Feedforward Control Based on Neural Networks for Hard Disk Drives

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We present a novel feedforward control based on neural networks to attenuate the effect of external vibrations on the positioning accuracy of hard disk drives. The neural network compensator, which is an add-on function on top of nominal feedback control, uses the accelerometer signals obtained from a sensor to detect external vibrations. Our feedforward control can be regarded as a nonlinear finite impulse response (FIR) that corresponds to linear FIR when the basis function of the neural network is linear. By neural network learning, the tracking performance of hard disk drives can be improved with no information on disturbance dynamics or sensor model. We have analyzed the stability of the proposed scheme by the Lyapunov criterion. Here, we give simulation results to demonstrate that our control scheme can eliminate the effect of external disturbances on positioning accuracy.

***Index Terms*—Feedforward control, hard disk drives, neural networks.**

I. INTRODUCTION

APPLICATIONS for hard disk drives have increased rapidly in recent years. Not only are portable computers popular, but the mobile communication industries have been equipped hard disk drives to store digital data. In the mobile environment, external vibrations and shocks increase the position error of the read/write head from the desired track, consequently reducing the performance of the hard disk drives. On the other hand, as the density of data on magnetic disk drives increases for higher capacity, more accurate positioning of read/write head will be needed especially in the presence of shocks and vibrations. Therefore, the improvement of positioning accuracy has become a critical issue in the design of hard disk drives.

There has been some work on external vibration rejection using accelerometers to measure external signals and injecting the accelerometer signals to the feedforward controllers. By matching the electromechanical impedance between the disturbance and the position error, the feedforward controller can cancel the effects of the disturbances. Several practical issues such as accelerometer beam resonances, low sample rate of the embedded servo on the disk drive, and widely varying accelerometer gains were discussed in [1] when using the signal from a rotational accelerometer to minimize the effects of the disturbances. Acceleration feedforward control with phase delay was considered by Baek and Lee [2] for the disturbance rejection of hard disk drives. In [3], the feedforward controller was designed by recursive least squares and fixed trace algorithm using the acceleration signal and the disturbance signal estimated from the disturbance observer. Du *et al.* [6] applied the H_∞ method in state space to design the feedforward controller to compensate for external vibration impact on the positioning accuracy of hard disk drives. Pannu and Horowitz [16] presented an adaptive feedforward controller acting as an add-on compensator to the existing fixed compensator. This approach is based on the identification of the unknown plant and disturbance model polynomials. Adaptive feedforward control with the FIR filter was established in [18] to improve the head positioning accuracy in hard disk drives. However, the gradient algorithm for updating the coefficients of the FIR controller depends on the internal model. In [20], infinite impulse response (IIR) filter and FIR filter based on the filtered-x LMS algorithm were developed to cancel the effects of the disturbances. The condition for convergence of the filtered-x LMS algorithm is that the product of the unknown dynamics and its estimated inverse is required to be strictly positive real. Huang and Messner [10] presented a novel disturbance observer for hard disk drives with rotary actuators to improve the access time. Ishikawa and Tomizuka [11] considered a pivot friction compensator using the combination of an accelerometer and a disturbance observer. In [21], the disturbance observer was proposed to obtain an estimate of the disturbance by using the position error signal and a nominal model of the plant. Yi and Tomizuka [22] discussed a two-degree-of-freedom control structure for read/write head servo systems of hard disk drives in which adaptive robust control and the disturbance observer are employed as a part of the feedback controller, and the zero phase error tracking is used to design the feedforward control. It should be noted that in almost all of the existing feedforward control schemes, the sensor model and disturbance dynamics are usually restricted to be linear and their mathematical models must be known or partly known.

Neural networks as nonlinear controllers offering distinct advantages over conventional controllers in achieving desired performances have received considerable attention in the control of nonlinear systems [7], [12], [13], [14], [17], [23], [24]. There are some papers dedicated to the neural network feedforward compensation in order to reject the effect of disturbances for improving tracking accuracy. In [15], the neural network feedforward control was used to eliminate the nonlinear disturbance torque in seeker stabilizing loop. The adaptive neural network feedforward compensation method was proposed by Gorinevsky and Feldkamp [8] for the idle speed control of a car engine. Although these neural network

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disturbance rejection control schemes give good simulation results, there are no theoretic results about stability analysis of the closed-loop systems.

