Neurocomputing 168 (2015) 505–519

Contents lists available at ScienceDirect

Neurocomputing

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

Weak fault diagnosis of rotating machinery based on feature reduction with Supervised Orthogonal Local Fisher Discriminant Analysis

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ARTICLE INFO

Article history:
Received 15 December 2014
Received in revised form
5 March 2015
Accepted 18 May 2015
Communicated by: Shen Yin
Available online 28 May 2015

Keywords:
Shannon mutual information (SMI)
Supervised Orthogonal Local Fisher Discriminant Analysis (SOLFDA)
Dimension reduction
Optimized Evidence-Theoretic *k*- Nearest Neighbor Classifier (OET-KNNC)
Weak fault diagnosis
Rotating machinery

ABSTRACT

A new weak fault diagnosis method based on feature reduction with Supervised Orthogonal Local Fisher Discriminant Analysis (SOLFDA) is proposed. In this method, the Shannon mutual information (SMI) between all samples and training samples is combined into SMI feature sets to represent the mutual dependence of samples as incipient fault features. Then, SOLFDA is proposed to compress the high-dimensional SMI fault feature sets of testing and training samples into low-dimensional eigenvectors with clearer clustering. Finally, Optimized Evidence-Theoretic *k*-Nearest Neighbor Classifier (OET-KNNC) is introduced to implement weak failure recognition for low-dimensional eigenvectors. Under the supervision of class labels, SOLFDA achieves good discrimination property by maximizing the between-manifold divergence and minimizing the within-manifold divergence. Meanwhile, an orthogonality constraint on SOLFDA can make the output sparse features statistically uncorrelated. Therefore, SMI feature set combining SOLFDA is able to extract the essential but weak fault features of rotating machinery effectively, compared with popular signal processing techniques and unsupervised dimension reduction methods. The weak fault diagnosis example on deep groove ball bearings demonstrates the advantage of the weak fault diagnosis method proposed in this paper.

1. Introduction

Rotating elements, such as bearings and gears, are widely used in machinery equipments. Mechanical faults occurring in bearings and gears often lead to fatal breakdowns in machinery equipments, and such failure can be catastrophic, resulting in costly downtime. Therefore, it is significant to accurately diagnose the existence of weak faults, i.e. the faults at an early stage in rotating elements [1]. The early fault features consist of transient signals that occur approximate periodically at a characteristic frequency. However, in most cases these signals are very weak as they can be buried in the strong background noises with a wide spread frequency band and the interference of the rotor rotating frequency with its harmonics [2]. Besides, there also exists severe signal attenuation between the weak fault source and the sensor collecting the fault signal if the sensor is placed far from the weak fault location [3]. Therefore, the difficulty in weak fault diagnosis focuses on how to extract or identify the weak fault features (i.e. transient components) from strong background noises, rotating frequency interference and signal attenuation.

Researchers have been searching for effective methods to detect weak faults of rotating elements. Numerous signal processing techniques have been proposed to extract the early fault feature, among which Autoregressive (AR) model [4], Fast Fourier Transform (FFT), Wigner–Ville Distribution (WVD) [5], Short Time Fourier Transform (STFT), Hilbert–Huang Transform (HHT) [6] and Wavelet Transform (WT) [7] are the most popular time-frequency analysis methods. However, AR model is just applicable to analyzing mutation signals with certainty, periodicity and energy aggregation, which are quite different from the uncertain, nonlinear and nonstationary weak fault signals of rotating machinery. Similarly, classical spectral analysis method FFT is incapable of detecting the nonlinear and nonstationary characteristics of weak faults under low signal-to-noise ratios. WVD usually generates cross-term when it is used to analyze multi-component signals. STFT method is restricted by fixed size of time-frequency window and thus cannot process multi-scale fault signals at early stage. HHT is influenced by the end effects and redundant intrinsic mode functions associated with Empirical Mode Decomposition (EMD) processes [6], in which large swings ultimately propagate inward and corrupt the entire data span. Wavelet method employs a fixed scale of decomposition to analyze signal without considering its characteristics. In summary, due to their intrinsic deficiencies, all

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http://dx.doi.org/10.1016/j.neucom.2015.05.076
0925-2312/

these signal processing approaches are inappropriate for feature mining of weak fault.

