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Neural Networks for Disturbance and Friction Compensation in Hard Disk Drives

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***Abstract*—In this paper, we show that the tracking performance of a hard disk drive actuator can be improved by using two adaptive neural networks, each of which is tailored for a specific task. The first neural network utilizes accelerometer signal to detect external vibrations, and compensates for its effect on hard disk drive position via feedforward action. In particular, no information on the plant, sensor and disturbance dynamics is needed in the design of this neural network disturbance compensator. The second neural network, designed to compensate for the pivot friction, uses a signum activation function to introduce nonlinearities inherent to pivot friction, thus reducing the neural network's burden of expectation. The stability of the proposed scheme is analyzed by the Lyapunov criterion. Simulation results show that the tracking performance of the hard disk drives can be improved significantly with the use of both neural networks compared to the case without compensation, or when only one of the networks is activated.**

I. Introduction

THE data density on magnetic disk drives has increased significantly in recent years, corresponding to a decrease of data track width and thus allowable position error of the read/write head. This calls for an improvement of the tracking accuracy of the voice-coil-motor (VCM) actuator. However, the quest for better tracking performance of the VCM actuator faces challenges from two major trends of the hard disk drive (HDD) development. Firstly, the hard disk drives are subject to more external vibrations and shocks as they are increasingly used in mobile devices. Secondly, the nonlinear pivot friction becomes more pronounced with the current trend towards smaller form factors and smaller VCM torque. Thus, the improvement of positioning accuracy under the presence of external disturbances and friction has become a major issue in the design of hard disk drives.

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To reduce the effect of the disturbances on the hard disk drives, a number of authors have proposed using accelerometers to measure external disturbances and injecting the accelerometer signal to a feedforward controller, which then outputs a feedforward signal into the system [1]-[8]. The drawback of almost all of the mentioned feedforward control schemes is that the mathematical models of the disturbance dynamics must be known or partly known.

Friction can cause tracking errors, large settling time and overshoot. The methods for friction compensation can be divided into two categories, namely the model-based [9]-[12] and the non-model based compensation [13]-[16]. The disadvantage of the model-based friction compensator is the reliance on a highly accurate model. Some non-model-based techniques such as disturbance observer and Kalman Filter have the drawback that a plant model is needed.

Because of the distinct advantages of neural networks as nonlinear controllers over conventional controllers in achieving desired performances, they have received considerable attention in the control community [17]-[20]. The efficacy of neural network feedforward compensator in rejecting the effect of disturbances for improving tracking accuracy was demonstrated via simulations in [21] and [22]. However there is a lack of theoretical results regarding the stability analysis of the closed loop system.

There are also some papers dedicated to friction compensation using neural networks [23]-[25]. The problem related to [23]-[25] is that the neural network tries to approximate the friction hard-nonlinearity via continuous functions, and this may require many neural network nodes and many training iterations to yield good results.

In this paper, we show that the tracking performance of a hard disk drive actuator can be improved by using two adaptive neural networks, each of which is tailored for a specific task. The first neural network utilizes accelerometer signal to detect external vibrations, and compensates for its effect on hard disk drive position via feedforward action. No dynamic knowledge of the plant, sensor and disturbance is needed in the design of the neural network disturbance compensator. This disturbance feedforward compensator can be interpreted as a nonlinear FIR filter, which is the extension of linear FIR filter whose basis function is linear. The second neural network, designed to compensate for the pivot friction, uses a signum activation function to introduce nonlinearities inherent to pivot friction, thus reducing the neural network's burden of expectation. The stability of the proposed scheme is analyzed by the Lyapunov criterion. Simulation results show that the tracking performance of the hard disk drives can improve significantly with the use of both neural networks compared to the case without compensation, or when only one of the networks is activated.

The paper is organized as follows. Section II gives the problem statement. In Section III, we present our control structure. The neural network disturbance and friction compensators are derived in Section IV. In Section V, simulation results are presented. Finally, in Section VI, conclusions will be drawn.

II. Problem Statement

The dynamics of the HDD system P can be expressed as

$$M\ddot{q} + F(\dot{q}) + \tau_d = \tau_u \qquad (1)$$

where q denotes the position of the VCM actuator, M is the unknown system inertia, τ_u is the control input torque, $F(\dot{q})$ represents the velocity dependent friction force, and τ_d is the disturbance torque acting on the system input which is caused by external vibration ω via the dynamics D (Fig. 1). Note that friction can also depend on position, but this dependence is negligible and thus is neglected here.