There are very few results on the feedforward compensation control for hard disk drives with unknown sensor model and nonlinear disturbance dynamics. The purpose of this paper is to present the neural network feedforward compensation scheme using the measured accelerometer signals to enhance the tracking performance for hard disk drives with no information on the sensor model and disturbance dynamics. In this method, the neural network is employed to provide the desired input to compensate for the disturbance effect on the tracking performance. The closed-loop system is proved to be stable and thereby there is no design tradeoff between disturbance rejection and stability. The proposed scheme is the extension of the linear FIR filter, which corresponds to the linear counterpart when the basis function of the neural network is linear.

The paper is organized as follows. Section II gives the problem statement. Section III describes the conventional feedforward control. The neural network feedforward compensation scheme is developed in Section IV. In Section V, the proposed method is illustrated through simulations. Conclusions are drawn in Section VI.

II. Problem Statement

Consider the dynamics of the hard disk drive (HDD) system given by

$$M\ddot{q} + F(q, \dot{q}) = u, y = q + d \tag{1}$$

where u and y are the system input and output, respectively, q is the position of the VCM-actuator tip, M is the unknown system inertia/mass, and the function $F(q, \dot{q})$ represents bias-forces due to static pivot, bearing friction or due to the VCM-flex-cable, d is the disturbance acting on the system output which is caused by the external vibration ω via the dynamics D.

Let us denote the desired position as q_d and the position tracking error as $e(t) = q_d - y = q_d - q - d$. Here we consider the general situation where q_d is time varying which covers the constant case. Fig. 1 shows the overall control scheme for external vibration compensation, where C_{nominal} is the nominal controller, C_f is the feedforward compensator, D is the unknown nonlinear model dynamics from the external vibration ω to the disturbance d. The shock sensor S is an accelerometer to measure the vibration and generates the accelerometer signal a.

The control objective is to design the feedforward compensator C_f based on the measured accelerometer signal a such that the HDD output tracks a given position with desirable dynamics in the presence of external vibrations.

III. Feedforward Control

It is well known that feedforward control is the common method to attenuate the impact of external disturbances on the system performances. The block diagram of the conventional feedforward controller is shown in Fig. 2, where P is the transfer function of the HDD model, S^{-1} is the inverse of the shock sensor S, $\hat{f}$ is the output of the feedforward compensator C_f.

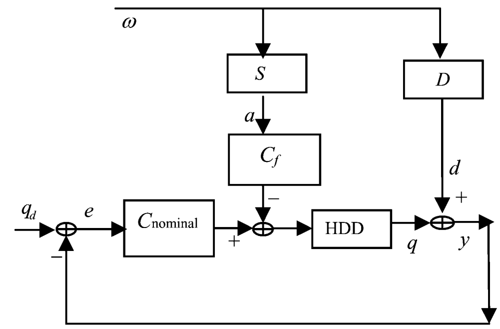

Fig. 1. Control structure of the HDD with vibration compensation.

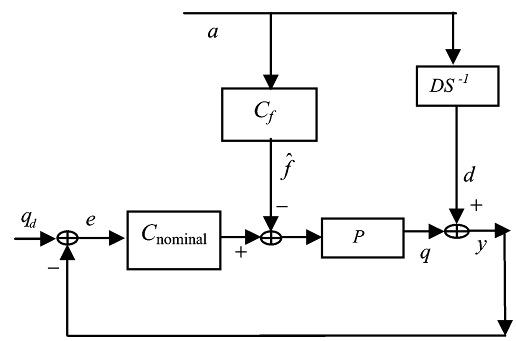

Fig. 2. Conventional feedforward control structure.

Remark 1: In Fig. 2, we assume the inverse of sensor model exists for the convenience of analysis. Under this assumption, Usui *et al.* [18] designed the adaptive FIR filter as the feedforward compensator to improve the head positioning accuracy for hard disk drives.

The system output y can be written as

$$y(s) = PC_{\text{nominal}}e - PC_f a + DS^{-1}a. \tag{2}$$

It can be seen that if we choose

$$C_f = P^{-1}DS^{-1} \tag{3}$$

then we have

$$y(s) = PC_{\text{nominal}}e \tag{4}$$

which implies that the effect of disturbances can be eliminated completely. However, this feedforward compensation method requires their linear models to be known *a priori*. In addition, it is unrealizable if the model S or P is non-minimum phase. Since the controller (3) is an algebraically optimal formulation, it may be physical unrealizable if the order of numerator is greater than that of denominator.

