



Automatic fault feature extraction of mechanical anomaly on induction motor bearing using ensemble super-wavelet transform



Wangpeng He^{a,b}, Yanyang Zi^{a,b,*}, Binqiang Chen^{a,c}, Feng Wu^{a,b}, Zhengjia He^{a,b}

^a School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an 710049, P.R. China

^b State Key Laboratory for Manufacturing and Systems Engineering, School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an 710049, P.R. China

^c School of Physics and Mechanical & Electrical Engineering, Xiamen University, Xiamen 361005, Fujian, P.R. China

ARTICLE INFO

Article history:

Received 18 December 2013

Received in revised form

30 July 2014

Accepted 6 September 2014

Available online 8 October 2014

Keywords:

Induction motor

Feature extraction

Bearing fault diagnosis

Super-wavelet transform

Q-factor

ABSTRACT

Mechanical anomaly is a major failure type of induction motor. It is of great value to detect the resulting fault feature automatically. In this paper, an ensemble super-wavelet transform (ESW) is proposed for investigating vibration features of motor bearing faults. The ESW is put forward based on the combination of tunable Q-factor wavelet transform (TQWT) and Hilbert transform such that fault feature adaptability is enabled. Within ESW, a parametric optimization is performed on the measured signal to obtain a quality TQWT basis that best demonstrate the hidden fault feature. TQWT is introduced as it provides a vast wavelet dictionary with time-frequency localization ability. The parametric optimization is guided according to the maximization of fault feature ratio, which is a new quantitative measure of periodic fault signatures. The fault feature ratio is derived from the digital Hilbert demodulation analysis with an insightful quantitative interpretation. The output of ESW on the measured signal is a selected wavelet scale with indicated fault features. It is verified via numerical simulations that ESW can match the oscillatory behavior of signals without artificially specified. The proposed method is applied to two engineering cases, signals of which were collected from wind turbine and steel temper mill, to verify its effectiveness. The processed results demonstrate that the proposed method is more effective in extracting weak fault features of induction motor bearings compared with Fourier transform, direct Hilbert envelope spectrum, different wavelet transforms and spectral kurtosis.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

The induction motor is a type of electrical machinery that plays an important role in modern manufacturing industry. This machinery is utilized as the major agent both in power generation (For example, wind energy) and power consumption (For example, Mechanical manufacturing). Therefore, it is necessary to detect early faults of induction motors. Major failures of induction motors can be broadly classified as: bearing related, stator related, rotor related, and others. Failure surveys have reported that almost 40–50% of all motor failures are bearing related [1,2]. Research of induction motor fault diagnosis

* Corresponding author at: School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an 710049, PR China. Tel./fax: +86 29 82663689.
E-mail address: ziyy@mail.xjtu.edu.cn (Y. Zi).

has drawn much attention on the vibration-based detecting of mechanical failures developed in induction motors, especially the rolling element bearing.

The widespread applications of rolling element bearings have inspired the emerging of many advanced technologies to monitor their health status. Actually, the modern development of vibration signal processing techniques pay significant attentions in enhancing their capacity of analyzing the non-stationary and transient nature of the measured vibration data. Local defects, such as include cracks, pits and spalls are likely to happen on the rolling surfaces. In many engineering applications, induction motors are operating with relatively low speed and high load, local defects are usually the early fault type. Vibration signal analysis is a most preferred approach to diagnose bearing's localized defects [3,4]. When a localized defect is induced on the bearing, periodic impulses will be generated due to the pass of rollers over the defect [5]. The impact between the rolling element and raceway will excite the bearing natural frequency, and the characteristic frequency is modulated as series of harmonic. However, these useful fault features are often immersed in heavy background noise. Hence, the key of motor bearing fault diagnosis is to extract the characteristic frequency from the modulated vibration signals.