During the past decades, the model-based fault detection methods have been a remarkable research topic. However, their applications on weak fault diagnosis of rotating machinery are unrealistic due to the sophisticated modeling procedure that prerequires physical and mathematical knowledge, regardless of their advantage in handling process dynamics [8,9]. Because of the simple forms and low design efforts compared with the model-based techniques, the multivariate statistical methods based on data-driven framework, e.g. Principal component analysis (PCA), partial least squares (PLS) and improved partial least squares (IPLS), are widely used for typical fault monitoring of machinery systems [8–11]. However, the weak fault diagnosis is generally a dynamic process because of the nonlinearity, non-stationarity and uncertainty of weak fault signals. Therefore, such multivariate statistical approaches are not suitable to recognize weak faults of rotating machinery due to their basic assumption under stationary and ideal signal conditions [8]. Recently, in view of the pros and cons of model-based and data-driven approaches, the model-data integrated approaches, including subspace identification methods (SIMs), iterative feedback tuning (IFT) and virtual reference feedback tuning (VRFT), have been proposed and aroused concern from both academic and industrial points of view [9]. However, the current model-data integrated approaches still have limitations in dealing with weak fault data that have non-Gaussian distributing disturbances and strong nonlinearity [8,9].

Weak fault diagnosis methods based on pattern recognition technology have the merits of powerful knowledge inference and error correction capability, and they have attracted more research attention recently. In the existing weak fault diagnosis theories based on pattern recognition, the collected signals are firstly analyzed by a fore-mentioned signal processing approach. Then, the secondary filtration approach with the aid of manual analysis, including envelope spectrum analysis or Hilbert demodulation, is used to extract authentic fault features. After that, the extracted fault components are converted into eigenvectors as feature representation of some incipient fault pattern via a sensitive index (e.g. correlation dimension, distance evaluation factors, information entropy, etc.). Finally, the eigenvectors are entered into pattern recognition algorithms in order to identify incipient fault [12,13]. Obviously, these theories are somewhat immature for two reasons as follows. Firstly, to extract weak fault features they usually adopt the aforementioned signal processing approaches that have inherent drawbacks, which make these theories unable to comprehensively dig nonlinear, weak and strongly coupled fault features. Secondly, the current rules of weak fault diagnosis based on pattern recognition rely on manual method to complete the optimization of weak fault feature [14]. In other words, the feature extraction quality and recognition accuracy of weak fault are mainly determined by professional knowledge and field experience of engineers, so that it is quite difficult to realize the high-precision of weak fault diagnosis.

In order to overcome the defects of existing approaches based on pattern recognition, a novel weak fault diagnosis method based on feature reduction with Supervised Orthogonal Local Fisher Discriminant Analysis (SOLFDA) is proposed in this paper. Firstly, the Shannon mutual information (SMI) between all samples and training samples is combined into SMI feature sets to represent the mutual dependence of samples, which can be regarded as incipient fault features. Secondly, with the proposed SOLFDA, high-dimensional SMI feature sets of the testing and training samples are reduced to low-dimensional eigenvectors with better discrimination. Finally, the sparse eigenvectors are entered into the Optimized Evidence-Theoretic k-Nearest Neighbor Classifier (OET-KNNC) for weak fault recognition. SOLFDA can maximize the between-manifold divergence and minimize the within-manifold divergence under the supervision of class labels. In addition, the extracted features via SOLFDA can be statistically uncorrelated by exerting an orthogonality constraint on the basis vector computation. Therefore, in contrast to manual feature refining and other unsupervised dimension reduction methods, SOLFDA can extract more effectively the essential but weak fault information and meanwhile, it is able to compress high-dimensional SMI feature set automatically. In a word, the dimension reduction with SOLFDA can realize the high-precision weak fault recognition, and can be applied to early fault diagnosis of bearing, axle or rotor, gear, turbine of aeroengine, blade of wind turbine and so on.