IV. Neural Network Feedforward Control

When the transfer functions of the models P, S and D are unknown or nonlinear, the feedforward controller given in (3) cannot eliminate the impact of the external vibrations on the positioning accuracy. In this section, we employ the neural network to deal with the disadvantages of the feedforward controller given by (3) for the compensation purposes.

Denote the reference error as $e_v = \dot{e} + \lambda_c e$, where $\lambda_c > 0$ is a scalar. Differentiating e_v and using (1), the HDD dynamics can be expressed by

$$\begin{aligned} M\dot{e}_v &= M\ddot{e} + M\lambda_c\dot{e} \\ &= F(q,\dot{q}) - u + M\ddot{q}_d + M\lambda_c\dot{e} - M\ddot{d}. \end{aligned} \tag{5}$$

From (5), we can see that if $d = 0$, then HDD dynamic equation can be written as

$$M\dot{e}_v = F(q,\dot{q}) - u + M\ddot{q}_d + M\lambda_c\dot{e}. \tag{6}$$

Assumption 1: The nominal control $u_{\mathrm{nominal}} = C_{\mathrm{nominal}}e$ can guarantee the tracking error e_v in (6) to be asymptotically convergent, that is, there exists a Lyapunov function $V_1(e_v) = 0.5Me_v^2$ such that the following property holds:

$$e_v(F(q,\dot{q}) - u_{\mathrm{nominal}} + M\ddot{q}_d + M\lambda_c\dot{e}) \le -Qe_v^2 \tag{7}$$

where Q is a positive constant.

As shown in Fig. 2, the control law of the HDD model (5) is given by

$$u = u_{\mathrm{nominal}} - \hat{f} \tag{8}$$

where $u_{\mathrm{nominal}} = C_{\mathrm{nominal}}e, \hat{f}$ is the estimate of the feedforward input whose desired value is given by

$$f = M\ddot{d}. \tag{9}$$

Remark 2: When the nonlinear term $F(q,\dot{q})$ in (1) is zero, the transfer function from the input u to the output y is the integral model described by

$$P(s) = \frac{1}{Ms^2}. \tag{10}$$

In this case, the desired feedforward input given in (9) becomes

$$f = P^{-1}d = P^{-1}DS^{-1}a. \tag{11}$$

This implies that if the models P, S and D are linear and known, the proposed control law (8) can be regarded as the feedforward control given by (3). Next we consider to design the neural network to approximate the desired feedforward input f when the models P, S and D are unknown and nonlinear. In particular, the neural network can achieve the equivalent of $P^{-1}DS^{-1}$ for the integral model (10).

It should be noted that the model for the hard disk drive is expressed in continuous-time domain, but the practical control algorithm is generally implemented in discrete-time domain. Therefore, let us consider sampled data at this point. This will further motivate the form of the feedforward control term. Given a prescribed sample period T, the desired feedforward input described in (11) can be converted into discrete-time version as

$$f = G(z^{-1})a, \tag{12}$$

$$G(z^{-1}) = \frac{1 + c_1z^{-1} + \cdots + c_{N1}z^{-N_1}}{1 + b_1z^{-1} + \cdots + b_{N2}z^{-N_2}} \tag{13}$$

where $G(z^{-1})$ is the discrete-time model of $P^{-1}DS^{-1}$ by discretizing it with any appropriate method, $c_1, \ldots, c_{N_1}, b_1, \ldots, b_{N_2}, N_1, N_2$ are proper parameters. Then the transfer function $G(z^{-1})$ can be expanded by long division [19], according to

$$G(z^{-1}) = 1 + g_1z^{-1} + \cdots + g_Nz^{-N} + \cdots. \tag{14}$$

The desired feedforward input f can be approximated by using the general discrete transfer function with limited order

$$f_p = (1 + g_1z^{-1} + \ldots + g_Nz^{-N})a \tag{15}$$

where f_p is the filter output.

Remark 3: If the transfer function $G(z^{-1})$ has an infinite impulse response (IIR), it could be used to perfectly obtain the desired feedforward input f. If $G(z^{-1})$ has a finite impulse response (FIR) but a very long one, the difference between f_p and f would be negligible [19]. This is valid in the steady state after the filter network has been primed.

