Online Anomaly Detection of Brushless DC Motor Using Current Monitoring Technique

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Abstract: Brushless DC (BLDC) motor fan is one of the most widely used electronic components for thermal management. Failures of fans will cause seriously problems, such as overheating, shut down and even burnt, in their host systems. Thus, anomaly detection of fan gains increasing attention. This paper investigates into anomaly detection of generalized-roughness bearing faults in BLDC motor fan using current monitoring technique. In the experiment, it was found that there were about 9% changes in current and rotary speed of fan when the BLDC motor behaved unusual. Mathematical modeling of BLDC motor and physics-of-failure analysis were employed to explain the experimental findings.

Keywords: Anomaly detection, bearing, brushless DC motor, fan, motor current

1. Introduction

Brushless DC (BLDC) motors are widely used in electronics-rich products, such as hard drive disks (HDDs), CD-ROMs, CD/DVD players, laser printers, and fans [1]. Although BLDC motors are reliable, their lifespans are still short compared with other electronic components, such as transformers, transistors, microchips. Schroeder and Gibson [2] reported that HDDs, fans, and CD-ROMs were the top ten failed components in electronics-rich products, among which motor failure was the predominant problem [2], [3]. Thus, anomaly detection of BLDC motors has received increasing attention, which aims to provide alert in advance.

To date, there are many existing techniques that can be used to perform anomaly detection of rotary machines. For example, vibration signals are widely used for diagnosing faults of rotary machines [4-6]; Oil-based information has been used to predict the wear condition in aircraft engine [7]; Acoustic noise (sound pressure level) is a good precursor to distinguish new and degraded fans [8]; Acoustic emission signals are used to detect gear fault [9]. The afore-mentioned techniques can be categorized as the sensor-based technologies, because they all need different sensors to monitor the corresponding signals. But it is often impossible to employ these kinds of techniques to monitor the health condition of rotary machines, because of difficult implementation, intrusive operation and high cost. In the last decade, more research works have focused on studying the feasibility of using current analysis for detecting and diagnosing induction motors faults [10-11]. Research work show current analysis technique is able to deliver promising results under different conditions. But there is still a need to research on detecting
generalized-roughness faults in motor bearing, because the failure characteristics of bearing faults may not exist or cannot be observed [12]. In this paper, based on our intensive experimental tests, we show that generalized-roughness faults in motor bearing could be detected using current analysis technique.

The use of current monitoring technique for fault detection is a non-invasive and sensor-less method. Current-based approach is proposed for online anomaly detection of BLDC motor fan under the assumption that there is a digital signal processor (DSP) in electronics-rich products. The proposed approach could be realized by connecting a resistor to a fan in series. Since the voltage of the resistor can be monitored by using a DSP as shown in Figure 1, the current of BLDC motor fan could be calculated accordingly. In the experiment, current probe was used to measure the motor current directly. The effectiveness of the proposed approach was illustrated by modeling of BLDC motor and validated by experimental fan tests.

![Figure 1: Schematic of Current Monitoring Technique](image)

2. Modeling of Brushless DC Motor

Mathematic modeling of BLDC motor are given as follows [1]. The electrical model of the BLDC motor shown in Figure 2 can be derived:

\[ V = L \frac{dI}{dt} + RI + E \] (1)

where \( E = k_e \omega \), \( k_e \) is the back electromotive force (back-EMF) constant, \( \omega \) is the rotary speed, \( V \) represents supply DC voltage, \( I \) is the armature current, \( L \) is the armature inductance which could be assumed to zero, \( R \) is the armature resistance.

![Figure 2: Equivalent Circuit of BLDC Motor](image)

The magnetic field is assumed to be constant. The electromagnetic torque \( T_e \) is proportional to armature current \( I \).

\[ T_e = k_r I \] (2)

where, \( k_r \) is the torque constant.

The mechanical property of the motor is as follows.

\[ T_e = J \frac{d\omega}{dt} + D\omega + T_f \] (3)

where, \( T_f \) is the friction torque, \( J \) is the rotor inertia, \( D \) is a the damping coefficient.
3. Experimental Setup

The data set analyzed in this paper was collected from a BLDC motor fan test. The BLDC motor has 2-phase stator, and 4-pole permanent magnet rotor. A Hall effect sensor is installed in the stator to control the motor by detecting the changing position of rotor. Since lubricant plays a vital role in BLDC motor bearings [13], the lubricant in the bearings is removed by putting the bearings into acetone for 30 minutes, to accelerate the degradation of bearing. Two fans were made using the no-lubricant bearings (Fan #1 and Fan #2) and two normal fans (Fan #3 and Fan #4) were used in the test.

These fans under test were powered by 12 V DC power supply to run under free airflow conditions continuously. The current of the BLDC motor was measured using a Tektronix current probe. The vibration signal of fan was also acquired simultaneously for reference. Schematic of the data acquisition system was shown in Figure 3. Seventy samples of current and vibration data were recorded every 15 minutes for each fan. Each sample had 40 seconds snapshot data. National Instruments’ LabVIEW was used for the data collection. The data sampling rate was 25.6 kHz.

