Two-Degree-of-Freedom Control of a Self-Sensing Micro-Actuator for HDD using Neural Networks

(Invited Paper)

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Abstract—The present paper describes a two-degree-of-freedom control of a self-sensing micro-actuator for a dual-stage hard disk drive using neural networks. The two-degree-of-freedom control system is comprised of a feedforward controller and a feedback controller. Two neural networks are developed for the two-degree-of-freedom control system, one for the inverse dynamic model for the feedforward controller and one for system identification for the generation of the desired self-sensing signal. The feedback controller can realize the identified self-sensing signal. The micro-actuator uses a PZT actuator pair, installed on the assembly of the suspension. The self-sensing micro-actuator can be used to form a combined actuation and sensing mechanism. Experimental results show that the neural network approach can be used effectively for the control and identification of the self-sensing micro-actuator system.

Keywords—two-degree-of-freedom control, neural network, self-sensing actuation, micro-actuator, hard disk drive

I. INTRODUCTION

A suspension assembly in the hard disk drive (HDD) can be excited by the airflow generated from a high-speed rotating magnetic disk, a non-circular track motion of the head/slider, which is caused by the resonance vibration modes of components, and other external disturbances. A servo system that can cope with these problems requires a very high servo bandwidth and position error signal sampling frequency. The sampling frequency of the position error signal is limited by the data storage efficiency of the conventional servo system. Active control of these problems and the vibration of components require additional vibration sensors and actuators. Many researchers have proposed the addition of extra vibration sensors and actuators. For example, the use of a piezoelectric actuator to actuate the suspension for the dual-stage servo system has been proposed, whereby one of the two piezoelectric strips is used as a vibration sensor and the other is used as the actuator [2]. However, using only half of the conventional micro-actuator pair as the sensor decreases the usual effect of the actuator by half and is not efficient.

One approach to solving these problems is the use of a self-sensing micro-actuator in the suspension to control the component vibration modes in order to increase the servo bandwidth of the dual-stage servo system [3]. The self-sensing actuation approach exceeds other vibration compensation approaches with respect to controlling dual-stage servo systems. However, care must be taken because the micro-actuator can actively and adaptively change the physical geometry and properties of the suspension assembly. Artificial neural networks can be used effectively for the identification and control of nonlinear dynamical systems, such as a flexible micro-actuator with a suspension assembly and a self-sensing system. In the present paper, in order to solve these problems and improve the performance of the dual-stage servo system for the HDD, a neural-network-based two-degree-of-freedom control has been proposed by utilizing the self-sensing sensors to damp the suspension assembly vibrations.

II. SUSPENSION ASSEMBLY WITH SELF-SENSING MICRO-ACTUATOR

Fig. 1. Suspension assembly with PZT micro-actuators.

This section describes the structure of the plant and its mechanical characteristics. Figure 1 shows a suspension assembly for a dual-stage HDD [4]. A suspension-based micro-
Fig. 2. Self-sensing signal $v_s$ can be obtained from a bridge circuit. It is possible to use two types of bridge circuits.

Fig. 3. Frequency response of the suspension assembly from control input of micro-actuator to slider displacement.

Fig. 4. Frequency response of the suspension assembly from control input to strain rate self-sensing signal.

Fig. 5. Frequency response of the suspension assembly from control input to strain self-sensing signal.

actuator utilizes a PZT actuator pair, which is located between the suspension and the base plate. A slider is installed on the tip of the suspension. When a control voltage is applied to the PZT micro-actuator pair, one of the two PZT strips extends and the other contracts. The PZT-actuator-actuated suspension can achieve a larger head element displacement by using the suspension length as a swinging radius. However, the increase in the servo bandwidth is limited by the resonance frequency of the suspension. The self-sensing actuation technique using this micro-actuator can detect the suspension modes of vibration.

In the present paper, only the suspension assembly in Fig. 1 is considered.