If S and D are the unknown nonlinear functions, then the desired feedforward input at the sampling time k can be expressed by

$$f(kT) = H(a(kT), \ldots, a((k-N)T)) + \Delta\phi_1 \tag{16}$$

where $H(a(kT), \ldots, a((k-N)T))$ is the unknown function, $\Delta\phi_1$ 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 for an increasing order N. Motivated by this, we select $x \equiv [a(kT), \ldots, a((k-N)T)]^T$ as the input of the neural network compensator. In what follows, the ideal neural network $w^{*T}\Phi(x)$ is used to estimate the function $H(\cdot)$ in (16) on a compact set $\Omega \subset R^{N+1}$, i.e.,

$$H(x) = w^{*T}\Phi(x) + \Delta\phi_2 \tag{17}$$

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 $\|w^*\| \le M^*$ on the compact set Ω, where $M^* > 0$.

Denote the estimate of the weight vector w^* as w. Therefore, the control law (8) becomes

$$u = u_{\mathrm{nominal}} - w^T\Phi(x). \tag{18}$$

Remark 4: Equation (16) derived from (12) shows that the desired feedforward input $f(kT)$ is the nonlinear function of the delayed values $a(kT), \ldots, a((k-N)T)$ of the accelerometer measurements due to the nonlinearity of the models S, D and P. This motivates the selection of these delayed values stored in the vector x as the input to the neural network. The neural network $w^T\Phi(x)$ is used to approximate the desired feedforward input $f(kT)$ by passing the input vector x through the nonlinear activation function $\Phi(x)$. If the basis function is chosen as $\Phi(x) = x$, the neural network compensator becomes an Nth order FIR filter. Therefore, the proposed neural network feedforward scheme can be regarded as the extension of the linear FIR filter [18].

Substituting (9) and (18) into (5), we obtain

$$M\dot{e}_v = F(q,\dot{q}) - u_{\text{nominal}} + w^T\Phi(x) + M\ddot{q}_d + M\lambda_c\dot{e} - f. \quad (19)$$

From (16), (17) and (19), we have

$$\begin{aligned} M\dot{e}_v &= F(q,\dot{q}) - u_{\text{nominal}} + w^T\Phi(x) \\ &\quad + M\ddot{q}_d + M\lambda_c\dot{e} - H(x) - \Delta\phi_1 \\ &= F(q,\dot{q}) - u_{\text{nominal}} + M\ddot{q}_d + M\lambda_c\dot{e} \\ &\quad - \bar{w}^T\Phi(x) - \Delta\phi_1 - \Delta\phi_2 \end{aligned} \quad (20)$$

where the weight estimation error is $\bar{w} = w^* - w$. The adaptive law based on the σ-modification for the parameter w is given by

$$\dot{w} = -\Gamma\Phi(x)e_v - \sigma\Gamma|e_v|w \quad (21)$$

where $\Gamma > 0$ is a gain matrix, $\sigma > 0$ is a scalar parameter. The first term in the adaptive law (21) is a continuous time version of the standard backpropagation algorithm. The second term is used to guarantee the bounded parameter estimate.

Theorem: Consider the HDD dynamics described by (1) with the control law (18) and the parameter update law (21), then the tracking errors e_v, e and network weight error $\bar{w}$ are uniformly ultimately bounded given specifically by the right-hand sides of (28), (31), and (29), respectively.

Proof: Consider the following Lyapunov function candidate:

$$V = \frac{1}{2}Me_v^2 + \frac{1}{2}\bar{w}^T\Gamma^{-1}\bar{w}. \quad (22)$$

By applying (20) and Assumption 1, we obtain the time derivative of V given by

$$\begin{aligned} \dot{V} &= e_v(F(q,\dot{q}) - u_{\text{nominal}} + M\ddot{q}_d + M\lambda_c\dot{e}) \\ &\quad - e_v\Delta\phi_1 - e_v\Delta\phi_2 + \bar{w}^T(\Gamma^{-1}\dot{\bar{w}} - e_v\Phi) \\ &\leq -Qe_v^2 - e_v\Delta\phi_1 - e_v\Delta\phi_2 \\ &\quad - \bar{w}^T(\Gamma^{-1}\dot{w} + e_v\Phi). \end{aligned} \quad (23)$$

Substituting (21) into (23), we obtain

$$\dot{V} \leq -Qe_v^2 - e_v\Delta\phi_1 - e_v\Delta\phi_2 + \sigma\bar{w}^T w|e_v|. \quad (24)$$

By completion of squares, we have

$$\begin{aligned} (\bar{w}^T w) &= (\bar{w}^T(w^* - \bar{w})) \\ &\leq \|\bar{w}\|\|w^*\| - \|\bar{w}\|^2 \\ &\leq \|\bar{w}\|M^* - \|\bar{w}\|^2 \\ &= -\left(\|\bar{w}\| - \frac{1}{2}M^*\right)^2 + \frac{1}{4}M^{*2}. \end{aligned} \quad (25)$$

