FPGA Adaptive Filter-Based Magnetic Bearing Displacement Sensor Fault Signal Processing and Analysis (Postprint)

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Abstract

For active magnetic bearing control systems employing differential mode for displacement measurement, this paper investigates the relationship between eddy current displacement sensor fault signals and controller output signals, analyzes the characteristics of displacement sensor outputs and controller outputs when different probes fail, introduces the working principle of adaptive filtering, and consequently proposes a sensor fault diagnosis method based on adaptive filtering. This method employs the difference between the two sensor output signals as a reference signal to filter the controller' s output signal, obtaining the correlation coefficient between the controller output signal and the difference signal of the two sensor outputs, thereby accurately identifying the faulty sensor based on the polarity of the correlation coefficient. Finally, simulations are conducted using Matlab, and experimental verification of the fault signals is performed using an adaptive filter based on Field Programmable Gate Array (FPGA). The results demonstrate that this method can accurately detect sensor faults and identify the faulty sensor.

Full Text

Fault Analysis of Magnetic Bearing Displacement Sensor Based on FPGA Adaptive Filter

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Abstract

For active magnetic bearing control systems that employ differential displacement measurement, this paper investigates the relationship between eddy current displacement sensor fault signals and controller output signals. The characteristics of displacement sensor outputs and controller outputs are analyzed for different probe failure scenarios. After introducing the working principle of adaptive filtering, a sensor fault diagnosis method based on adaptive filtering is proposed. This method uses the difference between the two sensor output signals as a reference signal to filter the controller' s output signal, obtaining a correlation coefficient between the controller output and the differential sensor signal. The faulty sensor can then be accurately identified based on the polarity of this correlation coefficient. Finally, Matlab simulations are performed, and experimental verification is conducted using an adaptive filter based on Field-Programmable Gate Array (FPGA). The results demonstrate that the proposed method can accurately detect sensor faults and identify the faulty sensor.

Keywords: Eddy current displacement sensor, field-programmable gate array, adaptive filtering, fault diagnosis

1 Introduction

Magnetic bearings are a novel type of bearing that utilizes electromagnets to generate controllable electromagnetic forces for contactless rotor suspension. Compared with conventional bearings, magnetic bearings offer numerous advantages including wear-free operation, no contamination, no lubrication requirements, and adjustable stiffness and damping [1]. However, magnetic bearing systems are far more complex than traditional bearings as they incorporate sensors, controllers, power amplifiers, and other components. Consequently, improving the reliability of magnetic bearing systems represents a current research focus. As the most critical component, sensor probes are installed near the rotor and are frequently subjected to vibration and high-speed airflow during operation, making them the most vulnerable to damage. Therefore, redundant sensor design has become one of the primary methods for enhancing system reliability [2].

The introduction of fault detection and diagnosis (FDD) systems in active magnetic bearing systems can improve reliability to some extent. The main task of an FDD system is to monitor the functionality of each subsystem in real-time. When a subsystem malfunctions, the FDD system automatically identifies the faulty unit and replaces it, thereby requiring the system to have functional redundancy. The key challenge in FDD systems lies in fault diagnosis and identification.

Active magnetic bearing systems typically employ differential displacement sensors to improve displacement detection performance. In this configuration, two displacement sensors (referred to as Sensor 1 and Sensor 2 in this paper) are installed at each degree of freedom to simultaneously detect rotor displacement. This paper presents a displacement sensor fault identification method for active magnetic bearing systems using differential displacement sensors. The method can detect sensor faults and identify the faulty sensor by analyzing the two displacement signals and the controller output signal.

[Figure 1: see original paper] Structure diagram of active magnetic suspension bearing system with differential displacement sensor

2 Differential Displacement Sensor Output Signals and Fault Signals and Their Relationship with Interference Forces

Figure 1 shows the structural block diagram of a single-degree-of-freedom active magnetic bearing system with differential eddy current displacement sensors. In the diagram, C(s) represents the controller; Ki is the current stiffness coefficient of the magnetic bearing; G(s) is the rotor model; Ks1 and Ks2 are the gains of Sensor 1 and Sensor 2, respectively; r is the reference input; f is the interference force on the rotor; d1 and d2 are interference signals applied to Sensor 1 and Sensor 2, respectively, used to simulate faults in Sensor 1 and Sensor 2; V1 and V2 are the output signals of Sensor 1 and Sensor 2, respectively; and uc is the controller output signal.