Let q_d be the desired position. The tracking error e can be expressed as

$$e = q_d - q\,. \qquad (2)$$

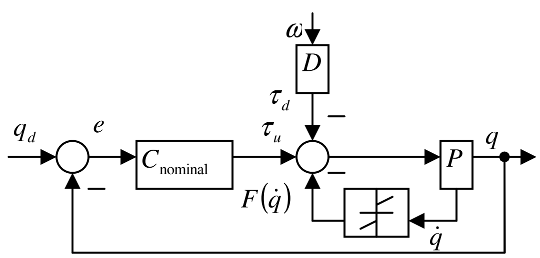

Fig. 1. Control structure of the HDD without additional compensations

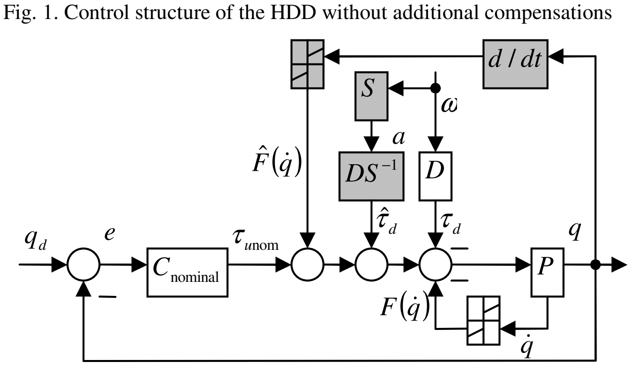

Fig. 2. Control structure with disturbance and friction compensations

The usual control scheme for external vibration compensation and friction compensation is shown in Fig. 2. There, S represents the accelerometer which measures the external vibration ω and generates the accelerometer signal a. If one knows the accurate model for D, S and friction, one can construct the disturbance compensator as DS^{-1}, and the friction compensator using the friction curve. However, in reality, D and friction are difficult to be modeled exactly, thus hindering the full potential of the feedforward compensation scheme.

The objective is thus to design the disturbance feedforward compensator and friction compensator without explicit knowledge about the disturbance model, sensor dynamics and accurate friction model.

III. Overall Control Structure

To bypass the need to explicitly model the disturbance, sensor and friction dynamic, we use neural networks (*NN*) to construct our compensators (Fig. 3). As shown in Fig. 3, we use two neural networks for two different tasks. The first neural network, designed for disturbance attenuation, takes the accelerometer signal a as the input data. This signal path is purely feedforward, thus we name this neural network disturbance feedforward compensator NN_{FF}. The second neural network, designed for friction compensation, uses the velocity $\dot{q}$ as input data. Because of the feedback involved, we abbreviate this friction compensator as NN_{FB}.