Substituting (25) into (24) yields

$$\begin{aligned} \dot{V} &\leq -Qe_v^2 - e_v\Delta\phi_1 - e_v\Delta\phi_2 \\ &\quad - \sigma\left(\|\bar{w}\| - \frac{1}{2}M^*\right)^2|e_v| + \frac{\sigma}{4}M^{*2}|e_v| \\ &\leq |e_v|\left\{-Q|e_v| - \sigma\left(\|\bar{w}\| - \frac{1}{2}M^*\right)^2 \right. \\ &\quad \left. + |\Delta\phi_1| + |\Delta\phi_2| + \frac{\sigma}{4}M^{*2}\right\}. \end{aligned} \quad (26)$$

By using $|\Delta\phi_1| \leq \varepsilon_1, |\Delta\phi_2| \leq \varepsilon_2$, (26) can be written as

$$\dot{V} \leq -|e_v|\left\{Q|e_v| + \sigma\left(\|\bar{w}\| - \frac{1}{2}M^*\right)^2 - \varepsilon_1 - \varepsilon_2 - \frac{\sigma}{4}M^{*^2}\right\}. \quad (27)$$

It can be shown that if

$$|e_v| \geq \frac{\varepsilon_1 + \varepsilon_2 + \frac{\sigma}{4}M^{*2}}{Q} \quad (28)$$

or

$$\|\bar{w}\| \geq \frac{1}{2}M^* + \sqrt{\frac{\varepsilon_1 + \varepsilon_2}{\sigma} + \frac{M^{*2}}{4}} \quad (29)$$

then $\dot{V} < 0$ is true, which implies that e_v, e and $\bar{w}$ are uniformly ultimately bounded [14]. Since $\dot{e} + \lambda_c e = e_v$ is a stable system, we can conclude that $e(t)$ is bounded by [14]

$$|e| \leq \frac{|e_v|}{\lambda_c}. \quad (30)$$

From (28) and (30), we have

$$|e| \leq \frac{\varepsilon_1 + \varepsilon_2 + \frac{\sigma}{4}M^{*2}}{Q\lambda_c} \quad (31)$$

as $t \to \infty$. □

V. Simulation

Consider the transfer function of VCM actuator with the high-frequency resonance models given by [5]

$$P(s) = \frac{K_v K_y}{s^2}\prod_{i=1}^{4} P_{r,i}(s) \quad (32)$$

where $K_v K_y = 6.4013 \times 10^7$

$$\begin{aligned} P_{r,1} &= \frac{0.912s^2 + 457.4s + 1.433 \times 10^8}{s^2 + 359.2s + 1.433 \times 10^8}, \\ P_{r,2} &= \frac{0.7586s^2 + 962.2s + 2.491 \times 10^8}{s^2 + 789.1s + 2.491 \times 10^8}, \\ P_{r,3} &= \frac{9.917 \times 10^8}{s^2 + 1575s + 9.917 \times 10^8}, \\ P_{r,4} &= \frac{2.731 \times 10^9}{s^2 + 2613s + 2.731 \times 10^9}. \end{aligned}$$

The frequency response of VCM actuator of the model (32) is shown in Fig. 3. The accelerometer model is given by [6]

$$S(z) = \left(\frac{z-1}{z}\right)^2. \quad (33)$$

The disturbance model from the external vibration acting on the actuator is given by [6]

$$D(s) = \frac{3.757\times10^{-6}s^3 + 0.3077s^2 + 1.381\times10^4 s + 8.374\times10^8}{s^3 + 1885s^2 + 1.777\times10^6 s + 8.374\times10^8}. \quad (34)$$

The desired trajectories are chosen as $q_d = 0, \dot{q}_d = 0$ and $\ddot{q}_d = 0$. The external vibration $\omega = 0.1\sin(\pi t/0.005)$ is introduced at $t = 0$. The simulations are done with the integral step of

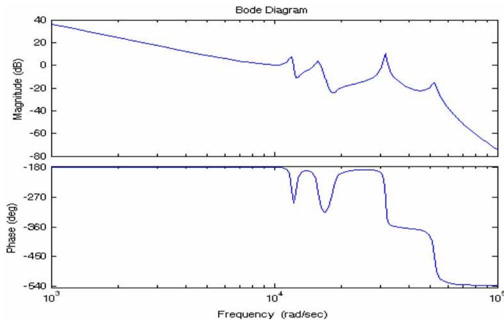

Fig. 3. Frequency response of the VCM actuator.