The self-sensing actuator combines the sensor and actuator mechanisms in one piezoelectric element [5]. The PZT micro-actuator strain signal $v_p$ can be obtained from a simple bridge circuit in Fig. 2. The simple bridge circuit is used to extract the piezoelectric strain signal $v_p$ from the output signal $v_s$ of the element. Note that the output signal $v_s$ includes an applied control voltage $v_c$ and a piezoelectric strain signal $v_p$. Two types of bridge circuits are possible in Fig. 2. The bridge circuit is composed of resistors $R_1$ and $R_2$ or capacitors $C_1$ and $C_2$. When resistors $R_1$ and $R_2$ or capacitors $C_1$ and $C_2$ are in series with capacitors $C_p$ and $C_f$, and is used to sense the time rate of strain or the strain. The voltage $v_c$ is the applied control input to the bridge circuit, and the voltage $v_p$ is the voltage generated by the piezoelectric effect.

The capacitance $C_p$ is the capacitance of the PZT micro-actuator. To remove the effects due to $v_c$, $v_2$ is subtracted from $v_1$. The residue is called the self-sensing sensor voltage $v_s$.

\begin{align*}
v_s &= \frac{C_p R_1}{C_p + R_1} \frac{dv_p}{dt} \quad \text{(RC bridge circuit.)} \\
v_s &= \frac{C_p}{C_p + C_1} v_p \quad \text{(CC bridge circuit.)}
\end{align*}

Therefore, sensor and actuator mechanisms can be used together to form one piezoelectric element.

Figure 3 shows the measured frequency response from the applied control voltage of the PZT micro-actuator to the slider displacement in the suspension assembly. The major vibration modes in the suspension assembly are the suspension first bending mode (B1), the suspension second bending mode (B2), the suspension third bending mode (B3), the suspension second torsion mode (T2) and the micro-actuator sway mode (Sway). The suspension bending modes are vibrations in the vertical direction. The sway mode is called the PZT micro-actuator actuation mode and is a vibration in the horizontal direction. The suspension bending modes and the torsion mode also appear as reaction modes because they are excited by the PZT micro-actuator. If the same experiment is conducted on the rotating magnetic disk, the suspension bending modes and the torsion mode might disappear, leaving only the micro-actuator sway mode.

Figures 4 and 5 show the measured frequency response from the applied control voltage of the PZT micro-actuator to the strain rate self-sensing sensor using the RC bridge circuit and
The control system design and system identification process are designed using multiple-layer artificial neural networks. Artificial neural networks have three layers, as shown in Fig. 6. The internal output signals of the hidden and output layers can be written as follows:

\[ u_i = \sum_j w_{ji} x_i + \theta_j \]  
\[ s_h = \sum_j v_{kj} h_j + \phi_h \]

where \( u_i \) is the output of a hidden layer, \( s_h \) is the output of an output layer, \( w_{ji} \) is the weight between an input layer and a hidden layer, and \( v_{kj} \) is the weight between a hidden layer and an output layer, \( \theta_j \) is the bias of a hidden layer, and \( \phi_h \) is the bias of an output layer. The neuron activation function of an input layer and an output layer is assumed to be a linear function, and the neuron activation function of hidden layer is a sigmoid function given by the following equation:

\[ h_j = f(u_i) = \frac{2}{1 + e^{x(-u_i)}} - 1 \]

In order to minimize the cost function \( J \),

\[ J = \frac{1}{2}(y_d - y)^2 \]

, the backpropagation method is used for the learning rule. The updating equation of the weights \( w_{ji} \) and \( v_{kj} \) is defined as

\[ w_{ji}(n+1) = w_{ji}(n) - \eta \frac{\partial J(n)}{\partial w_{ji}(n)} \]
\[ v_{kj}(n+1) = v_{kj}(n) - \eta \frac{\partial J(n)}{\partial v_{kj}(n)} \]

where \( \eta \) is the weight value and \( \eta \) is the learning rate of the weight parameters.

Figure 7 shows the configuration of an experimental system based on the self-sensing approach. In the present paper, the experimental system was not implemented on a spin stand test. The neural network controller is designed using Matlab/Simulink, the solution of the controller is downloaded into the DSP system (dSPACE DS1103). Control input voltage \( v_c \) calculated by the DSP system with a sampling time of 0.1 [msec] is applied to the bridge circuit through a D/A converter and a piezoelectric driver. Sensor voltage \( v_s \) output from the bridge circuit is differentially amplified between \( v_1 \) and \( v_2 \) using a differential amplifier (Analog Device). The output voltage \( v_s \) of the differential amplifier is sent to an A/D converter. A laser Doppler vibrometer (LDV, Graphtec) is used to monitor the velocity \( v \) of the slider. The cut-off frequency of a low pass filter in LDV is 2,000 Hz. The displacement signal \( w \) is calculated via an analog integration circuit. The displacement data in the figures do not show the true value of the displacement exactly.