From Figure 1, the relationship between the two sensor output signals and the fault signals and interference forces can be derived as:

Vd = V1 - V2 = (1 + Ks2KiG(s)C(s))d1 - (1 + Ks1KiG(s)C(s))d2 + (Ks1 - Ks2)G(s)f

Assuming the two sensors have identical characteristics, i.e., Ks1 = Ks2 = Ks, Equation (2) can be simplified to:

Vd = Ks(d1 - d2)

From Equation (3), when the two sensors have identical characteristics, the difference between the two displacement sensor output signals depends only on the sensor fault signals. This characteristic can be utilized for sensor fault detection: whenever Vd is non-zero, it indicates a sensor fault. In practical applications, the two sensors cannot be perfectly identical, so an allowable error threshold Vtol is defined. If the difference signal between the two sensors satisfies:

|Vd| Vtol

the sensor is considered fault-free; otherwise, a sensor fault is detected.

3 Sensor Fault Detection Principle

Sensor faults manifest in various forms. In this system, sensor faults are primarily categorized into two types: incomplete faults and complete faults. Incomplete faults mainly include drift bias faults and fixed bias faults, caused by bias currents or voltages and temperature drift in operational sensors. Complete faults mainly include open-circuit and short-circuit faults, resulting from broken sensor signal lines or unconnected chip pins and short-circuited signal lines in the sensor hardware circuit.

4 Fault Sensor Identification

Equation (3) shows that a fault in either sensor will cause Vd to change. Therefore, while Vd can detect sensor faults, it cannot identify which sensor is faulty. Identification requires analysis of additional signals. Based on the system block diagram in Figure 1, the relationship between the controller output voltage and sensor interference signals and rotor interference forces can be derived as:

uc = -2(1 +)Ks(d1 + d2) - G(s)C(s)/(1 +)f

Let:

ucs = -2(1 +)Ks(d1 + d2)

ucf = -G(s)C(s)/(1 +)f

Then Equation (4) can be simplified to:

uc = ucs + ucf

When Sensor 1 fails (only interference signal d1 present), d2 = 0 and Vd = Ksd1. Substituting into Equation (5) yields:

ucs = -2(1 +)Ksd1 = -C(s)/[2(1 +)]Vd

When Sensor 2 fails (only interference signal d2 present), d1 = 0 and Vd = -Ksd2. Substituting into Equation (5) yields:

ucs = 2(1 +)Ksd2 = C(s)/[2(1 +)]Vd

Equations (8) and (10) can be written as:

ucs = (-1)^n C(s)/[2(1 +)]Vd

where n = 1 indicates Sensor 1 is faulty and n = 2 indicates Sensor 2 is faulty.

Sensor faults may involve both DC and AC interference, so Vd may contain both components:

Vd = Vd0 + Vda

where Vd0 represents the DC component and Vda represents the AC component.

From Equation (11), the relationship between ucs and Vd is frequency-dependent, so ucs can be further expressed as:

ucs = (-1)^n (k0Vd0 + kk0Vda)

where k0 = 2(1 +)|s=0 and kk0 = 2(1 +)|s=jk0, with k0 being the sensor AC interference frequency.

Equation (13) shows that if Sensor 1 is faulty, the proportional coefficients between ucs and Vd0, Vda are negative; if Sensor 2 is faulty, the proportional coefficients are positive. Therefore, analyzing these coefficients can identify the faulty sensor.

This paper employs digital correlation filtering to analyze the signals and determine the correlation coefficients. Digital correlation filtering accurately extracts components correlated with a reference signal from the original signal based on correlation principles. The principle is shown in Figure 2 [Figure 2: see original paper] [4-5]. In the diagram, s is the original signal; r is the reference signal; e is the error signal; and y is the compensation signal. The original signal s consists of a component correlated with r and an interference component: s = kr + n(t).

[Figure 2: see original paper] Digital filtering principle

The filter adjusts the weighting factor w of the reference signal using the Least Mean Square (LMS) algorithm to adjust the compensation signal, minimizing the variance of the error signal. As the algorithm executes, the weighting factor w converges to k, and the compensation signal y becomes the component of the original signal s that is correlated with the reference signal r. Using Vd0 and Vda as reference signals to perform correlation filtering on uc allows analysis of the proportional coefficients between ucs, Vd0, and Vda. The block diagram is shown in Figure 3 [Figure 3: see original paper].

[Figure 3: see original paper] LMS adaptive filter block diagram

The correlation filtering algorithm is:

yi = w1,iVda,i + w2,iVd0,i ei = Vc,i - yi w1,i+1 = w1,i + 2 eiVda,i w2,i+1 = w2,i + 2 eiVd0,i

where is the algorithm convergence factor; w1,i and w2,i are the current weights for Vda and Vd0; w1,i+1 and w2,i+1 are the next weights; yi is the current compensation signal; and ei is the current error between the original and compensation signals.

