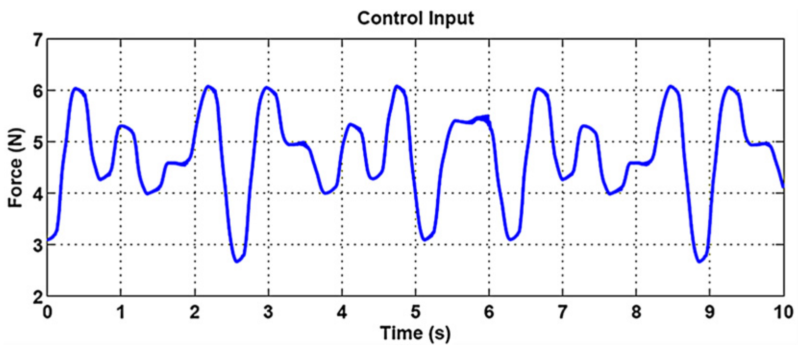

Fig. 14. The bounded control input.

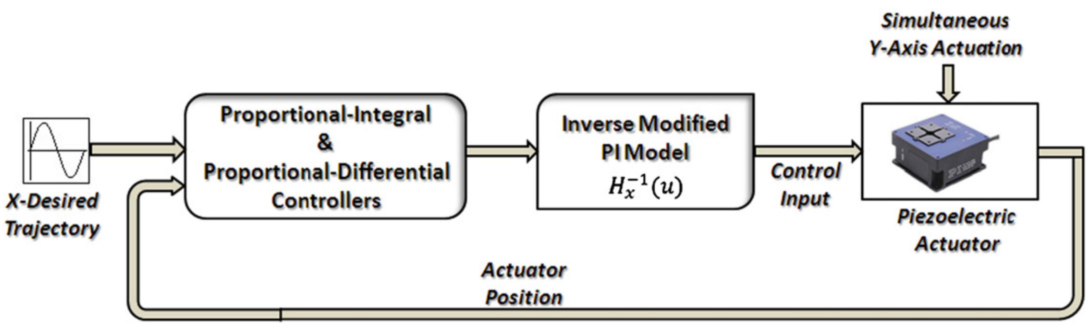

Fig. 15. The block diagram of the performance investigation by other controllers.

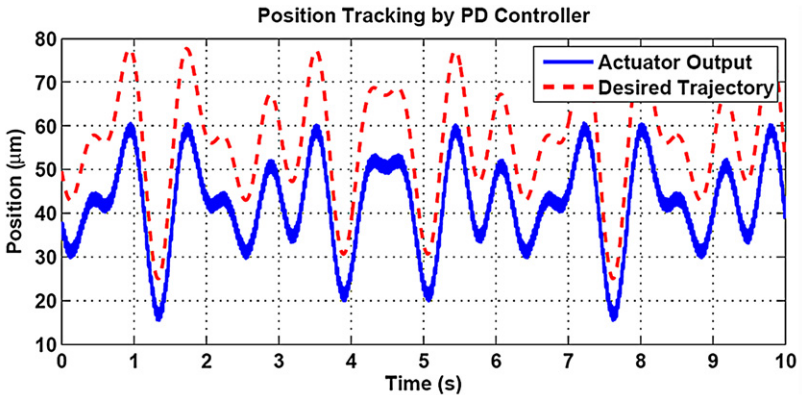

Fig. 16. Tracking result by the PD controller with feedforward hysteresis compensation.

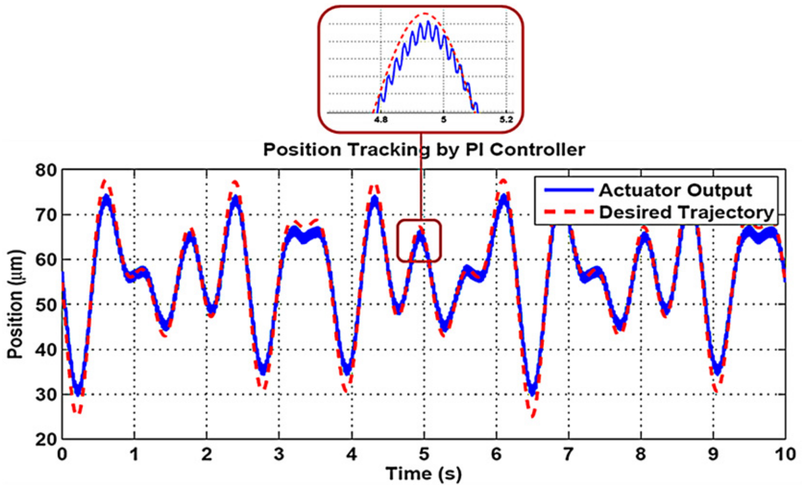

Fig. 17. Tracking result by the PI controller with feedforward hysteresis compensation.

