Measurement 118 (2018) 181–193

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

Intelligent fault diagnosis method for rotating machinery via dictionary learning and sparse representation-based classification

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ARTICLE INFO

Keywords:
Intelligent fault diagnosis
Rotating machinery
Dictionary learning
K-SVD
Sparse representation-based classification

ABSTRACT

Wind power has developed rapidly over the past decade where study on wind turbine fault diagnosis methods are of great significance. The conventional intelligent diagnosis framework has led to impressive results in many studies over the last decade. Despite its popularity, the diagnosis result is affected severely by the feature selection and the performance of the classifiers. To address this issue, a novel method to diagnose wind turbine faults via dictionary learning and sparse representation-based classification (SRC) is proposed in this paper. Dictionary learning algorithm is capable of converting the atoms in the dictionary into the inherent structure of raw signals regardless of any prior knowledge, indicating that it is a self-adaptive feature extraction approach, which avoids the challenge of feature selection in traditional methods. Next, recognition and diagnosis can be solved by the simple SRC without additional classifier, exploiting the sparse nature that the key entries in sparse representation vector are assigned to the corresponding fault category for a test sample. The validity and superiority of the proposed method are validated by the experimental analysis. Moreover, we find that, in terms of robustness under variable conditions and anti-noise ability, the performance of the proposed method always significantly outperforms the traditional diagnosis methods, leading to a promising application prospect.

1. Introduction

Many countries have developed wind power as an alternative energy source under the severe conditions regarding energy and environment, and the capacity of wind turbines keeps growing at a speed of over 20%. Due to high fault rates, high maintenance cost, high downtime loss, and the inconvenience of detecting failures, condition monitoring and fault diagnosis (CMFD) technologies are focal points in wind turbine research [1].

Wind turbine is a complex mechatronics system, mainly including mechanical chains, power generation, measurement and control systems, and so on. Currently, one great challenge is to establish an intelligent diagnosis system where all subsystem information is integrated, from mechanical to electrical [2]. Therefore, any CMFD system should emphasize a certain subsystem by considering its structure, working conditions, proper data acquisition, applicable signal processing and diagnosis techniques. Our research in this work addresses the diagnosis method for the mechanical chain in a direct-drive wind turbine. Based on the existing failure surveys of wind turbine, it has been found that faults mostly occur in some critical components, including wind blades, main shaft, bearing, etc. [3]. In particular, imbalance may be the possible fault of the blades, resulting in the deformation of the rotor after long-term unbalanced loading [4]. Faults in the main shaft, such as misalignment and bearing pedestal looseness, are usually associated with the structural support and can induce vibration to the whole mechanical system with fractional or multiple rotating frequency [5]. Bearings are the most widely used components in wind turbines and are also subject to faults frequently. Cracking or breakage of bearing components (inner race, outer race, rolling element and cage) will cause impact under working conditions, which may lead the machine to break down or even disastrous accidents [6].

To date, vibration analysis has been accepted as the most widely used diagnosis method in a comprehensive comparison with other signals in wind turbine CMFD such as acoustic emissions, temperature, lubricating oil parameters and SCADA dataset [7]. Once the vibration signal is acquired, different signal processing methods and data-mining techniques can be applied for fault diagnosis. Previous diagnosis studies have mainly been composed of two categories. In the first category, the failure mode can be decided by detecting the characteristic frequency in spectral analysis only using signal processing methods. Various

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https://doi.org/10.1016/j.measurement.2018.01.036
Received 20 October 2016; Received in revised form 20 December 2017; Accepted 23 January 2018

advanced approaches have been proposed and analyzed with experimental and industrial cases, such as wavelet transform (WT) and empirical mode decomposition (EMD), tackling some of the limitations of traditional Fourier transform [8,9]. However, a good deal of expertise is necessary and a responsible decision can only be made by specialists, which creates difficulties in situations such as online monitoring and practical engineering application [10]. Hence, as the second category of methods, the data-driven diagnosis method, which combines the artificial intelligence (AI) methods with signal processing techniques to facilitate intelligent automatic diagnosis, have received increased attention [11–17]. The diagnosis procedure includes three important steps: feature extraction, training and the classification. Once the determined characteristics are extracted from the raw signals, classification models can be trained via machine learning techniques, so as to make decision intelligently when similar patterns come afterwards. Nowadays, many theories and techniques have been utilized to design the classification models, such as artificial neural networks (ANN), support vector machine (SVM), ensemble learning methods and Bayesian methods [15–17].

Although this strategy has gained much popularity and success, the selection and optimization of features that have different sensitivities to condition changes is a challenge with limited prior knowledge [18,19]. Additionally, in the training process, the optimization of structural parameters for certain classifiers, such as the penalty factor and kernel function in SVM, is a key step to acquire the significantly higher diagnosis accuracy, which increases the complexity of the procedure and computational expense [16,17]. Moreover, since the performance of the classifier usually changes with the application object and extracted features, the selection of proper classifier directly affects the diagnosis result. Thus, the development of a novel diagnosis method for extracting effective features self-adaptively without prior knowledge and simplifying the classification model is promising. Some recently reported ideas such as unsupervised feature learning [20] and image processing-based approaches [21,22], have been suggested to address the above-mentioned concerns.