$ts = 0.00005$s, and the simulation initial conditions are $q(0) = 0, \dot{q}(0) = 0$. The nominal PID model is given by [5]

$$C_{\text{nominal}}(z) = \frac{0.50495z^2 - 0.99147z + 0.48653}{z^2 - 1.09091 + 0.09091} \frac{0.2696}{z - 0.7304}. \tag{35}$$

The controller is constructed by

$$u = u_{\text{nominal}} - w^T \Phi(a(k), a(k-1), a(k-2)) \tag{36}$$

where $w = [w_1, w_2, w_3]^T$, the network basis function is $\Phi(a(k), a(k-1), a(k-2)) = [S(a(k)), S(a(k-1)), S(a(k-2))]^T$ with the sigmoidial function $S(x) = 2/(1 + e^{-x/0.1}) + 1.2$. The parameters are chosen as $\lambda_c = 500, \sigma = 8, \Gamma = \text{diag}(\Gamma_1, \Gamma_2, \Gamma_3)$ with $\Gamma_i = 1.08 \times 10^{-3}$ for $i = 1, 2, 3$. The neural network weights are simply initialized at zero.

To illustrate the effectiveness of the proposed neural network compensator (NNC), the conventional linear feedforward controller (LFC) described in (3) is used to compare the performance. The model parameters in (3) are chosen as $\hat{P}(s) = (1 + \gamma_1)6.4013 \times 10^7/s^2$, and

$$\hat{D}\hat{S}^{-1} = (1+\gamma_2)DS^{-1} = (1+\gamma_2) \cdot \frac{3.757e{-}6z^5 + 3.717e{-}5z^4 + 4.796e{-}5z^3 + 1.097e{-}5z^2}{z^5 - 4.906z^4 + 9.627z^3 - 9.448z^2 + 4.636z - 0.9101} \tag{37}$$

where γ_1, γ_2 are the gain variation factors. Since the estimated plant model is the integral model, the filter $F(s) = 1/(\lambda s + 1)^2, \lambda > 0$, is used to make C_f in (3) realizable, i.e., $\lambda = 2.5 \times 10^{-4}$. Fig. 4 shows the results for three different control schemes. The neural network output is shown in Fig. 5, which implies that the weights are bounded during the learning process. The sum of the position error square for the nominal PID without feedforward compensation is 0.0449, while the corresponding values for the NNC and the LFC are 0.0071 and 0.0141, respectively. It can be seen that the add-on neural network compensation controller exhibits satisfactory performance. Note that the proposed NNC scheme does not require the dynamic knowledge of the plant, disturbance and sensor. However, the LFC needs their linear models to be known. To show the effect of the different parameters γ_1, γ_2 in the LFC on the performance, the simulations are repeated as shown in Fig. 6. It is observed that if $\gamma_1, \gamma_2 \neq 0$, LFC performance is degraded. The larger uncertainties in the models can lead to larger position errors.

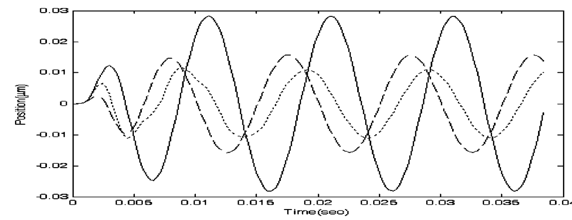

Fig. 4. Output responses (solid line: nominal PID without feedforward compensation; dotted line: NNC; dashed line: LFC with $\gamma_1 = -0.3, \gamma_2 = 0$).

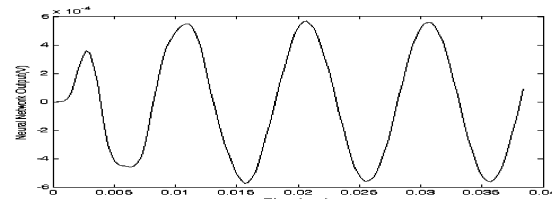

Fig. 5. Neural network output.