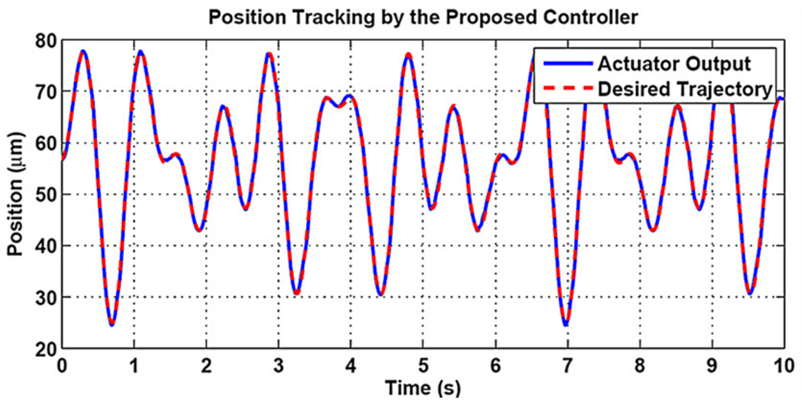

Fig. 18. Tracking result by the proposed controller.

4.3. Simultaneous two axes control

For the second trial, both axes would be controlled simultaneously. In such a case, each axis actuation affects the other's positioning. The desired trajectories are $x_d = 40 + 30\sin(t)$ and $y_d = 40 + 30\cos(t)$ for the X and Y axes, respectively. Networks gains are set as mentioned in Table 2.

Implementing designed controllers, the appropriate planar trajectory tracking as shown in Fig. 19 is achieved. Finally tracking errors are as shown in Fig. 20.

Table 2
Network gains for two axes control.

Parameter	Value	Parameter	Value
K_{1x}	50	K_{1y}	50
K_{2x}	100	K_{2y}	100
K_{3x}	2500	K_{3y}	2000
K_{4x}	500	K_{4y}	500

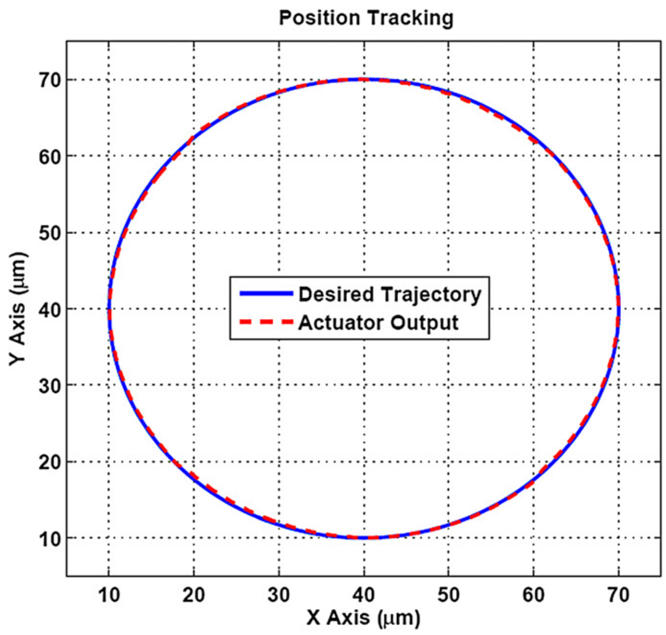

Fig. 19. Planar trajectory tracking.

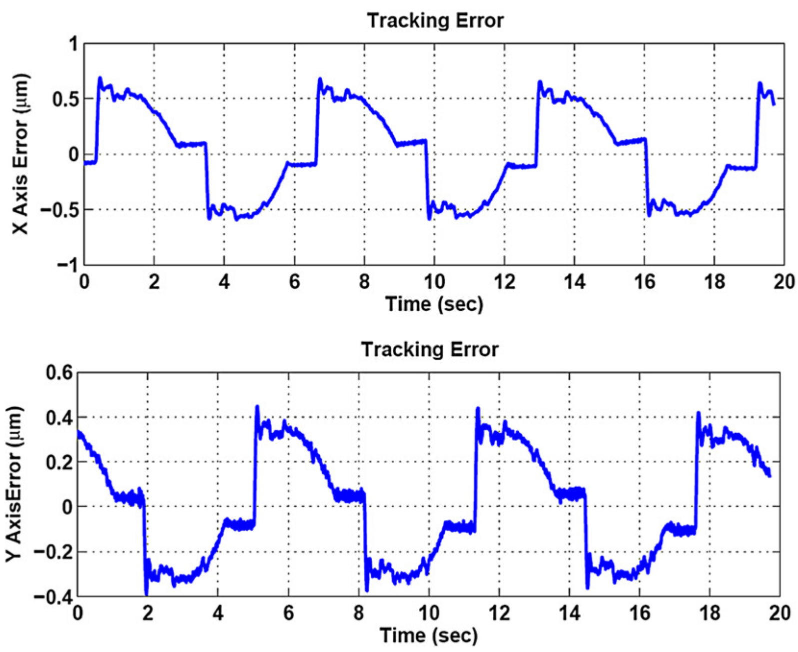

Fig. 20. Axes tracking error.

5. Conclusion

The modified PI model has been used for both hysteresis identification and feedforward compensation. Therefore, the nonlinear dynamic of hysteretic behavior is transformed to the linear model. As a result, inappropriate effects of hysteresis behavior are relaxed. ACE (*Axes Coupling Effect*) is accounted in the dynamic model as a nonlinear relation of different axes motion. Due to model uncertainties, a robust controller is proposed for precise position tracking. Eliminating dynamic parameter and AFC identification, a neural network structure estimates unknown dynamic part of the controller. The stability of the closed loop system was analytically proved. Experimental results validate the controller performance by precise multi-frequency trajectory tracking in the presence of axes coupling. The comparative investigation with other control schemes confirms the precise performance of the proposed controller. Simultaneous trajectory tracking for both axes is appropriately achieved.

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