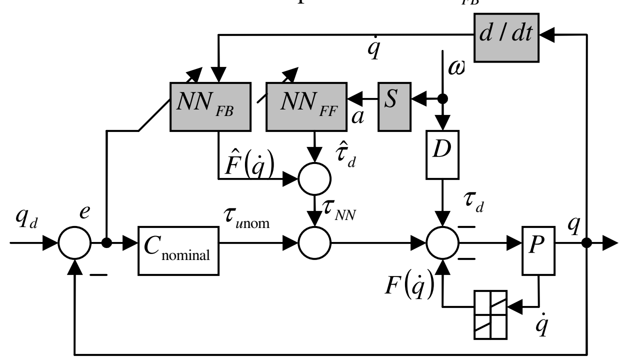

Fig. 3. Control structure with two neural network compensators

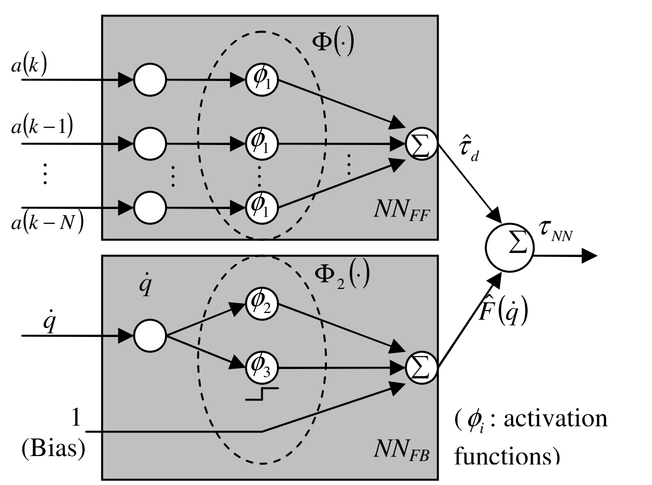

Fig. 4. Two neural network, the second one with signum activation function

To reduce the second neural network's burden of modeling the friction, we choose one of its activation functions as the signum function (Fig. 4). This physically-motivated choice of activation function purposely introduces nonlinearity inherent to pivot friction, and lessens significantly the number of neural nodes needed to model friction accurately, compared to the cases with only smooth activation functions [23]-[25].

IV. NEURAL NETWORK CONTROL

In this section, the neural network compensators are derived. As mentioned earlier, the derivation of the neural networks does not rely on any plant, sensor, disturbance and friction model.

Define an extended tracking error as

$$e_v = \dot{e} + \lambda e \tag{4}$$

where λ is a positive scalar. Differentiating e_v and using (1) and (2), the HDD dynamics can be expressed as

$$M\dot{e}_v = -\tau_u + M\ddot{q}_d + M\lambda\dot{e} + F(\dot{q}) + \tau_d . \tag{5}$$

From (5), it can be seen that if friction and external disturbance are non-existent, i.e. if $F(\dot{q}) = \tau_d = 0$, then the HDD dynamics can be written as

$$M\dot{e}_v = -\tau_u + M\ddot{q}_d + M\lambda\dot{e} . \tag{6}$$

The following assumption is reasonable and simplifies the stability proof later:

Assumption 1: The nominal control $\tau_{u\text{nom}}$ guarantees the tracking error e_v in (6) to be asymptotically convergent, i.e. there exists a Lyapunov function $V_1(e_v) = \frac{1}{2}Me_v^2$ such that

$$\dot{V}_1(e_v) = e_v\left(M\ddot{q}_d + M\lambda\dot{e} - \tau_{u\text{nom}}\right) \le -Qe_v^2 \tag{7}$$

where Q is a positive constant.

If we design the control law as

$$\tau_u = \tau_{unom} + \tau_{NN} = \tau_{unom} + \hat{F}(\dot{q}) + \hat{\tau}_d \tag{8}$$

then the disturbance torque and the friction in (5) can be cancelled.

A. Disturbance compensation network

Note that

$$\hat{\tau}_d^* = \tau_d = \left(DS^{-1}\right)a \tag{9}$$

where $\hat{\cdot}^*$ denotes the optimal estimate of the argument. Since D and S are unknown (possibly) nonlinear functions, we approximate (9) as a nonlinear FIR function

$$\hat{\tau}_d^* = H\left(a(kT),\ldots,a((k-N)T)\right) + \Delta\phi_1 \tag{10}$$

where $H\left(a(kT),\ldots,a((k-N)T)\right)$ is the unknown nonlinear function, T is the sampling interval, and $\Delta\phi_1$ is the approximation difference between the FIR and IIR filters. This approximation error satisfies $|\Delta\phi_1| \le \varepsilon_1$, where $\varepsilon_1 > 0$, and decreases as the order N increases.

Define

$$x = \left[a(kT),\ldots,a((k-N)T)\right]^T . \tag{11}$$

Now, a neural network $NN_{FF} := w^T\Phi(x)$ is derived. The ideal neural network $w^{*T}\Phi(x)$ will approximate the function $H(x)$ in (10) in a compact set $\Omega \subset R^{N+1}$, i.e.

$$H(x) = w^{*T}\Phi(x) + \Delta\phi_2 \tag{12}$$

where $w^* \in R^L$ is the optimal network parameter, $\Phi(x) \in R^L$ is the basis function of the neural network, and $\Delta\phi_2$ is the network approximation error satisfying $|\Delta\phi_2| \le \varepsilon_2$, where $\varepsilon_2 > 0$.

Assumption 2: The optimal weight w^* is bounded by $\|w^*\| \le W$ on the compact set Ω, where $W > 0$.