After the filter stabilizes, w1 = k0 and w2 = kk0. From Equation (13), if w1 and w2 are negative, Sensor 1 is faulty; if w1 and w2 are positive, Sensor 2 is faulty.

5 Simulation Analysis

This paper investigates a single-degree-of-freedom active magnetic bearing and performs Matlab simulations of the proposed sensor fault identification algorithm. A sinusoidal interference force is applied to the rotor to simulate centrifugal forces during rotation, and a biased sinusoidal interference signal is applied to the sensor to simulate probe faults. The interference force applied to the rotor is:

$f = \sin(600\ t)$

The interference signal applied to the sensor is:

$sd = 0.5 + \sin(200\ t)$

[Figure 4: see original paper] shows the signal waveforms and identification results when Sensor 1 fails, and [Figure 5: see original paper] shows the results when Sensor 2 fails.

[Figure 4: see original paper] Signal waveforms and recognition result when sensor 1 fails

[Figure 5: see original paper] Signal waveforms and recognition result when sensor 2 fails

In Figure 4, trace 1 is Sensor 1' s output signal; trace 2 is Sensor 2' s output signal; trace 3 is the DC correlation coefficient; and trace 4 is the AC correlation coefficient. The results show that when Sensor 1 fails, both identified coefficients are negative; when Sensor 2 fails, both coefficients are positive, consistent with theoretical analysis.

6 Experimental Verification

Compared with analog filters, digital filters offer advantages including high signal-to-noise ratio, excellent transition band performance, high reliability and scalability, and flexible design. Consequently, hardware implementation of adaptive filters has been a research focus in adaptive signal processing. With the development of dedicated digital signal processing chips, the realizability and processing speed of digital filters have greatly improved. Field-Programmable Gate Array (FPGA), as a new type of digital signal processing chip, features fast digital signal processing, parallel data processing, direct hardware design using hardware description languages, shortened development cycles, reduced costs, and easy upgrading and modification.

This paper designs an LMS adaptive filter based on FPGA and applies it to an active magnetic bearing system for processing and analyzing differential displacement sensor signals to identify and diagnose sensor faults. The FPGA adaptive filter uses the difference signal between two differential displacement sensor outputs as the reference signal to filter the controller output signal, obtaining weight coefficients for sensor fault determination. The experiment studies one radial degree of freedom of an active magnetic bearing, with results shown in [Figure 6: see original paper] and [Figure 7: see original paper].

[Figure 6: see original paper] The impact on the sensor and the controller when sensor 1 fails and the result of fault identification

[Figure 7: see original paper] The impact on the sensor and the controller when sensor 2 fails and the result of fault identification

In Figures 6 and 7, trace 1 is Sensor 1’ s signal; trace 2 is Sensor 2’ s signal; trace 3 is the controller output signal; trace 4 is the DC reference signal weight; and trace 5 is the AC reference signal weight. In the Figure 6 experiment, an interference signal is applied to Sensor 1’ s processing circuit at time ts1 to simulate a probe 1 fault. The results show that before ts1, the rotor remains stably suspended; after ts1, the rotor begins to vibrate slightly but remains suspended. Both sensor signals exhibit varying degrees of vibration but remain within normal ranges. Simultaneously, the algorithm’ s calculation results begin to change gradually and stabilize at a negative value approximately 0.35 seconds after the fault occurs.

In the Figure 7 experiment, an interference signal is applied to Sensor 2’ s processing circuit at time ts2 to simulate a probe 2 fault. The results show that before ts2, the rotor remains stably suspended; after ts2, the rotor begins to vibrate slightly but remains suspended. Both sensor signals exhibit varying degrees of vibration but remain within normal ranges. Simultaneously, the algorithm’ s calculation results begin to change gradually and stabilize at a positive value approximately 0.35 seconds after the fault occurs.

7 Conclusion

This paper investigates sensor fault detection methods for active magnetic bearing systems employing differential displacement sensors, analyzing characteristics and identification methods for different sensor fault types. A fault sensor identification algorithm based on LMS adaptive filtering is proposed for sensor functional degradation faults. The theoretical feasibility of the algorithm is first proven, followed by Matlab simulation studies and experimental verification using an FPGA-based adaptive filter for fault signal processing. The results demonstrate that the proposed method can effectively identify faulty sensors. This research provides a new implementation method for improving the reliability of active magnetic bearing displacement detection systems.

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Note: Figure translations are in progress. See original paper for figures.