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Omnidirectional regeneration (ODR) of proximity sensor signals for robust diagnosis of journal bearing systems

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ABSTRACT

Some anomaly states of journal bearing rotor systems are direction-oriented (e.g., rubbing, misalignment). In these situations, vibration signals vary according to the direction of the sensors and the health state. This makes diagnosis difficult with traditional diagnosis methods. This paper proposes an omnidirectional regeneration method to develop a robust diagnosis algorithm for rotor systems. The proposed method can generate vibration signals in arbitrary directions without using extra sensors. In this method, signals are generated around the entire circumference of the rotor to consider all possible directions. Then, the directionality of each state is proved by mathematically and is evaluated using a proposed metric. When a directional state is determined, the classification is carried out on all of the generated signals. When a non-directional state is found, the classification is performed on only one of the generated signals to minimize computational load without sacrificing accuracy. The proposed ODR method was validated using experimental data. The classification results show that the proposed method generally outperforms the conventional classification method. The results support the proposed concept of using ODR signals in diagnosis procedures for journal bearing systems.

1. Introduction

Journal bearing rotor systems are frequently used in industrial machines that require safe and reliable operation. For example, turbines and pumps in power plants use journal bearings to maintain system safety even in heavy load and high-speed conditions. Because the fluid in the bearings supports the rotors, stable operation is possible without direct contact between the rotor and the stator. Although a particular rotor system may satisfy all design requirements, uncertainties in operation can cause the system to operate in an unexpected way. Sometimes, improper maintenance can cause a sudden failure or an accident; this can result in disastrous consequences. Thus, to prevent catastrophic events, large rotor systems require an anomaly diagnosis system.

Diagnosis systems for rotors frequently use data-driven methods [1–7]. These methods follow three steps: data acquisition, feature generation, and classification. First, in the data acquisition step, signals from each health state are obtained. Most rotor diagnosis systems use vibration signals, because vibration signals can accurately represent the health state of

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Nomenclature

C	regularization parameter of the optimization problem for support vector machine
D	directionality metric of health states
N	number of possible ODR signals by θ
$S(f)$	power spectrum
$S_N(f)$	set of the power spectrum from N ODR signals
V	time signal
$\overline{V}$	mean of the time signal
X_i-Y_i	Cartesian coordinate system by X_i and Y_i axes
b	bias of the hyper-plane
d	dimension of the feature vector
u_i	label of the ith feature vector
$\boldsymbol{v}_i$	ith feature vector
$\boldsymbol{w}$	normal vector to the hyper-plane
θ	angle of rotation
ξ_i	slack variable of ith feature data

the system. Next, the feature generation step is composed of two sub-steps: feature extraction and selection. The acquired data are used to generate key features that should distinguish the health states of the rotor system. Various signal processing techniques have been developed to extract features from the data. Noise reduction, such as time synchronous averaging, can be performed [8,9]. Angular resampling can also reduce the noise, as well as produce an equal number of data points per cycle [10,11]. After these preprocessing techniques are applied, features are extracted. Time- and frequency-domain analysis are widely used methods for feature extraction [12–14]. Time-frequency analysis is another technique specifically for transient signals [15,16]. Hilbert-Huang transform [17], empirical mode decomposition (EMD) [18], and wavelet transform [19] are used to extract features from various rotor systems. After the candidate features are extracted, key features must be selected for robust anomaly detection. Through the feature selection process, the optimal feature subset can be obtained [20–23]. Finally, the classification is performed using machine learning algorithms focused on the selected optimal features. Artificial neural networks (ANN) [14,24], support vector machine (SVM) methods [25–29], linear discriminant analysis (LDA) [25,30], and related techniques can be used for the classification.

Normally, two vibration signals are acquired from two fixed sensors at an axial position in the journal bearing system. However, employing two sensors at fixed orientations may not detect direction-oriented anomalies. For example, an impact rubbing in an arbitrary direction may not be detected by fixed sensors. A simple mathematical model of the rubbing confirms dependency on the orientation of sensors. This underscores the need for the use of omnidirectional signals for robust diagnosis.

Some prior research efforts have tried to consider direction in rotor diagnosis by using the orbit shape and the full-spectrum of vibration signals. Yan et al. [31] modified the orbit into seven different features to identify the state of the steam turbine generator. Wang et al. [32] quantified the orbit information with isometric feature mapping to identify faults in rotors. Other researchers also tried to quantify the orbit shape to make more accurate diagnosis of rotors [33–36]. However, in the process of quantifying the orbit shape, detailed physical interpretation of vibration signals may be diminished. In other work, the full-spectrum of vibration signals was used to see forward and backward whirling frequency components by using x- and y- signals [37–40]; however, the method could not consider vibration signals in all directions.

Thus, to overcome these problems with existing methods, we propose an omnidirectional regeneration (ODR) method that can robustly diagnose rotor health states. The proposed method considers omnidirectional vibration signals without installing extra sensors. While ODR makes use of the basic concepts of conventional, data-driven diagnosis steps, the classification and the feature generation steps are revised. As a result, the ODR method outperforms the conventional method of using signals from fixed sensors. The effectiveness of our proposed approach of considering the directionality of the health state using the ODR method was validated using experimental data from a testbed.

This paper is organized as follows. Section 2 briefly states the experimental setup and provides an overview of conventional, data-driven diagnosis steps. Section 3 presents the proposed ODR-based method with physical interpretation and its procedure. Section 4 shows that the ODR-based method outperforms the conventional one for anomaly diagnosis. A summary of the research is provided in Section 5.

2. Overview of journal bearing rotor diagnosis systems

Supervised-learning methods are the most popular methods used for diagnosis of journal bearing rotor systems. Vibration signals in the rotor systems are commonly used for supervised diagnosis methods. This section provides an overview of supervised-learning methods and our research testbed. Section 2.1 describes the configuration of the testbed and the vibra-