Summarizing (9), (10) and (12), we obtain

$$\begin{aligned}\hat{\tau}_d^* &= \tau_d = H(x) + \Delta\phi_1 \\ &= w^{*T}\Phi(x) + \Delta\phi_1 + \Delta\phi_2\end{aligned} \tag{13}$$

We thus design the neural network disturbance compensator and hence the estimated $\hat{\tau}_d$ as

$$\hat{\tau}_d = w^T\Phi(x). \tag{14}$$

B. Friction compensation network

Next, note that

$$\hat{F}(\dot{q})^* = F(\dot{q}) . \tag{15}$$

Since the friction $F(\dot{q})$ is difficult to be modeled accurately, we use neural network to approximate it as

$$\hat{F}(\dot{q})^* = F(\dot{q}) = w_2^{*T}\Phi_2(x_2) + \Delta\phi_3 \tag{16}$$

In (16),

$$x_2 = [\dot{q} \quad 1] \tag{17}$$

is the network input vector, $w_2^* \in R^L$ is the optimal network parameter, $\Phi_2(x_2) \in R^L$ is the basis function of the neural network, and $\Delta\phi_3$ is the network approximation error satisfying $|\Delta\phi_3| \le \varepsilon_3$, where $\varepsilon_3 > 0$. The ideal neural network $w_2^{*T}\Phi_2(x_2)$ will approximate the true friction in a compact set Ω_2.

Assumption 3: The optimal weight w_2^* is bounded by $\|w_2^*\| \le W_2$ on the compact set Ω_2, where $W_2 > 0$.

Thus, we design the neural network friction compensator as

$$\hat{F}(\dot{q}) = w_2^T\Phi_2(x_2). \tag{18}$$

C. Network weight tuning algorithm

Substituting (8), (13), (14), (16), and (18) into (5), we obtain

$$\begin{aligned}M\dot{e}_v &= -\tau_u + M\ddot{q}_d + M\lambda\dot{e} + F(\dot{q}) + \tau_d \\ &= -\tau_{unom} - \hat{F}(\dot{q}) - \hat{\tau}_d + M\ddot{q}_d + M\lambda\dot{e} + F(\dot{q}) + \tau_d \\ &= -\tau_{unom} - w_2^T\Phi_2(x_2) - w^T\Phi(x) + M\ddot{q}_d + M\lambda\dot{e} \\ &\quad + w_2^{*T}\Phi_2(x_2) + \Delta\phi_3 + w^{*T}\Phi(x) + \Delta\phi_1 + \Delta\phi_2 \\ &= -\tau_{unom} + M\ddot{q}_d + M\lambda\dot{e} - \overline{w}^T\Phi(x) - \overline{w}_2^T\Phi_2(x_2) + \Delta\phi\end{aligned} \tag{19}$$

where

$$\overline{w} = w - w^* \tag{20}$$

$$\overline{w}_2 = w_2 - w_2^* \tag{21}$$

are the weight estimation errors, and

$$\Delta\phi = \Delta\phi_1 + \Delta\phi_2 + \Delta\phi_3 . \tag{22}$$

The adaptation law for the parameters w and w_2 are

$$\dot{\overline{w}} = \dot{w} = \Gamma\Phi(x)e_v - \sigma\Gamma|e_v|w \tag{23}$$

$$\dot{\overline{w}}_2 = \dot{w}_2 = \Gamma_2\Phi_2(x_2)e_v - \sigma_2\Gamma_2|e_v|w_2 . \tag{24}$$

where Γ and Γ_2 are adaptation gains which determine the rate of convergence, while σ and σ_2 are parameters which determine the robustness of the adaptive systems against external disturbances.

Theorem: The control laws (8), (14), (18) and the parameter update laws (23), (24) guarantee that the tracking errors e_v and e as well as the weight estimation errors $\overline{w}$, $\overline{w}_2$ to be uniformly ultimately bounded.

