Feedforward control based on neural networks for disturbance rejection in hard disk drives

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Abstract: A feedforward control based on neural networks to attenuate the effect of external vibrations on the positioning accuracy of hard disk drives (HDDs) is presented. The adaptive neural network compensator utilises accelerometer signals to detect external vibrations. No information on the plant, sensor and disturbance dynamics is needed in the design of the adaptive neural network compensator. The stability of the proposed scheme is analysed by the Lyapunov criterion. Experimental results show that the tracking performance of HDDs can be improved significantly by using the feedforward controller when compared with the case without compensation.

1 Introduction

The application of hard disk drives (HDDs) has extended successfully to portable devices such as laptops, digital camcorders and MP3 players. In this mobile environment, the HDDs are subject to external vibrations and shocks that reduce the tracking performance of the read/write head. At the same time, the data density on magnetic disk drives has increased significantly, which corresponds to a decrease in data track width and allowable position error of the read/write head. Thus, the improvement in positioning accuracy under the presence of external disturbances has become a major issue in the design of HDDs.

A number of authors have proposed using accelerometer to measure external disturbances and injecting the accelerometer signal to a feedforward controller to reduce the effect of the disturbances on the HDDs. Abramovitch [1] discussed and proposed some solutions to several practical issues, such as accelerometer beam resonances and widely varying accelerometer gains, which will hinder the full potential of acceleration feedforward schemes if not properly dealt with. Baek and Lee [2] proposed phase delay correction to counter the accelerometer phase lag. In [3], the transfer function from external vibration to plant input is identified via recursive least square algorithm using the acceleration signal and the disturbance signal, which is estimated from disturbance observer. Du et al. [4] applied the H_∞ method in state space to design the feedforward controller to compensate for external vibration impact on the positioning accuracy of the voice coil motor (VCM) actuator. Pannu and Horowitz [5] considered the identification of both the plant and the disturbance model, and then designed an adaptive feedforward controller acting as an add-on compensator to the existing fixed compensator. Jinzenji et al. [6] used the dual accelerometers to detect angular acceleration in HDDs and compensate for its effects on the position accuracy. Adaptive feedforward control with the finite impulse response (FIR) filter was established in [7], but the gradient algorithm for updating the coefficients of the FIR controller relies on the exact internal model. In [8], infinite impulse response (IIR) filter and the FIR filter based on the filtered-x least

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mean square (LMS) algorithm were developed to compensate for the effects of the disturbances. The product of the unknown dynamics and its estimated inverse needs to be strictly positive real to guarantee convergence of the filtered-x LMS algorithm. It should be noted that in almost all of the existing feedforward control schemes, the sensor model and the disturbance dynamics are usually restricted to be linear and their mathematical models must be known or partly known. The necessity of the disturbance dynamics is a major drawback, because they can be time varying, non-linear and can rarely be modelled accurately.

Neural networks as non-linear controllers have received considerable attention in the control of non-linear systems, because they offer distinct advantages over the conventional controllers in achieving the desired performances [9–13]. Some papers are dedicated to the neural network feedforward compensation to reject the effect of disturbances in improving tracking accuracy. Lin and Hsiao [14] used the neural network feedforward control to eliminate the non-linear disturbance torque in seeker stabilising loop, whereas Gorinevsky and Feldkampf [15] developed the adaptive neural network feedforward compensator for the idle speed control of a car engine. Although these neural network disturbance rejection schemes give good simulation results, there are no theoretical results about the stability analysis of the closed-loop system.

In this paper, we present an adaptive neural network feedforward scheme using measured accelerometer signals to compensate for the effect of external vibrations on the tracking performance. The neural network weights are tuned online based on the feedback of the tracking error, i.e. the weights tuning scheme is effectively based on unsupervised learning. In particular, no dynamic knowledge about the sensor model and the disturbance model is needed. Furthermore, the closed loop is proven to be stable, and thus there is no design trade-off between disturbance rejection and stability. The feedforward control can be interpreted as a non-linear FIR filter, which is the extension of linear FIR filter whose basis function is linear. The efficacy of the proposed method is verified through experiments.

The paper is organised as follows. Section 2 gives the problem statement. In Section 3, the neural network feedforward compensation scheme is presented. Detailed information about the experimental as well as the experimental results is given in Section 4 and 5 respectively. Finally, in Section 6, conclusions are drawn.