The last three decades have seen the rapid advancement of many signal processing methods such as Wigner distribution [6], short-time Fourier transform [7], cyclostationary analysis [8], empirical mode decomposition (EMD) [9], spectral kurtosis (SK) [10–12], and wavelet transform [13–15]. Wavelet transform (WT), evolving from Fourier transform, has made great progress in the theory and applications of induction motor fault diagnosis [16–19]. A remarkable advantage of WT is its multi-resolution analysis capability, which is extremely suitable for detecting transient vibration signatures. WT converts a signal in time domain into time-frequency domain through a series of convolution operations between the analyzed signal and a wavelet basis [20]. The essence of WT is a similar measurement between the signal and the wavelet basis functions. Thus, the meaningful fault feature extraction of WT is focused on the construction and selection of a proper wavelet basis. Traditionally, WT can be classified as Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), and Wavelet Packet Transform (WPT). Among the varieties of wavelet analysis, CWT [21,22] and WPT [23,24] have not been widely applied in the field of motor fault diagnosis compared to the widely used DWT based techniques [25–29]. However, the effectiveness of DWT is weakened by a few inevitable limitations [30]. First, DWT is sensitive to translation of the input signal, which causes waveform distortion in extracting impulse features. Second, DWT has fixed dyadic frequency domain partition manner, which may separate useful features into adjacent subbands. Third, wavelet functions of DWT are of low oscillation, which weakens its ability in matching high oscillatory vibration features [31,32].

In consideration of the practical needs in induction motor fault diagnosis, it is apparent that a wavelet basis with a fixed predetermined basis does not sufficient to complete this work. Therefore, an ensemble super-wavelet (ESW) transform is proposed for implementing automatic fault feature extraction of induction motors in this paper. Compared with conventional wavelet bases, ESW is a feature-dependent technique with self adaptability that searched the optimal wavelet basis and generates the optimal wavelet scale with indicated fault features. The ESW relies on the abundant wavelet dictionary intrinsic in the tunable Q-factor wavelet transform (TQWT), with which the Q-factor (defined as the ratio of its center frequency to its bandwidth) is easily tunable [33–35], which makes it suitable for revealing fault-related information from non-stationary vibration signals sampled on machines [36–39]. The ESW can automatically select a desired wavelet basis without artificially specified. The adaptivity of the ESW is implemented by maximum fault feature ratio, which is defined based on Hilbert transform. Note that the fault feature ratio is defined in order to match the oscillatory behavior of fault features excited by local defects on motor bearings. Meanwhile, the relationship between the energy ratio of last subband to the total energy (*LER*) and decomposition levels is illustrated. Then based on this relationship, a decomposition stopping criterion is presented to select an appropriate data-driven decomposition level of the TQWT adaptively in this paper.

The ESW technique for motor bearing fault diagnosis consists of three major steps. Firstly, we define a stopping criterion to select decomposition levels adaptively. Then, based on the maximum Hilbert envelope spectrum fault feature ratio we defined, a technique of tuning Q-factor adaptively is presented. Finally, the useful fault features can be extracted adaptively for the purpose of fault diagnosis. Moreover, the proposed method based on TQWT is applied to incipient fault diagnosis of motor bearings in engineering applications, and the satisfactory diagnosis results validate its effectiveness and feasibility. Due to its operation simplicity in extracting fault features from vibration signals, the proposed TQWT-based feature extraction technique has potential to become an effective tool in bearing fault diagnosis of induction motors. Moreover, for the purpose of fault diagnosis, unlike other signal processing methods which need manual analysis, the implemented of this proposed technique does not require too much specialized knowledge.

The rest of the paper is organized as follows. The summary of TQWT is introduced in Section 2. Section 3 provides a detailed description of fault feature ration based on Hilbert transform. In Section 4, the proposed adaptive feature extraction technique, namely the ESW is presented. In Section 5, two simulation signals were formulated to validate the effectiveness of the proposed method. Section 6 applies the proposed method to fault diagnosis of induction motor bearings in a temper mill and a wind turbine for further validation of its effectiveness. Finally, conclusions are summarized in Section 7.

2. Summary of the TQWT theory

For the sparse wavelet representation of a signal, the Q-factor of a wavelet should be chosen to match the oscillatory behavior of the signal under analysis. Specifically, the wavelet transform with a low Q-factor is suitable for processing piecewise smooth signals, while a relatively high Q-factor is useful for processing oscillatory signals [33]. Recently, a wavelet transform, namely the TQWT, has been developed for discrete-time signals for which the Q-factor is easily and continuously adjustable [34].

Download English Version:

<https://daneshyari.com/en/article/559353>

Download Persian Version:

<https://daneshyari.com/article/559353>

[Daneshyari.com](https://daneshyari.com)