Proof: Consider the following Lyapunov function candidate

$$V = \frac{1}{2}Me_v^2 + \frac{1}{2}\overline{w}^T\Gamma^{-1}\overline{w} + \frac{1}{2}\overline{w}_2^T\Gamma_2^{-1}\overline{w}_2 . \tag{25}$$

By applying (19) and Assumption 1, the time derivative of V is given by

$$\begin{aligned}\dot{V} &\le -Qe_v^2 - e_v\overline{w}^T\Phi(x) - e_v\overline{w}_2^T\Phi_2(x_2) + e_v\Delta\phi \\ &\quad + \overline{w}^T\Gamma^{-1}\dot{\overline{w}} + \overline{w}_2^T\Gamma_2^{-1}\dot{\overline{w}}_2 \\ &= -Qe_v^2 + e_v\Delta\phi + \overline{w}^T\left(\Gamma^{-1}\dot{\overline{w}} - e_v\Phi(x)\right) \\ &\quad + \overline{w}_2^T\left(\Gamma_2^{-1}\dot{\overline{w}}_2 - e_v\Phi_2(x_2)\right)\end{aligned} \tag{26}$$

Substituting (23) and (24) into (26), we obtain

$$\dot{V} \le -Qe_v^2 + e_v\Delta\phi - \sigma\overline{w}^T w|e_v| - \sigma_2\overline{w}_2^T w_2|e_v| . \tag{27}$$

Using the inequalities

$$\overline{w}^T w \le \left(\|\overline{w}\| + \frac{1}{2}\|w^*\|\right)^2 - \frac{1}{4}\|w^*\|^2 \tag{28}$$

$$\overline{w}_2^T w_2 \le \left(\|\overline{w}_2\| + \frac{1}{2}\|w_2^*\|\right)^2 - \frac{1}{4}\|w_2^*\|^2 \tag{29}$$

we obtain

$$\begin{aligned}\dot{V} &\le -Qe_v^2 + e_v\Delta\phi - \sigma\left(\|\overline{w}\| + \frac{1}{2}\|w^*\|\right)^2|e_v| + \frac{\sigma}{4}\|w^*\|^2|e_v| \\ &\quad - \sigma_2\left(\|\overline{w}_2\| + \frac{1}{2}\|w_2^*\|\right)^2|e_v| + \frac{\sigma_2}{4}\|w_2^*\|^2|e_v| \\ &\le |e_v|\left(-Q|e_v| + |\Delta\phi_1| + |\Delta\phi_2| + |\Delta\phi_3| + \frac{\sigma}{4}\|w^*\|^2 + \frac{\sigma_2}{4}\|w_2^*\|^2\right) \\ &\le |e_v|\left(-Q|e_v| + \varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \frac{\sigma}{4}W^2 + \frac{\sigma_2}{4}W_2^2\right)\end{aligned} \tag{30}$$

It can be seen that $\dot{V}$ will be negative whenever

$$|e_v| \ge \frac{\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \frac{\sigma}{4}W^2 + \frac{\sigma_2}{4}W_2^2}{Q} . \tag{31}$$

Thus, $|e_v|$ will decrease from its initial value until it is smaller than the term on the right hand side of (31) and will not leave the bound again. This implies that e_v and the weight errors $\overline{w}$, $\overline{w}_2$ are uniformly ultimately bounded. Because $e_v = \dot{e} + \lambda e$ is a stable system, it can be concluded by [19], [26] that as $t \to \infty$,

$$|e| \le \frac{|e_v|}{\lambda} \le \frac{\varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \frac{\sigma}{4}W^2 + \frac{\sigma_2}{4}W_2^2}{Q\lambda} \tag{32}$$

V. SIMULATION RESULTS

A MATLAB/Simulink block diagram is constructed according to Fig. 3. By ignoring the friction force (because friction is to be modeled separately) and high frequency resonances, the hard disk drive can be represented by:

$$P(s) = \underbrace{\frac{4.0968 \cdot 10^7}{s^2}}_{\text{Double Integrator}} \cdot \underbrace{\frac{1.421 \cdot 10^9}{s^2 + 2262s + 1.421 \cdot 10^9}}_{\text{Resonance Mode}} . \tag{33}$$

The simulated "true" friction force is modeled using the Tustin's friction model [11]

$$F(\dot{q}) = 0.000032\dot{q} + 0.01\,\mathrm{sgn}(\dot{q}) + 0.01e^{-|\dot{q}|}\,\mathrm{sgn}(\dot{q}) - 0.0005 \tag{34}$$

where the first term in (34) is the viscous friction, the second term is the coulomb friction, the third term is the Striebeck friction and the last term is some bias.

The nominal controller $\tau_{u\mathrm{nom}}$ is designed based on the double integrator model in (33), ignoring the resonance mode. The closed loop poles are places at $-5441 \pm 3142i$.

