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Thermal image based fault diagnosis for rotating machinery

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HIGHLIGHTS

- Eight rotating machine faults/conditions are induced using five different bearings.
- Lubrication inadequacy in bearings is detectable using thermal imaging.
- Outer-raceway faults are detectable using thermal imaging.
- Rotor imbalance is detectable using thermal imaging.
- Two new features for thermal image based fault detection are proposed.

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ABSTRACT

Infrared imaging is crucial for condition monitoring as the thermographic patterns will differ depending on the fault or machine condition. Currently, a limited number of machine faults have been studied using thermal imaging. Therefore, this paper proposes a novel automatic fault detection system using infrared imaging, focussing on bearings of rotating machinery. The set of bearing faults monitored contain faults for which state-of-the-art techniques have no general solutions such as bearing-lubricant starvation. For each fault, several recordings are made using different bearings to ensure generalization of the fault-detection system. The system contains two image-processing pipelines, each with their own respective purposes. The first pipeline focusses on detecting rotor imbalance, regardless of the bearing faults. The second pipeline focusses on the bearing faults, regardless of whether the machine is balanced or not. Within the first pipeline, imbalance is detected by differencing the consecutive image frames which are subsequently summarized by their distribution along the image axes. For the second pipeline, three features are introduced which are the standard deviation of the temperature, the Gini coefficient, and the Moment of Light. The final system is able to distinguish between all eight different conditions with an accuracy of 88.25%.

1. Introduction

Rotating machines are often required to operate non-stop to avoid costs. Therefore, if a non-disruptive fault occurs, maintenance is not always immediately performed. Furthermore, the affected machine may be located remote or even offshore, making effective maintenance scheduling even more difficult. By not knowing details of the fault, such as location and severity, efficient counter-measures cannot be taken. As a result, fault escalation is possible, reducing the remaining useful lifetime of the machine. Consequently, future corrective maintenance can become more expensive as the costs for repairing or replacing the broken components, as well as the cost due to down time, may increase. Hence, preventing machines from failing has become an important focus regarding maintenance decisions. By employing preventive maintenance, which makes use of condition monitoring (CM) to detect early faults, downtime and costs can be reduced.

CM is done by monitoring a set of physical properties of a machine using a combination of sensors. By monitoring these signals, several faults can be detected, such as bearing damage, rotor imbalance, shaft misalignment and lubricant contamination. Vibration analysis, which is a robust CM technique, can detect several types of bearing faults and machine conditions, such as

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outer-raceway faults, inner-raceway faults, rolling-element faults, cage-faults, imbalance, and misalignment. However, smearing faults are much harder to detect as a they do not result in a new cyclic frequency as opposed to the aforementioned bearing faults [1]. Furthermore, vibration analysis or acoustic emission can be intrusive as sensors need to be mounted on, or within the machine. Also, techniques such as lubricant analysis are disruptive since human interference is required for lubricant sampling, resulting in additional downtime.

To improve automated CM, alternative signals need to be considered such as temperature. Temperature, which is usually measured using a thermocouple, has proven to be a valuable signal to monitor as faults can cause a temperature increase [2–4]. As a result, research focusing on infrared (IR) imaging for automated CM gained attention in recent years [5]. IR imaging enables non-contact, non-intrusive, fine-grained and single-sensor based temperature measurements, which is ideal for condition monitoring with the aim of autonomously diagnosing faults.

This research focusses on automated early-stage bearing fault detection using IR imaging. IR imaging has already been applied to detect shaft misalignment, rotor imbalance, bearing looseness and general bearing faults as discussed in Section 2. Therefore, this paper focuses on faults that are not timely and reliably detectable by current state-of-the-art techniques, such as different levels of bearing lubrication degradation, additional to outer-raceway faults. All conditions are tested during both, imbalanced and balanced machine conditions, as presented in Section 3. To detect these faults, both specific features and a system architecture are proposed for which the classification results are presented and discussed in Section 4. Finally, Section 5 summarizes the main conclusions and future work.