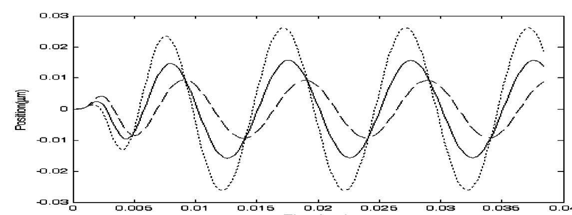

Fig. 6. Output responses for LFC with different parameters γ_1, γ_2 (dashed line: $\gamma_1 = 0, \gamma_2 = 0$; solid line: $\gamma_1 = 0, \gamma_2 = 0.3$; dotted line: $\gamma_1 = -0.3, \gamma_2 = 0.3$).

If the activation function $\Phi(x)$ of the neural network is linear, i.e., $\Phi(x) = Kx$, the proposed NNC becomes the linear adaptive FIR (LAFIR) filter. Next, we will compare the NNC with the LAFIR under the same conditions. We select $x = [a(k), a(k-1), \ldots, a(k-5)]$ and $K = 132$. The parameters are chosen the same as described above except the learning parameter $\Gamma = \text{diag}(\Gamma_1, \ldots, \Gamma_i, \ldots, \Gamma_6), \Gamma_i = 6 \times 10^{-4}$ and $13.9, i = 1, \ldots, 6$, for the NNC and the LAFIR, respectively. Fig. 7 shows the responses for the NNC and the LAFIR. It is shown that the NNC performs better performance against disturbances over the LAFIR although the two schemes can deal with the disturbance rejection for hard disk drives with unknown sensor model and unknown disturbance dynamics. The addition of nonlinear basis functions can improve the learning ability, which leads to the satisfactory performance.

VI. Conclusion

This paper considers external vibration rejection control for hard disk drives using acceleration feedforward compensation. The neural network compensator with σ-modification adaptive law has been developed to provide the required feedforward compensation input for hard disk drives in the presence of external vibrations. The proposed neural network compensator is the nonlinear extension of the corresponding linear FIR. In addition, no information on the plant, sensor and disturbance dynamics is needed in the design of the neural network compen-

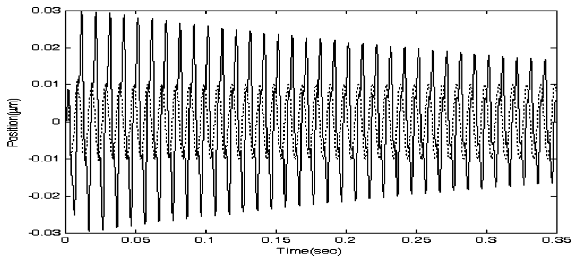

Fig. 7. Output responses (solid line: LAFIR; dotted line: NNC).

sator. The stability of the closed-loop systems is proved by the Lyapunov approach. The appealing advantage is that the neural network feedforward compensator can be added in the existing nominal feedback process without affecting the system stability. Simulation results show that the proposed controller provides a better performance in the external disturbance rejection compared to the nominal controller without feedforward compensation, the linear FIR compensator and the conventional linear feedforward compensator with model uncertainties. It should be noted that the proposed scheme requires an accelerometer to detect the external vibrations and generate the input signal for the neural network compensator. Due to the development of low cost but high quality accelerometers, the proposed scheme can be considered to be a practical method in eliminating the impact of external vibrations on the performances of hard disk drives.

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REFERENCES

[1] D. Y. Abramovitch, "Rejecting rotational disturbances on small disk drives using rotational accelerometers," in *Proc. 1996 IFAC World Congr.*, San Francisco, CA, Jul. 1–8, 1996.

[2] S. E. Baek and S. H. Lee, "Vibration rejection control for disk drives by acceleration feedforward control," in *Proc. 38th Conf. Decision and Control*, Phoenix, AZ, Dec. 1999, pp. 5259–5262.

[3] N. Bando, S. Oh, and Y. Hori, "External disturbance rejection control based on identification of transfer characteristics from the acceleration sensor for access control of hard disk system," in *Advanced Motion Control*, Maribor, Slovenia, 2002, pp. 52–56.

[4] H. Berghuis and H. Nijmeijer, "A passivity approach to controller-observer design for robots," *IEEE Trans. Robot. Automation*, vol. 9, no. 6, pp. 740–754, 1993.

[5] B. M. Chen, T. H. Lee, K. Peng, and V. Venkataramanan, *Hard Disk Drive Servo Systems*. New York: Springer, 2006.

[6] C. L. Du, S. S. Ge, and F. L. Lewis, "H_∞ compensation of external vibration impact on servo performance of hard disk drives in mobile applications," *Int. J. Adapt. Contr. Signal Process.*, vol. 22, pp. 374–387, 2008.