The neural network is trained using displacement signal \( w \) for inverse dynamics, and this signal is used as a feedforward controller. Figure 8 shows the control system using the neural network.
network. The desired trajectory $w_d$ is shown in Fig. 9. The experimental conditions are shown in Table II.

The objective of the experiment is to control the displacement of a slider. In the experiment, $[w_d(t), w_d(t + 1), \ldots, w_d(t + 5)]$ are used as the neural network input. Figures 11 and 12 show a comparison of the open loop results and the neural-network-based feedforward control. The experimental results for the velocity signals indicate excellent control performance. The feedforward control results are compared with the open loop results, and quick and precise tracking control can be realized, except for the low-frequency noise of the LDV. The time response of the displacement shows the tracking error due to the quantization error.

VI. NEURAL-NETWORK-BASED SYSTEM IDENTIFICATION

In this section, the system identification process is conducted on the displacement of the slider $w$ and self-sensing sensor signal $v_s$. Figure 13 shows the identification system. The neural network identifier is employed for the modeling of the transfer function $v_s/w$. The number of neurons for three layers of the neural network identifier and the learning rate parameter $\eta$ are shown in Table III. Here, $[w(t), w(t-1), \ldots, w(t-3)]$ are used as the neural network input. Training of the neural-network-based system identification is conducted off-line.

Figure 14 shows a comparison of the time response between the self-sensing voltage obtained using the results of Fig. 12 and the identification neural network model. The results coincided with each other.

VII. NEURAL-NETWORK-BASED
TWO-DEGREE-OF-FREEDOM CONTROL

Figure 15 indicates the block diagram of the two-degree-of-freedom control system with the neural network. The feed-
(a) Responses of input voltage $v_i$ in Fig. 10 obtained from experiments.

(b) Feedforward control using a neural network.

Fig. 12. Experimental results obtained using an RC bridge circuit.

Fig. 13. Neural-network-based system identification process.

Forward controller is designed using a neural-network-based inverse dynamics system in Section V, and the feedback controller can be realized using the identified self-sensing signal in Section VI. After successfully learning the signals in Sections V and VI, the neural network output signals $v_{cd}$ and $v_{sd}$ are used as the desired trajectory. Two neural networks are conducted off-line. The performance of the DSP is not sufficient for realizing the online real-time neural-network-based control system because the amount of calculation required is too great.

Figure 16 shows the experimental results obtained using the strain rate self-sensing signal. In the two-degree-of-freedom control, the feedback gain $K_{fb}$ is chosen to be 10. Figure 17 shows the experimental results obtained using the strain self-sensing signal. In the two-degree-of-freedom control, the feedback gain $K_{fb}$ is chosen to be 15$+0.001$ s. The tip velocity of the head gimbal assembly can follow the desired trajectory using the presented control system. The results show that the neural-network-based two-degree-of-freedom control system is better than the neural-network-based feedforward control system.

VIII. CONCLUSION

Two-degree-of-freedom control of a self-sensing micro-actuator for an HDD using a neural network has been presented. The piezoelectric self-sensing actuator is a piezoelectric transducer that is used simultaneously as a sensor and an actuator. The self-sensing actuator is a linear estimator that generates an estimate of the strain signal, or its derivative. The structure of the estimator is rather crude and is largely...
dependent on the added electric circuitry. It should be possible to construct better estimates of the required signals using an optimal estimation method such as an extended Kalman Filter or neural networks. Two neural networks have been developed for the two-degree-of-freedom control system: one for the inverse dynamics model for the feedforward controller and one for system identification for the generation of the desired self-sensing signal. The neural network for inverse dynamics as the feedforward controller has been introduced for online and real-time control, and the end point of the slider has been shown to follow a desired trajectory. However, two neural networks could not be executed online and in real time. The performance of our DSP system (DS1103) is not approximate for realizing the online real-time neural-network-based control system because the amount of calculation required is too great.

For two-degree-of-freedom control, faster and more precise tracking can be realized using a neural network.

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