2 Problem statement

The dynamics of the HDD system can be expressed as

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

$$y = q + d \qquad (2)$$

where q denotes the position of the VCM-actuator tip in the absence of disturbance, M is the system inertia, u is the control input and the function $F(q, \dot{q})$ represents bias forces due to pivot friction or the flex-cable, d is the disturbance acting on the system output, which is caused by external vibration ω, and y is the actual position of the VCM-actuator in the presence of disturbance.

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

$$e(t) = q_d - q - d \qquad (3)$$

The overall control scheme for external vibration compensation is shown in Fig. 1. P is the plant to be controlled, C_{nominal} is the nominal controller, C_f is the feedforward compensator, D is the unknown disturbance dynamics from external vibration ω to the disturbance d, and S is the accelerometer, which measures the vibration and generates the accelerometer signal a.

Remark 1: The symbol $(\cdot)^*$ will hereafter be used to denote the ideal value of $(\cdot)$.

From Fig. 1, it can be seen that if

$$C_f = C_f^* = P^{-1}DS^{-1} \qquad (4)$$

the effect of disturbance can be eliminated completely. However, this feedforward compensation method relies heavily on a priori models of the plant, sensor and disturbance. If these models are not known exactly, the feedforward controller given by (4) cannot eliminate the impact of the external vibrations on the positioning accuracy.

The objective is thus to design the feedforward compensator C_f without explicit knowledge about the plant, sensor and disturbance dynamics, such that the effect of external vibration on positioning accuracy can be reduced.
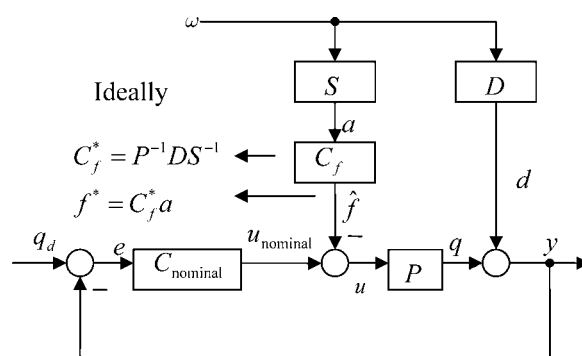

Figure 1 *Control structure of the HDD with vibration compensation*

3 Neural network feedforward control

In this section, the neural network compensator is derived. It can be seen that the derivation does not rely on any plant, sensor or disturbance model, and that the neural network will compensate for the effects of external vibrations on VCM-actuator.

Define an extended tracking error as

$$e_v = \dot{e} + \lambda_c e \qquad (5)$$

where λ_c is a positive scalar. Note that this extended tracking error is widely used in robotics (e.g. [11]) and sliding mode control (e.g. [16]).

Differentiating e_v and using (1), (2) and (3), the HDD dynamics can be expressed as

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

From (6), it can be seen that if $d = 0$, then the HDD dynamics can be rewritten as

$$M\dot{e}_v = F(q, \dot{q}) - u + M\ddot{q}_d + M\lambda_c\dot{e} \qquad (7)$$

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

Assumption 1: The nominal control u_{nominal} guarantees the tracking error e_v in (7) to be asymptotically convergent, i.e. there exists a Lyapunov function $V_1(e_v) = (1/2)Me_v^2$ such that

$$\dot{V}_1(e_v) = e_v\big(F(q, \dot{q}) + M\ddot{q}_d + M\lambda_c\dot{e} - u_{\text{nominal}}\big) \leq -Qe_v^2 \qquad (8)$$

where Q is a positive constant.

Remark 2: The design of the nominal controller is well understood in the HDD control literature. There are many methods for performing this design, including frequency shaping, H-infinity control and optimal control. As this is not the focus of this study, we will not go into too many details here.

If we design the control law as

$$u = u_{\text{nominal}} - \hat{f} \qquad (9)$$

where $\hat{f}$ is the feedforward control signal whose desired value is

$$f^* = M\ddot{d} \qquad (10)$$

then the term $M\ddot{d}$ in (6) can be cancelled.