2. Related literature

IR imaging is commonly used for manual inspection of, for example cracks, isolation, subsurface moisture, corrosion, gas flow, air flow, and welding processes [5]. As opposed to manual inspection, automatic IR based condition monitoring does not require a human expert to interpret the thermal images. The advantage of automatic fault diagnosis is very useful for several fields, such as electrical equipment monitoring, as faulty devices can potentially disrupt operational conditions of machinery or even cause fire [6]. Therefore, in the work of Huda et al. [6–9], Jadin et al. [10] and Eftekhari et al. [11], practical applications of image processing and machine learning algorithms applied on IR imaging have been proposed to detect faulty electrical components.

Just as electrical equipment monitoring can benefit from IR imaging, rotating machinery also recently gained noticeable attention [12–18]. The focus of previous research has been on the detection of conditions such as shaft misalignment, bearing looseness, rotor imbalance and general bearing faults. To detect these conditions, several types of image processing and machine learning steps are used after one another. Often, the first step of the image processing pipeline will consist of extracting the region of interest (ROI). This can be done manually or via an algorithm such as Otsu thresholding together with k-means clustering [12] or watershed-based algorithms [14]. When the ROI is segmented, the second step can consist of enhancing the image, hereby revealing useful features [15]. From this (enhanced) ROI, statistical features are derived such as the standard deviation, mean, skewness, kurtosis, variance, entropy, energy, central moments, maximum and minimum [12]. It is also possible to extract statistical features from the histogram [15,16] or the components of the discrete wavelet decomposition of the thermal image [17,18]. In the penultimate step, undiscriminating features are often removed or fused together to create better features. Algorithms used for this step include principle component analysis [14], independent component analysis [16], discriminant analysis [15] or relief algorithm [17,18]. The resulting features are afterwards used to determine the condition of the rotating machine. To diagnose the possible faults, the features are used in classification algorithms such as support vector machine [16,13], relevance vector machine [15], self-organizing map [12] or linear discriminant analysis [17,18]. Most of these approaches will result in a system that can accurately detect the latent machine condition with an accuracy of 74% up to 100% [12–18]. Nevertheless, the classification algorithms have often been trained and tested on IR images of the same bearing, therefore not ensuring generalization of the system. Furthermore, the faulty and healthy conditions researched so far using infrared imaging are also easily detectable using vibration measurements, as for example in the frequency spectrum of vibration measurements a peak will be present at the rotation frequency when there is imbalance [19]. Within our approach, different test-runs of some novel faults and conditions regarding infrared CM are considered, created using a set of different bearings, as discussed in the next section.

3. Methodology

In this section, the architecture of our IR-based fault detection system is discussed. As a machine learning approach is used, a large set of data is required to train the classification model. Therefore, a data set was built using the set-up discussed next.

3.1. Test set-up

The used set-up, related details and thermal camera details can be seen in Fig. 1, Tables 1 and 2 respectively. The set-up is placed in a dark room to eliminate additional noise in the IR recordings due to external influences. Additional to the IR camera, next to the set-up, two thermocouples are mounted to measure the ambient temperature. Also, only the condition of the right bearing is changed which is the one furthest removed from the motor. The faults and conditions introduced are:

1. Healthy bearing (HB).
2. Mildly inadequately lubricated bearing (MILB).
3. Extremely inadequately lubricated bearing (EILB).
4. Outer-raceway fault (ORF).
5. Healthy bearing during imbalance (HB-IM).
6. Mildly inadequately lubricated bearing during imbalance (MILB-IM).
7. Extremely inadequately lubricated bearing during imbalance (EILB-IM).
8. Outer-raceway fault during imbalance (ORF-IM).

Some example bearing images can be seen in Fig. 2. The ORF consist of three thin shallow grooves that are added mechanically on the bearings' outer-raceway (Fig. 2c). Also added to the bearing is grease as lubrication. To calculate the amount of grease required, Eq. (1) is used, where D is the outer diameter of the bearing and B the inner diameter [20]. For the used bearings $D = 52$ mm and $B = 18$ mm.

$$m = D * B * 0.0027[g] \tag{1}$$

Both the HBs and those with an ORF contain 2.5 g of grease, additional to the 20 g of grease of the grease reservoir within the housing, so that the housing cavities are filled to the recommended 60% [21]. For the MILBs, the grease reservoir is removed and the grease on the bearing is diluted. Similarly, for the EILBs no