The remainder of this paper is organized as follows. Section 2 introduces the basic theory of SMI. In Section 3, the SOLFDA algorithm is derived in detail. Then, the OET-KNNC theory is discussed in Section 4. In Section 5, the weak fault diagnosis experiment of deep groove ball bearings is performed to verify the proposed method, and experimental results are analyzed. Finally, Section 6 concludes the paper.

2. Shannon mutual information (SMI)

One of the principal issues in weak fault diagnosis based on pattern recognition is the weak feature extraction, i.e., selecting a most relevant variable set as the weak fault feature of a testing sample. However, as aforementioned, all the common signal processing approaches are inapplicable to weak fault feature extraction. In order to accurately measure the relevance between testing samples and training samples for the learning task, it is proposed to measure the dependence of the former on the latter in this paper. SMI is just one important and novel dependence measure that can capture linear and nonlinear relations [15]. In fact, SMI has been recently used as a feature selector to extract the most relevant variables in the fields of graphic identification and text categorization. Moreover, it is not difficult for SMI to calculate mutual information efficiently under limited sample size conditions. The theoretical analysis on SMI is provided as follows.

The entropy $H(\vec{\mathbf{x}})$ of a random vector (i.e., variable) $\vec{\mathbf{x}}$ (sometimes written as $H(P(\vec{\mathbf{x}}))$), is a function of probability distribution $P(\vec{\mathbf{x}})$ since the $H(\vec{\mathbf{x}})$ only lies on $P(\vec{\mathbf{x}})$ instead of the actual values of $\vec{\mathbf{x}}$. Shannon entropy is able to well measure the uncertainty of $\vec{\mathbf{x}}$ and further quantify the difficulty in predicting the variable. The definition of Shannon entropy can be represented as an expectation value

$$H(\vec{\mathbf{x}}) = -E[\log P(\vec{\mathbf{x}})] = -\sum_{x}[p(x)\log(p(x))] \tag{1}$$

where $p(x) = P(X = x)$ $(x \in \vec{\mathbf{x}})$ denotes the probability distribution function of variable $\vec{\mathbf{x}}$. Thus, the Shannon entropy can be considered as the average amount of information in variable $\vec{\mathbf{x}}$. In other words, it is just the removed uncertainty after the actual feature of $\vec{\mathbf{x}}$ is revealed.

Based on the Shannon entropy, mutual information $I(\vec{\mathbf{x}};\vec{\mathbf{y}})$, in which variable $\vec{\mathbf{x}}$ is known, can represent the uncertainty reduction amount of variable $\vec{\mathbf{y}}$ as follows:

$$I(\vec{\mathbf{x}};\vec{\mathbf{y}}) = H(\vec{\mathbf{x}}) + H(\vec{\mathbf{y}}) - H(\vec{\mathbf{x}},\vec{\mathbf{y}}) \tag{2}$$

Notably, $I(\vec{\mathbf{x}};\vec{\mathbf{y}})$ is also the KL divergence of the product of marginal probability distributions $P(\vec{\mathbf{x}})$ and $P(\vec{\mathbf{y}})$ from the joint probability distribution $P(\vec{\mathbf{x}},\vec{\mathbf{y}})$ [15]

$$I(\vec{\mathbf{x}};\vec{\mathbf{y}}) = D_{KL}(P(\vec{\mathbf{x}},\vec{\mathbf{y}})\,||\,P(\vec{\mathbf{x}}) \cdot P(\vec{\mathbf{y}})) = \sum_{x}\sum_{y}\left[p(x,y)\log\left(\frac{p(x,y)}{p(x) \cdot p(y)}\right)\right] \tag{3}$$

where $p(x,y) = P(X = x,\ \ Y = y)$ $(x \in \vec{\mathbf{x}},\ y \in \vec{\mathbf{y}})$.