[7] S. S. Ge and C. Wang, "Adaptive neural control of uncertain MIMO nonlinear systems," *IEEE Trans. Neural Networks*, vol. 15, no. 3, pp. 674–692, 2004.

[8] D. Gorinevsky and L. A. Feldkamp, "RBF network feedforward compensation of load disturbance in idle speed control," *IEEE Contr. Syst. Mag.*, vol. 16, no. 6, pp. 108–121, 2001.

[9] E. G. Grochowski, R. F. Hoyt, and J. S. Heath, "Magnetic hard disk drive form factor evolution," *IEEE Trans. Magn.*, vol. 29, no. 6, pp. 4065–4067, Nov. 1993.

[10] Y. Huang and W. Messner, "A novel disturbance observer design for magnetic hard drive servo systems with a rotary actuator," *IEEE Trans. Magn.*, vol. 34, no. 4, pp. 1892–1894, Jul. 1998.

[11] J. Ishikawa and M. Tomizuka, "Pivot friction compensation using an accelerometer and a disturbance observer for hard disk drives," *IEEE Trans. Mechatronics*, vol. 3, no. 3, pp. 194–201, 1998.

[12] E. B. Kosmatopoulos, M. M. Polycarpou, M. A. Christodoulou, and P. A. Ioannou, "High-order neural network structures for identification of dynamical systems," *IEEE Trans. Neural Networks*, vol. 6, no. 2, pp. 422–431, 1995.

[13] J. Levin, N. O. Pérez-Arancibia,, P. A. Ioannou, and T. C. Tsao, "A neural-networks-based adaptive disturbance rejection method and its application to the control of hard disk drives," *IEEE Trans. Magn.*, vol. 45, no. 5, pp. 2140–2150, May 2009.

[14] F. L. Lewis, S. Jagannathan, and A. Yesildirek, *Neural Network Control of Robot Manipulators and Nonlinear Systems*. London, U.K.: Taylor and Francis, 1999.

[15] C. L. Lin and Y. H. Hsiao, "Adaptive feedforward control for disturbance torque rejection in seeker stabilizing loop," *IEEE Trans. Contr. Syst. Technol.*, vol. 9, no. 1, pp. 108–121, 2001.

[16] S. Pannu and R. Horowitz, "Adaptive accelerometer feedforward servo for disk drives," in *Proc. 36th Conf. Decision and Control*, San Diego, CA, Dec. 1997, pp. 4216–4218.

[17] M. M. Polycapou and M. J. Mears, "Stable adaptive tracking of uncertain systems using nonlinearly parameterized on-line approximator," *Int. J. Contr.*, vol. 70, no. 3, pp. 363–384, 1998.

[18] K. Usui, M. Kisaka, A. Okuyama, and M. Nagashima, "Reduction of external vibration in hard disk drives using adaptive feedforward control with single shock sensor," in *Proc. Advanced Motion Control*, Istanbul, Turkey, 2006, pp. 138–142.

[19] B. Widrow and E. Walach, *Adaptive Inverse Control*. Upper Saddle River, N.J.: Prentice-Hall, 1996.

[20] M. T. White and M. Tomizuka, "Increased disturbance rejection in magnetic disk drives by acceleration feedforward control and parameter adaptation," *Contr. Eng. Pract.*, vol. 5, no. 6, pp. 741–751, 1997.

[21] M. T. White, M. Tomizuka, and C. Smith, "Rejection of disk drive vibration and shock disturbances with a disturbance observer," in *Proc. Amer. Contr. Conf.*, Jun. 1999, pp. 4127–4131.

[22] L. Yi and M. Tomizuka, "Two-degree-of-freedom control with robust feedback control for hard disk servo systems," *IEEE Trans. Mechatronics*, vol. 4, no. 1, pp. 17–24, 1999.

[23] S. Cao, B. Wang, J. Zheng, W. Huang, L. Weng, and W. Yan, "Hysteresis compensation for giant magnetostrictive actuators using dynamic recurrent neural network," *IEEE Trans. Magn.*, vol. 42, no. 4, pp. 1143–1146, Apr. 2006.

[24] F. J. Lin, P. H. Shen, S. L. Yang, and P. H. Chou, "Recurrent radial basis function network-based fuzzy neural network control for permanent-magnet linear synchronous motor servo drive," *IEEE Trans. Magn.*, vol. 42, no. 11, pp. 3694–3705, Nov. 2006.