The neural network for disturbance attenuation is constructed as a nonlinear FIR filter with delayed accelerometer signal as inputs (Fig. 4)

$$\begin{aligned}\hat{\tau}_d &= w^T\Phi(a(k), a(k-1), \cdots, a(k-4)) \\ &= w^T[S(a(k)), S(a(k-1)), \cdots, S(a(k-4))]\end{aligned} \tag{35}$$

with the sigmoidal function

$$S(x) = \frac{2}{1 + e^{-x}} - 1 . \tag{36}$$

The second neural network for friction compensation is constructed as follows:

$$\begin{aligned}\hat{F}(\dot{q}) &= w_2^T\Phi_2(\dot{q}, 1) \\ &= w_2^T[S_2(\dot{q}), 0.05(\mathrm{sgn}(\dot{q})), 1]\end{aligned} \tag{37}$$

with the sigmoidal function

$$S_2(x) = \frac{2}{1 + e^{-0.1x}} - 1 \tag{38}$$

The velocity signal $\dot{q}$ as well as $\dot{e}$ in the extended tracking error are obtained by differentiating q and e respectively with differential filter of bandwidth 500 Hz. To reduce chattering, the sgn function is approximated using a saturation function.

The parameters are chosen as $\lambda = 500$, $\sigma = 0.1$, $\Gamma = I_5$, $\sigma_2 = 0.1$ and $\Gamma_2 = 0.05 \cdot I_3$ where I_n denotes the $n \times n$ identity matrix. All the weights are simply initialized at zero.

The accelerometer transfer function is

$$S(s) = \frac{-1.104 \cdot 10^8}{0.0003183 s^3 + 1.268 s^2 + 6.333 \cdot 10^4 s + 1.963 \cdot 10^8} \quad (39)$$

whereas the disturbance filter $D(s)$ is modeled via a 50th order transfer function (not shown here).

Finally, to make the simulation more realistic, the plant, the controller and the neural compensator are digitalized using a sampling frequency of 20 kHz. Some measurement noise is also added to the plant and accelerometer outputs.

A. Friction compensation when no external vibration

To show that the neural network compensator with signum activation function works well, we shall first show the simulation results when no external vibrations are present.

Firstly, the reference position q_d is set as zero. When only the nominal controller is switched on, we see that there is a steady state error due to the presence of unknown friction. This steady state error is eliminated when the friction compensator is activated (Fig. 5).

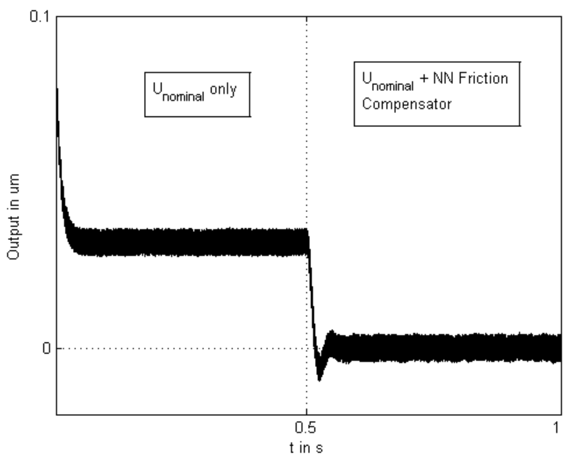

Fig. 5. Position with and without friction compensation, zero reference

Next, the reference q_d is set to be sinusoidal. The tracking error for a 80Hz sinusoidal reference of amplitude 8 micrometers with and without friction compensation is shown in Fig. 6. One sees that the friction compensator indeed reduces the tracking error. In Fig. 7, the output of the neural network friction compensator is compared to the true friction given in (34). One sees that the neural network output resembles the true friction, and that there are indeed "jumps" in the neural network output, thus validating that the signum activation function helps the neural network learn the friction discontinuity.