In this study, a novel data-driven fault diagnosis algorithm for wind turbine is proposed by exploiting sparse representation for classification along with dictionary learning (DL) technology. As a derivative method from signal processing, the basic assumption of sparse representation is to represent the natural signals by a sparse linear combination of atoms in a fixed dictionary [23,24]. Recently, sparse representation theory has become an increasingly popular topic of research in the fields of image denoising [25], image super-resolution reconstruction [26], image restoration [27], and image fusion [28]. Furthermore, the identifying information in sparse representation vector provide convenience for subsequent recognition and classification [29,30]. Wright et al. proposed a novel classification model: sparse representation-based classification (SRC), using its discriminative nature, which has been proven to outperform SVM in terms of face recognition [29]. Researchers have also performed valuable studies on the application of SRC to industrial tasks. Yang et al. proposed a robust identification approach based on SRC framework to resist random excitation for locating damage and assessing damage severity [31]. Tang et al. presented a new fault diagnosis method for rotating machinery using SRC and random dimension reduction mapping, and a high recognition accuracy was achieved with early detection of the weak faults [32]. Wu employed SRC to diagnose different types of faults in the Tennessee Eastman Process, which is a complex industrial process containing 41 measured monitoring variables, and acquired a quite satisfactory diagnosis rate with only a few training samples [33]. Yu et al. extended the SRC (with a combination of L1-norm and L2-norm) to the classification of machinery vibration signals, achieving superior properties in comparison with state-of-the-art classifiers [34].

Another dictionary learning techniques, such as the method of optimal directions (MOD) and K-singular value decomposition (K-SVD) [35,36], designed to capture the inherent characteristic and structure of raw signals self-adaptively, have been accepted as a powerful dictionary building approach in the recently explored studies [37–41]. Actually, the sparse level of sparse representation vector may be unsatisfied with the dictionary constructed by raw samples or standard bases in some cases as it largely depends on the capacity of the fixed dictionary to reveal the nature of signals. Consequently, in this paper, a dictionary learning process is regarded as a pre-step to integrate the feature extraction and model training without complex processing and prior knowledge to enhance the performance of SRC.

The novelty of this work is by applying this new algorithm to the fault diagnosis of wind turbines and proving its superiority in a comprehensive comparison with traditional methods in the aspects of accuracy, stability, robustness under variable conditions and anti-noise ability. In addition, the experimental scheme provides wind sources with a wind tunnel to drive the wind turbine test rig rather than motor drive. Even though the similar faults have been extensively investigated for rotating machinery, it is still tough to realize the accurate diagnosis in real wind turbines due to the varying conditions of load and speed. The experiment is capable of simulating the actual running status more realistically. The remaining parts are organized as follows. The theoretical background on sparse representation theory and dictionary learning technique is introduced in Section 2. The proposed diagnosis procedure via dictionary learning and sparse representation-based classification is presented in Section 3. In Section 4, a numerical simulation and the parameters selection are analyzed. Section 5 is the experimental verification. The wind turbine test rig and experimental scheme are shown, and a discussion of results is conducted to verify the proposed DL-SRC method compared with some traditional methods. Finally, the conclusions and further work are drawn in Section 6.

2. Theoretical background

2.1. Basic idea of sparse representation theory

Recently, sparse representation theory has received increased interest of scientists in the field of signal and image processing. The basic model of this idea can be illustrated in Fig. 1. This model assumes that a digital signal can be represented as a sparse linear combination of the atoms, which are from a fixed over-complete dictionary. Generally speaking, for an input signal $y \in R^n$, it can be expressed as $y = \boldsymbol{D}x$, where $\boldsymbol{D} \in R^{n\times K}$ is the dictionary and $x \in R^K$ is the representation coefficient vector. The dictionary matrix $\boldsymbol{D}$ contains K atoms $d_i \in R^n, i = 1,...,K$ as its columns. If the $n < K$, the dictionary is over-complete. When the dictionary $\boldsymbol{D}$ and input signal y are fixed, we hope

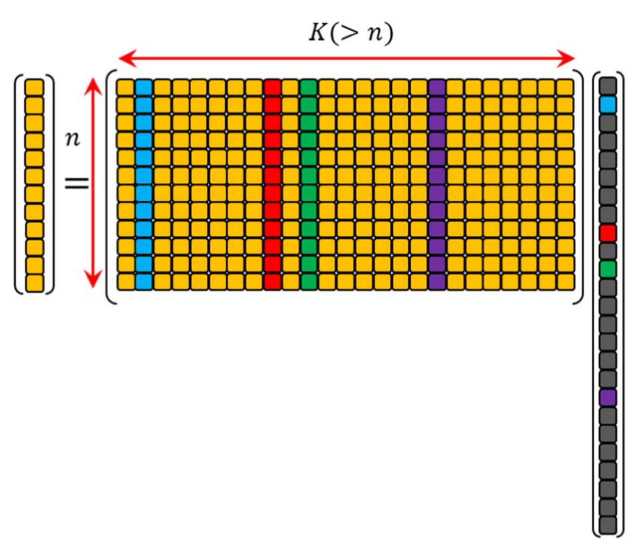

Fig. 1. Matrix representation of sparse representation theory.