Because $\ddot{d}$ is not measurable, we can equivalently require that

$$f^* = C_f^* \cdot a \qquad (11)$$

where $C_f^* = P^{-1}DS^{-1}$ for the effect of the disturbance to be cancelled (from (4) and Fig. 1). Since S and D are unknown non-linear functions, we approximate (11) as a non-linear FIR function

$$f^*(kT) = H(a(kT), \ldots, a((k-N))T) + \Delta\phi_1 \qquad (12)$$

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

Denote

$$x = [a(kT), \ldots, a((k-N)T)]^{\text{T}} \qquad (13)$$

Next, a neural network $w^{\text{T}}\Phi(x)$ is derived. The ideal neural network $w^{*\text{T}}\Phi(x)$ will approximate the function $H(x)$ in (12) in a compact set $\Omega \subset R^{N+1}$, i.e.

$$H(x) = w^{*\text{T}}\Phi(x) + \Delta\phi_2 \qquad (14)$$

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 $|\Delta\phi_2| \leq \varepsilon_2$, where $\varepsilon_2 > 0$.

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

Summarising (10), (12) and (14), we obtain

$$f^* = M\ddot{d} = w^{*\text{T}}\Phi(x) + \Delta\phi_1 + \Delta\phi_2 \qquad (15)$$

The neural network to be implemented is (see Fig. 2)

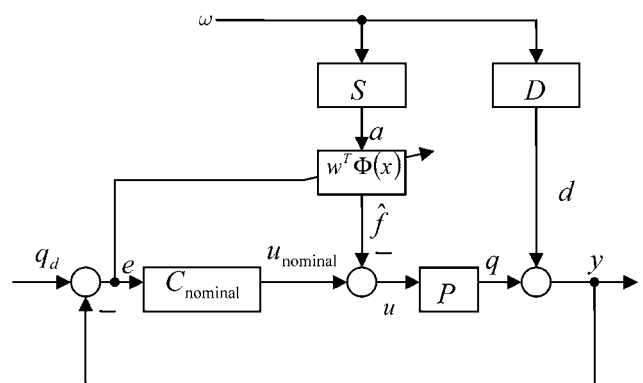$$\hat{f} = w^{\text{T}}\Phi(x) \qquad (16)$$

Figure 2 *Adaptive neural network feedforward compensator*

Remark 3: The neural network compensator (16) can be interpreted as a non-linear FIR filter for the following reasons: First, if $\Phi(x)$ is chosen as x (linear), then $\hat{f} = w^{\mathrm{T}}x$ is exactly the linear FIR filter. Therefore we think of $\hat{f} = w^{\mathrm{T}}\Phi(x)$ as the extension of the FIR filter. Second, as can be seen from the structure of the neural network compensator (Fig. 4), the output of the compensator $\hat{f}$ is not fed back directly to its input, which is similar to linear FIR filter. Finally, the output of linear FIR filter is bounded as long as its input and weights are bounded; the same can be said here for the neural network compensator: its output will be bounded because the weights are bounded (proof to be given later), whereas the boundedness of its input is not crucial here because the non-linear activation function $\Phi(x)$ will yield bounded values.

Substituting (9), (15) and (16) into (6), we obtain

$$
\begin{aligned}
M\dot{e}_v &= F(q,\dot{q}) - u_{\mathrm{nominal}} + M\ddot{q}_d + M\lambda_c\dot{e} - M\ddot{d} + \hat{f} \\
&= F(q,\dot{q}) - u_{\mathrm{nominal}} + M\ddot{q}_d + M\lambda_c\dot{e} - \bar{w}^{\mathrm{T}}\Phi(x) \\
&\quad - \Delta\phi_1 - \Delta\phi_2
\end{aligned}
\tag{17}
$$

where

$$
\bar{w} = w^* - w
\tag{18}
$$

is the weight estimation error.

The adaptation law for the parameter w is given by

$$
\dot{\bar{w}} = -\dot{w} = \Gamma\Phi(x)e_v + \sigma\Gamma|e_v|w
\tag{19}
$$

where $\Gamma > 0$ is a gain matrix and $\sigma > 0$ is a scalar parameter.

Theorem: The control law (9) together with (16) and the parameter update law (19) guarantee the tracking errors e_v, e and the weight estimation error $\bar{w}$ to be uniformly ultimately bounded.