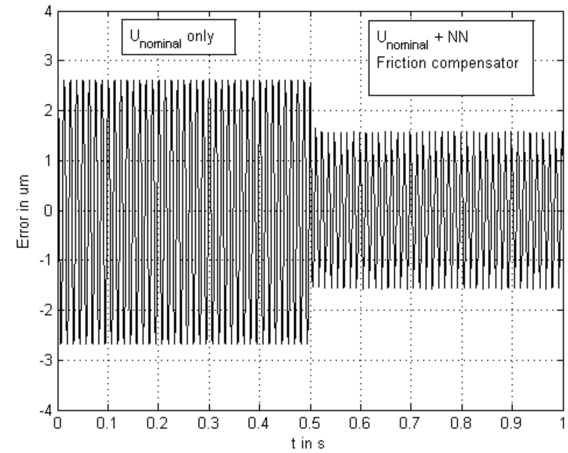

Fig. 6. Tracking error, sinusoidal reference

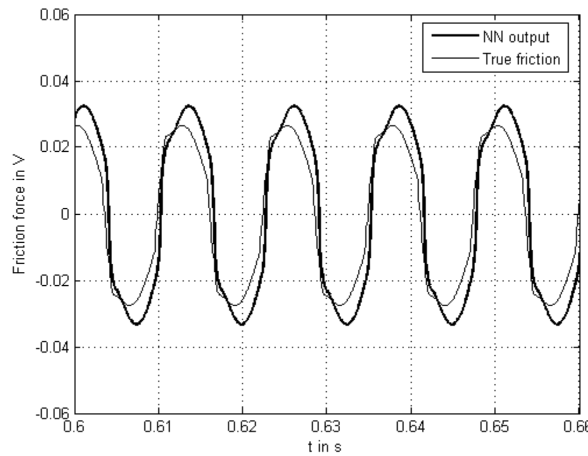

Fig. 7. Modeled and true friction; "jumps" clearly seen

B. Disturbance and Friction Compensation

Next, we shall also test the efficacy of the disturbance compensator. The desired position q_d is zero. The VCM position, with and without the disturbance and friction compensators, for different external vibrations are shown in Fig. 8 and Fig. 9.

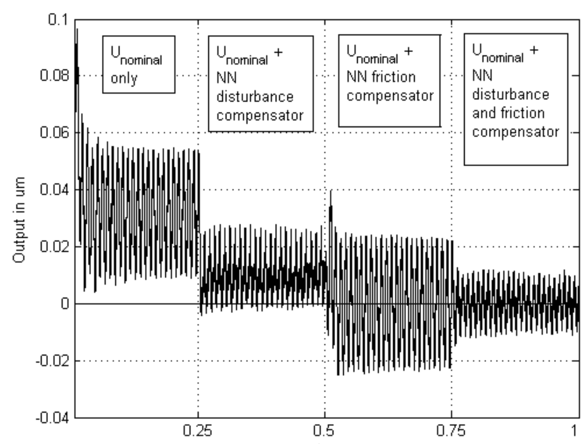

Fig. 8. VCM Position (external vibration 100 Hz, 1.4 g acceleration)

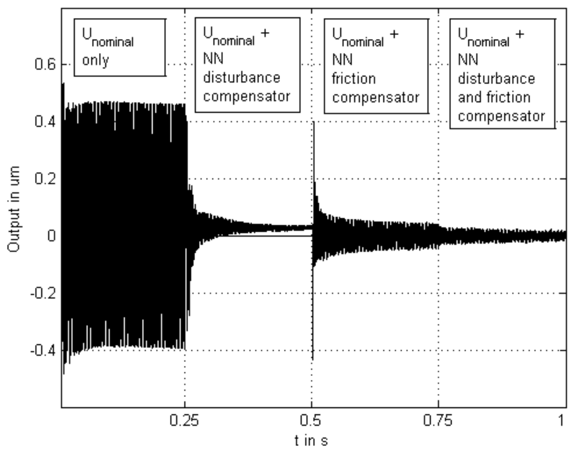

Fig. 9. VCM Position (external vibration 300 Hz, 1.4 g acceleration)

It can be observed that the disturbance compensator reduces the amplitude of the tracking error significantly, whereas the bias due to friction is eliminated by the friction compensator. Activated together, the disturbance and friction compensator improves the tracking performance of the VCM under the presence of disturbance and friction. Similar results are obtained for all 1.4 g vibrations within the range of 50 Hz and 300 Hz.

VI. Conclusion

In this paper, we designed two adaptive neural networks for two different tasks. The first neural network is designed for disturbance attenuation, whereas the second neural network is designed for friction compensation. To reduce the number of nodes necessary to model the friction nonlinearity, we choose one of the activation functions of the friction compensator to be signum function, in order to introduce nonlinearity inherent to friction. The efficacy of our scheme in rejecting disturbance and friction is shown through realistic simulation.

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