A Short Survey on Fault Diagnosis of Rotating Machinery using Entropy Techniques

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Abstract. Fault diagnosis is significant for identifying latent abnormalities, and implementing fault-tolerant operations for minimizing performance degradation caused by failures in industrial systems, such as rotating machinery. The emergence of entropy theory contributes to precisely measure irregularity and complexity in a time series, which can be used for discriminating prominent fault information in rotating machinery. In this short paper, the utilization of entropy techniques for fault diagnosis of rotating machinery is summarized. Finally, open research trends and conclusions are discussed and presented respectively.

Key words: Fault diagnosis, Rotating machinery, Entropy

1 Introduction

In recent decades, the world has witnessed a tremendous growth in the theory and practice of fault diagnostic approaches, which have been widely and successfully applied in fault diagnosis of rotating machinery, such as failure detection in rotors, rolling bearings and shafts. As a result, signal-based fault diagnosis has been a prominent technique to analyze non-linear and non-stationary signals. In this kind of diagnostic methods, feature extraction is one of the significant steps for characterizing fault information of interest in fault detection and identification. The traditional time-frequency domain parameters include peak value, mean value, root mean square (RMS), power spectrum, and RMS of the spectrum difference, etc. Apart from that, in the recent decade, entropy-based features have been applied extensively in the field of fault diagnosis by means of evaluating the irregularity and complexity in signals with different conditions.

2 Fault Diagnosis based on Entropy Methods

Entropy techniques can be considered as a powerful measurement tool that is capable of quantifying the irregularity in a time series. The occurrence of defects in rotating components usually produces subcritical frequencies and finally

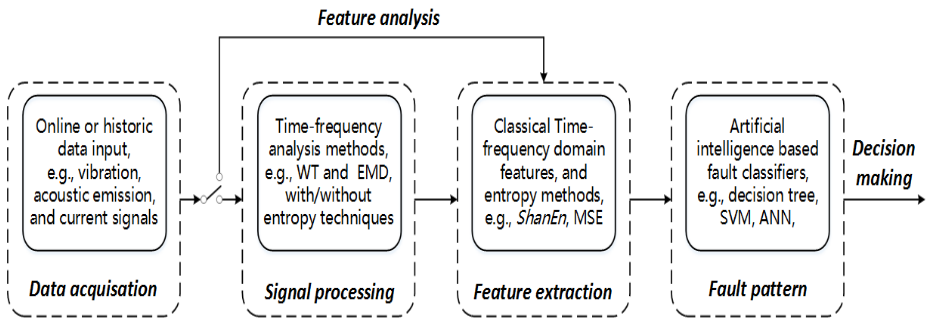

Fig. 1: Data flow of fault diagnosis of rotating machinery based entropy methods.

increases the amplitude of impulses in signals obtained from rotating machines, such as vibration and acoustic signals. According to literatures, the steps in fault diagnosis using entropy methods can be categorized into two main classes: 1) selection of multi-scale decomposed vectors obtained from multi-resolution analysis (MRA), such as wavelet transform (WT); 2) feature extraction of desired decomposed vectors or original signals. The traditional procedure of signal-based fault diagnosis using entropy methods is illustrated in Fig. 1. The most commonly used entropy features include power spectrum energy ($PowerEn$), Shannon entropy ($ShanEn$), approximate entropy ($ApEn$), sample entropy ($SampEn$), fuzzy entropy ($FuzzyEn$), permutation entropy ($PerEn$), and their corresponding multiple scale entropies.

2.1 Single-scale Entropy Approaches

$PowerEn$ is one of useful tools that is adopted to describe how the energy of a signal or a time series is distributed within time domain [1], which can be defined as the absolute-value squared of the time series. $ShanEn$, named after Claude Shannon, was developed to solve the measurement problem of system's disorder in microscopic particle in information theory. Generally, $PowerEn$ is applied together jointly with $ShanEn$ to determine decomposed vectors obtained from MRA, such as wavelet coefficients and intrinsic mode functions (IMFs) obtained from WT and empirical mode decomposition (EMD) methods respectively. Later in 1990s, $ApEn$ was proposed by Pincus to determine changing complexity from data. Subsequently, $SampEn$ and $FuzzyEn$, as a modification of $ApEn$ were later developed to overcome the drawbacks that $ApEn$ subjected to, such as problems of small value obtained from short length of data and lack of relative consistency. To compare the effectiveness of $ApEn$, $SampEn$ and $FuzzyEn$, comparative study was conducted in [2], where it was found that $FuzzyEn$ yields more satisfying results when characterizing signals with different complexity. Similarly, $PerEn$ [3] was also developed and applied as a measure of complexity.