Proof: Consider the following Lyapunov function candidate

$$
V = \frac{1}{2}Me_v^2 + \frac{1}{2}\bar{w}^{\mathrm{T}}\Gamma^{-1}\bar{w}
\tag{20}
$$

By applying (17) and Assumption 1, the time derivative of V is given by

$$
\begin{aligned}
\dot{V} &\leq -Qe_v^2 + e_v\bar{w}^{\mathrm{T}}\Phi(x) - e_v\Delta\phi_1 - e_v\Delta\phi_2 + \bar{w}^{\mathrm{T}}\Gamma^{-1}\dot{\bar{w}} \\
&= -Qe_v^2 - e_v\Delta\phi_1 - e_v\Delta\phi_2 - \bar{w}^{\mathrm{T}}\left(-\Gamma^{-1}\dot{\bar{w}} + e_v\Phi(x)\right)
\end{aligned}
\tag{21}
$$

Substituting (19) into (21), we obtain

$$
\dot{V} \leq -Qe_v^2 - e_v\Delta\phi_1 - e_v\Delta\phi_2 + \sigma\bar{w}^{\mathrm{T}}w|e_v|
\tag{22}
$$

Using the inequality

$$
\begin{aligned}
\bar{w}^{\mathrm{T}}w &= \bar{w}^{\mathrm{T}}(w^* - \bar{w}) \\
&= \bar{w}^{\mathrm{T}}w^* + \bar{w}^{\mathrm{T}}\bar{w} \\
&\leq \|\bar{w}\|\|w^*\| - \|\bar{w}\|^2 \\
&\leq \|\bar{w}\|W - \|\bar{w}\|^2 \\
&= \left(\|\bar{w}\| - \frac{1}{2}W\right)^2 + \frac{1}{4}W^2
\end{aligned}
\tag{23}
$$

we obtain

$$
\begin{aligned}
\dot{V} &\leq -Qe_v^2 - e_v\Delta\phi_1 - e_v\Delta\phi_2 - \sigma\left(\|\bar{w}\| + \frac{1}{2}W\right)^2|e_v| \\
&\quad + \frac{\sigma}{4}W^2|e_v| \\
&\leq |e_v|\Bigg(-Q|e_v| + |\Delta\phi_1| + |\Delta\phi_2| \\
&\qquad - \sigma\left(\|\bar{w}\| - \frac{1}{2}W\right)^2 + \frac{\sigma}{4}\|w^*\|^2\Bigg) \\
&\leq |e_v|\Bigg(-Q|e_v| + \varepsilon_1 + \varepsilon_2 - \sigma\left(\|\bar{w}\| - \frac{1}{2}W\right)^2 + \frac{\sigma}{4}W^2\Bigg)
\end{aligned}
\tag{24}
$$

It can be seen from (24) that $\dot{V}$ will be negative whenever

$$
|e_v| \geq \frac{\varepsilon_1 + \varepsilon_2 + \frac{\sigma}{4}W^2}{Q} = B_{ev}
\tag{25}
$$

or

$$
\|\bar{w}\| \geq \frac{1}{2}W + \sqrt{\frac{\varepsilon_1 + \varepsilon_2}{\sigma} + \frac{W^2}{4}} \equiv B_{\bar{w}}
\tag{26}
$$

Thus, $|e_v|$ will decrease from its initial value until it is smaller than B_{ev} and B_w, respectively. This implies that e_v and the weight error $\bar{w}$ are uniformly ultimately bounded. Because $e_v = \dot{e} + \lambda_c e$ is a stable system, it can be concluded from [11, 16] that as $t \to \infty$,

$$
\|\bar{w}| \geq \frac{1}{2}W + \sqrt{\frac{\varepsilon_1 + \varepsilon_2}{\sigma} + \frac{W^2}{4}} \equiv B_{\bar{w}}
\tag{27}
$$

$\square$

4 Details of the experiment

4.1 Experimental set-up

The scheme of the experimental set-up is shown in Fig. 3. An HDD Baracudda 7200.10, Seagate, CA, USA is mounted onto the shaker Vibration Exciter Type 4808, Brüel & Kjaer, Nærum, Denmark using a support plate.
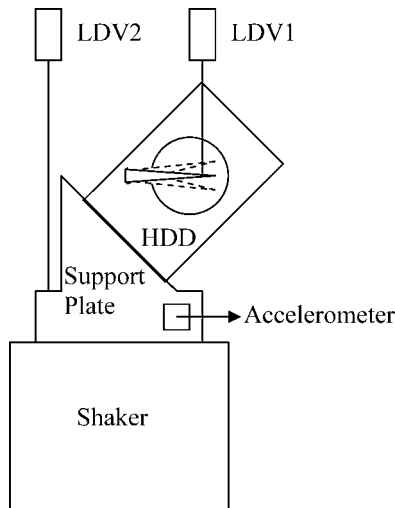
Figure 3 *Experimental setup*