![Figure 3: Schematic of the Experimental Setup](image)

Table 1 lists the original characteristics of four fans used in the test. The motor current shown in this paper is represented by a voltage signal. It is because that the output of current probe is a voltage signal, and we use this voltage signal directly. Since it is a 4-pole permanent magnet rotor, the Hall effect sensor detects four times change in magnetic field, which leads to two cycles of motor current with every rotation. Therefore, the motor current signal could also indicate the rotary speed of rotor.

<table>
<thead>
<tr>
<th>Fan No.</th>
<th>Vibration (g)</th>
<th>Current (V)</th>
<th>RPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>0.125</td>
<td>0.0047</td>
<td>3030</td>
</tr>
<tr>
<td>#2</td>
<td>0.103</td>
<td>0.0048</td>
<td>3000</td>
</tr>
<tr>
<td>#3</td>
<td>0.129</td>
<td>0.0039</td>
<td>3060</td>
</tr>
<tr>
<td>#4</td>
<td>0.135</td>
<td>0.0052</td>
<td>2970</td>
</tr>
</tbody>
</table>

4. Results and Discussion

BLDC motor fan bearings degraded as expected due to the loss of lubricant in Fan #1 and Fan #2, while Fan #3 and Fan #4 worked as normal ones during the test as shown in Figures 4-7. Considering the very light loading condition in BLDC motor fans, their bearings underwent the generalized-roughness faults. The degradation of motor bearings in Fan #1 and Fan #2 were also reflected in the increased vibration signal (Figure 4 (a) and Figure 5 (a)) and the audible sound. The increased friction due to the lack of lubricant
damaged the bearing surfaces and resulted in small pieces of metal dropping off. Defective bearing surface and dropped metal were ground by the continuous operation of bearings. Hence, vibration signal could become weaker. As the defects grew, vibration signal increased, but it was dynamic and unstable. However, anomalies (vibration signals reduced to healthy ones, motor current increased, and rotary speed reduced) occasionally happened, as shown in Figure 4 and Figure 5 (Sample no. 7-14, 17, 41-42, 46-47 and 61 in Fan #1 and Sample no. 14, 16, 22, 25-27, 37-38, 41, 44 and 47 in Fan #2). Two more detailed sample signals (Sample no. 7 of Fan #1 and Sample no. 25 in Fan #2) were shown in Figure 8 and Figure 9. Motor current and rotary speed of Fan #1 and Fan #2 were comparable stable, but they changed significantly (motor current increased about 9% and rotary speed reduced about 9%) when anomalies happened. As a side note, Fan #1 and Fan #2 emitted the audible sound after they ran for 1 hour; the audible sound also changed when anomalies happened.

These anomalies could be further explained as follows. Since the dynamic bearing loads in BLDC motor fan are very light comparing with its basic dynamic load ratings [14], [15] and the lubrication condition is poor in Fan #1 and Fan #2, slippage may happen in the bearings. As we all know that the force caused by sliding friction is greater than the force caused by rolling friction considering other things being equal. The vibration also reduces when sliding friction (slippage) happens in the bearings. According to equation (1), in the case of the input voltage is constant, sliding friction in the bearings leads to the increase of friction torque, consequently, reduces the rotary speed and increases motor current. This is also confirmed by the analysis of mathematic modeling of BLDC motor further. According to equation (2), the electromagnetic torque increases due to the increased current. Since the rotary speed of rotor reduces, the friction torque should increase referring to equation (3). Therefore, slippage happens in the bearings when fan behaves unusual.

In practice, BLDC motor current could be monitored online by series with a resistor in the fan circuit, as shown in Figure 1. It is a simple, convenient, and low-cost way compared with using sensors, such as accelerometers and sound level meters, to indicate the health condition of fan. The unusual behaviors of BLDC motor (about 9% changes in current and rotary speed of rotor) due to the degraded bearings in the test could be easily detected by current monitoring technique. These results show that generalized-roughness faults in motor bearings could also be detected by current monitoring technique.

5. Conclusions

Although the signals such as vibration and acoustic noise are good precursors to indicate the health condition of BLDC motor fan, it is unrealistic and expensive to monitor these signals online in electronics-rich products. Current monitoring technique is a good candidate for this purpose, but there is still a need to research on detecting generalized-roughness faults in motor bearing, which the fan bearings will experience. Referring to the results from fans test and mathematical modeling of BLDC motor, current signal could also indicate the health conditions of BLDC motor. There are about 9% changes in motor current and rotary speed when BLDC motor behaves unusual. Moreover, current monitoring technique can be easily implemented as proposed in Figure 1 for online anomaly detection for fan, as well as in other electronics-rich products which BLDC motors are widely used.
Figure 4: Evolution of Measured Signals of Fan #1 Due to the Degraded Bearing (a) Vibration, (b) Current, and (c) Rotary Speed

Figure 5: Evolution of Measured Signals of Fan #2 Due to the Degraded Bearing (a) Vibration, (b) Current, and (c) Rotary Speed
Figure 6: Evolution of Measured Signals of Fan #3 Due to the Degraded Bearing (a) Vibration, (b) Current, and (c) Rotary Speed

Figure 7: Evolution of Measured Signals of Fan #4 Due to the Degraded Bearing (a) Vibration, (b) Current, and (c) Rotary Speed
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Figure 8: Sample no. 7 of Fan #1 (a) Vibration, (b) Current, and (c) Rotary Speed

Figure 9: Sample no. 25 of Fan #2 (a) Vibration, (b) Current, and (c) Rotary Speed

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References


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