2.2 Multiple-Scale Entropy Approaches (MEA)

The concept of analyzing and measuring a time series from multiple scales was proposed by Costa, who proposed that the single-scale entropy algorithm yielded contradictory results when applied to real-world data sets obtained in health and disease states. On this basis, a variety of MEA methods have been proposed and widely applied in the field of fault diagnosis, such as multiscale entropy (MSE) [4], multiscale fuzzy entropy (MFE) [5], multiscale permutation entropy (MPE) [6]. The key ideas behind the concept of MEA methods can be simply concluded as two major steps as described: 1) obtain multiple-scale time series from the original time series through a coarse-grained procedure at a scale factor of τ (τ is the length of non-overlapping windows); 2) apply corresponding single scale entropy method to estimate complexity in each coarse-grained time series.

Recently, entropy-based approaches have been successfully applied in not only selection of dominant decomposed vectors but also fault feature extraction in applications of fault diagnosis of rotating components, such as shafts, bearings, gearboxes, and rotors. In this short paper, the utilization of entropy-based methods for fault diagnosis of rotating machinery in the recent decade is summarized, as presented in Table I. It presents a comprehensive view of entropy-based applications and functionalities regarding to fault diagnosis of rotating machinery. In addition, it concludes a variety of entropy-based techniques that can be adaptively chosen by researchers to be applied in the field of fault diagnosis for rotating machinery.

3 Open Research Trends

It should be pointed that feature extraction has significant effects on the efficiency and accuracy of fault detection and identification in rotating machinery. In addition, due to the fact that industrial systems are becoming more and more complex in recent decades, continuing effects are still essential to be continuously put into improving the confidence of reliability and safety of industrial process. Some challenges are therefore needed to be focused, which are listed as following:

1. Robustness of the entropy methods under various operating conditions
2. Consistency in values of similarity and parameters selected
3. Removal of the magnitude influence of the data sets
4. Enrichment and modification of the entropy techniques
5. Able to deal with non-linear and non-stationary signals
6. Capable of identifying defects with increasing severity

4 Conclusions

In this short paper, most commonly used entropy techniques are briefly introduced. After that, the utilization of entropy-based methods for fault diagnosis

Table 1: A summary of recent methods for fault diagnosis of rotating machinery using entropy techniques.

Author	Year	Object	Signal monitored	Signal processing	EEA method		classifier used
					Type	Role	
Bin [7]	2012	motor	vibration	WPT and EMD	*Power Energy*	vector selection	ANN
Tabrizi [8]	2015	bearing	vibration	WPT and EEMD	*Power Energy*	vector selection	SVM
Kankar [9]	2011	bearing	vibration	CWT	entropy ratio	parameter selection	SOM, SVM, ANN
Gu [10]	2012	shaft	AE	DWT	$ShanEn$	feature extraction	N/A
Camarena [11]	2016	motor	vibration	N/A	$ShanEn$	feature extraction	k-Means
He [12]	2012	bearing	AE	N/A	$ApEn$	feature extraction	N/A
Sampaio [13]	2016	shaft	vibration	N/A	$ApEn$	feature extraction	N/A
Lin [14]	2017	gear and bearing	vibration	SLA and WSM	$ApEn$ and $SampEn$	feature extraction	N/A
Liang [15]	2015	gearbox	AE	WT-EMD	$SampEn$	vector selection	SVM
Wu [16]	2016	bearing	vibration	EMD	MSE	vector selection	decision tree
Pan [17]	2016	motor	vibration	N/A	MSE	feature extraction	SVM
Verma [18]	2016	motor	vibration, current	N/A	MSE	feature extraction	ANN
Aouabdi [19]	2017	gearbox	current	DWT	PCA-MSE	feature extraction	N/A
Chen [20]	2016	gearbox	vibration	LMD	$FuzzyEn$	vector selection	ANFIS
Metha [21]	2016	bearing	vibration	N/A	MFE	feature extraction	VPMCD
Zhao [22]	2016	bearing	vibration	EEMD	MFE	feature extraction	SVM
Zheng [23]	2017	bearing	vibration	N/A	composite MFE	feature extraction	ensemble SVM
Wu [24]	2012	bearing	vibration	N/A	MPE	feature extraction	SVM
Vakharia [25]	2015	bearing	vibration	CWT	MPE	parameter selection	ANN, SVM
Zhang [26]	2015	bearing	vibration	EEMD	$PerEn$	vector selection	SVM
Yi [27]	2017	bearing	vibration	TSSA	$PerEn$	vector selection	N/A

of rotating machinery is summarized. In addition, future trends are proposed to improve the effectiveness of entropy-based diagnostic methods. However, with increasing efforts been put into the entropy methods applied in characterizing fault information, it is believed that entropy-based techniques would be constituently applied as promising techniques in fault diagnosis of rotating machinery.

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