The support plate is triangular so that the VCM-actuator is perpendicular to the laser beam (LDV1) of the Laser Doppler Vibrometer Polytec OFV 512, Polytec, Waldbronn, Germany when not shaken. A second LDV (LDV2) is used to measure the position of the support plate, such that the signal LDV1-LDV2 represents the relative movement of the VCM-actuator with respect to the HDD. An accelerometer KXPA4-2050, Kionix, New York, USA is attached to the support plate to measure the linear acceleration of shaker. Also used but not shown in Fig. 3 are the computer in which the controller algorithm is programmed using MATLAB Simulink MATLAB 6.0, The MathWorks, MA, USA, and the dSPACE DS1103, dSPACE system GmbH, Paderborn, Germany.

4.2 Nominal controller

Although the model of the VCM-actuator as well as the design of the nominal controller are not needed for the design of our neural network disturbance compensator, they are mentioned here for the information of the reader.
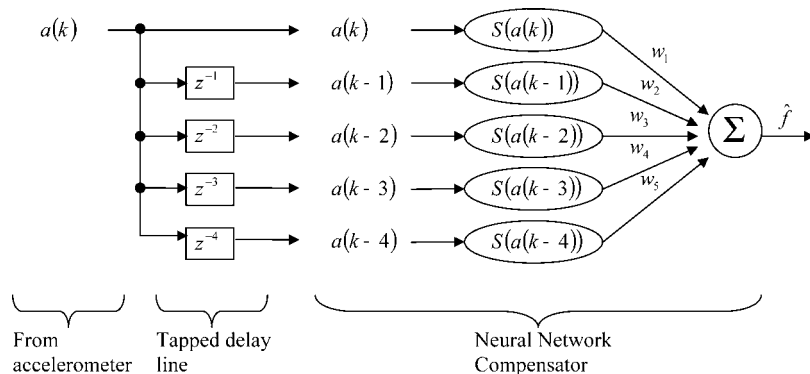
The HDD can be modelled as

$$P(s) = \underbrace{\frac{4.0968 \times 10^7}{s^2}}_{\text{Double Integrator}} \times \underbrace{\frac{1.421 \times 10^9}{s^2 + 2262 \cdot s + 1.421 \times 10^9}}_{\text{Resonance Mode}} \quad (28)$$

The nominal state feedback controller is designed based on the double integrator model in (28), ignoring the resonance modes. We augment the system state with an integral state and place the closed-loop poles at $[-5918.8 \quad -4.6841 \pm 4.4686i]$, whereas the observer poles are placed at $[-5000 \quad -5000]$.

4.3 Neural network compensator

The neural network compensator is constructed as a non-linear FIR filter with delayed accelerometer signals as inputs, which are then mapped to the output via a non-linear function and some weightings (Fig. 4):

$$w^{\mathrm{T}}\Phi(a(k), a(k-1), a(k-2), a(k-3), a(k-4)) \quad (29)$$

where $w = [w_1, w_2, w_3, w_4, w_5]^{\mathrm{T}}$, and the network basis function

$$\Phi(a(k), a(k-1), a(k-2), a(k-3), a(k-4))$$
$$= [S(a(k)), S(a(k-1)), S(a(k-2)), S(a(k-3)), S(a(k-4))] \quad (30)$$

with the sigmoidal function

$$S(x) = \frac{2}{1 + e^{-x}} - 1 \quad (31)$$

The parameters are chosen as $\lambda_c = 500, \sigma = 0.1$ and $\Gamma = \mathrm{diag}(\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5)$ with $\gamma_i = 1$ for $i = 1, 2, 3, 4, 5$. The neural network weights are simply initialised at zero.

Remark 4: The number of nodes was chosen based on the experimental observations: the disturbance attenuation performance of the neural network compensator improved as we increased the number of nodes from 1 to 5, but no significant improvement was observed when we further
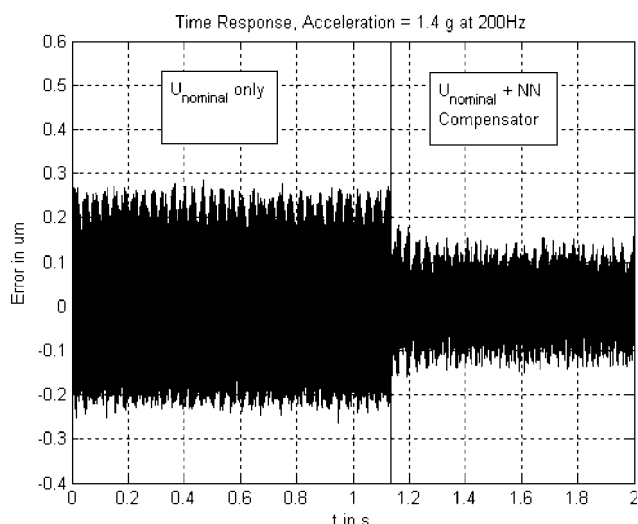

Figure 4 *Neural network compensator*

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Figure 5 *Tracking error with and without disturbance compensation, acceleration = 200 Hz, 1.4g*

increased the number of nodes. Thus, we fixed five neural nodes for our compensator. Likewise, the sigmoidal function was chosen in favour of the Radial Basis Function $\exp(-x^2)$ because of the better experimental result. On the other hand, the number of hidden layers is fixed as 1, because the neural network we used is linear with respect to the weights.

5 Experimental results

5.1 Time plots at particular disturbance frequencies

The shaker is programmed to shake at 200 and 250 Hz with an acceleration of 1.4g. Figs. 5 and 6 show the significant reduction of error when the neural network disturbance compensator is switched on. In fact, the error magnitude decreased by 40% and 70%, respectively, in the two cases.
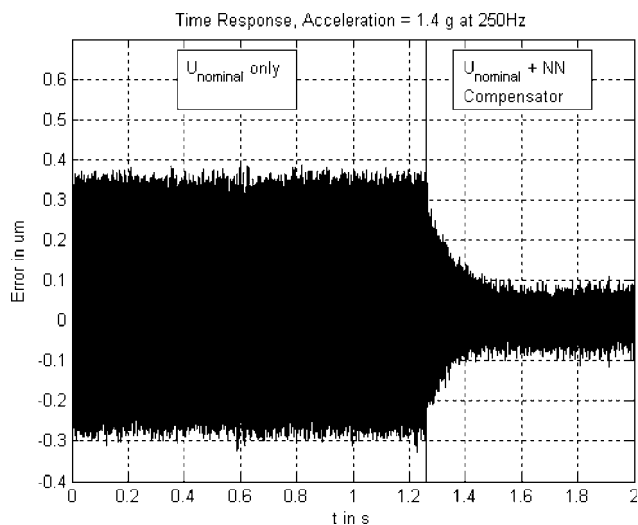

Figure 6 *Tracking error with and without disturbance compensation, acceleration = 250 Hz, 1.4g*
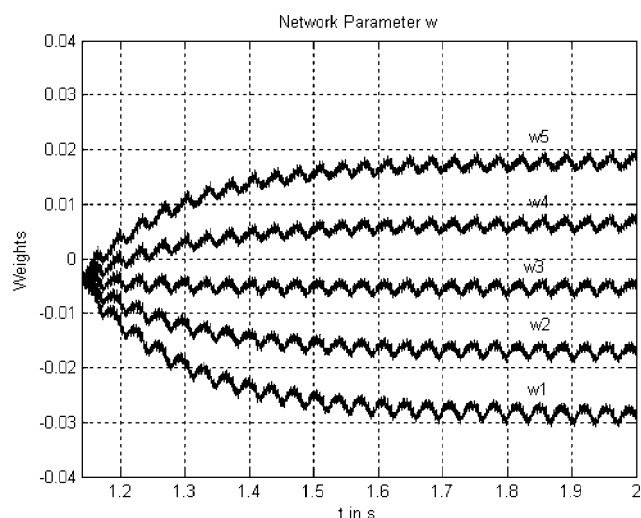

Figure 7 *Evolution of the neural network weights, acceleration = 200 Hz, 1.4g*

The evolution of the neural network weights are plotted in Figs. 7 and 8. One sees that the convergence of the weights is achieved in less than 1 s.

5.2 Attenuation of disturbance over a frequency range

To see the efficacy of the neural network disturbance compensation scheme over a wider range of frequencies and different accelerations, we program the shaker to shake with 1g and 0.3g acceleration, and with the frequency swept from 80 to 500 Hz.

Fig. 9 shows the tracking error when the shaker shakes at 1g. One sees that when the compensator is switched on, the magnitude of the tracking error is lower in the range 100–500 Hz, with a small exception at around 140 Hz. When the shaker shakes at 0.3g, the tracking error is also reduced
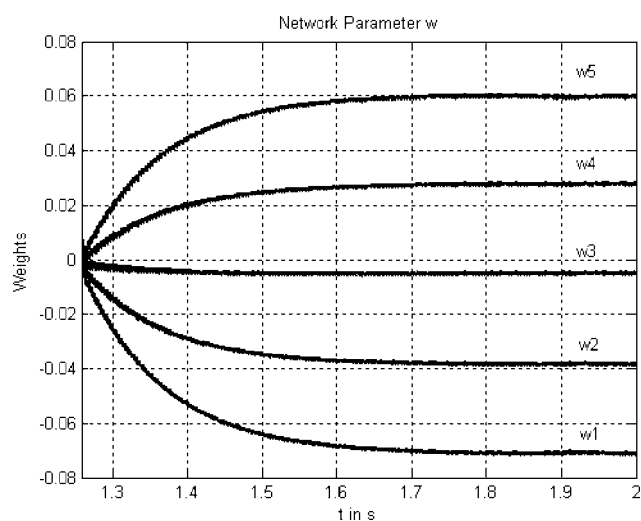

Figure 8 *Evolution of the neural network weights, acceleration = 250 Hz, 1.4g*
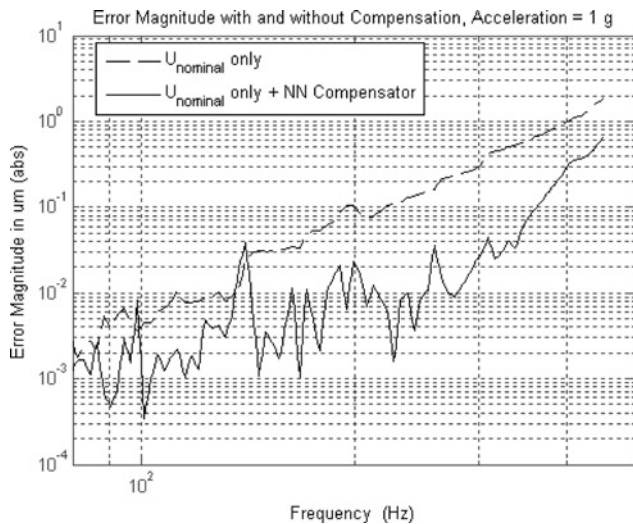
Figure 9 *Error magnitude when acceleration = 1g, frequencies 80−500 Hz*
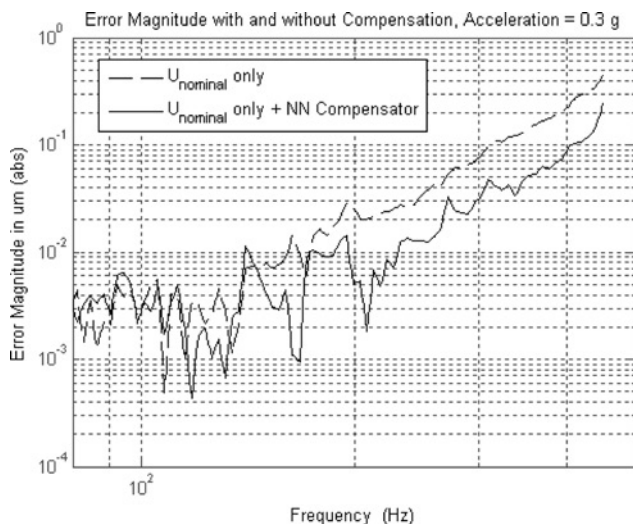

Figure 10 *Error magnitude when acceleration = 0.3g, frequencies 80−500 Hz*

in the range 200−500 Hz when the compensator is activated (see Fig. 10). This shows the improved disturbance rejection using the neural network compensator.

6 Conclusions

In this study, an adaptive neural network feedforward compensator for the rejection of external vibrations for HDDs is developed. The compensator uses an accelerometer to measure the external vibrations, and adapts itself to reduce the position error. The appealing advantage of the neural network feedforward scheme is that it does not require any prior knowledge about the sensor and disturbance dynamics. Experimental results have verified the efficacy of the compensator in reducing the effect of external vibrations on the positioning accuracy of HDDs.

7 Acknowledgment

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