Mechanical Systems and Signal Processing 109 (2018) 330–351

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

Hyper-spherical distance discrimination: A novel data description method for aero-engine rolling bearing fault detection

Tong Lin [a], Guo Chen [a,*], Wenli Ouyang [b], Quande Zhang [a], Hongwei Wang [c], Libo Chen [c]

[a] College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China
[b] Innovative Research Center, China Aero-Polytechnology Establishment, Beijing 100076, China
[c] Beijing Aeronautical Technology Research Center, Beijing 100076, China

ARTICLE INFO

Article history:
Received 9 July 2016
Received in revised form 16 September 2017
Accepted 9 January 2018

Keywords:
Fault detection
Rolling bearing
Condition monitoring
Feature fusion
Degradation assessment
Feature transform
Aero-engine

ABSTRACT

A novel method called hyper-spherical distance discrimination (HDD) is proposed in order to meet the requirement of aero-engine rolling bearing on-line monitoring. In proposed method, original multi-dimensional features extracted from vibration acceleration signal are transformed to the same dimensional reconstructed features by de-correlation and normalization while the distribution of feature vectors is transformed from hyper-ellipsoid to hyper-sphere. Then, a simple model built up by distance discriminant analysis is used for rolling bearing fault detection and degradation assessment. HDD is compared with the support vector data description (SVDD) and the self-organizing map (SOM) in rolling bearing fault simulation experiments. The results show that the HDD method is superior to the SVDD and SOM in terms of recognition rate. Besides, HDD is applied to a run-to-failure test of aero-engine rolling bearing. It proves that the evaluating indicator obtained by HDD method is able to reflect the degradation tendency of rolling bearing, and it is also more sensitive to initial fault than the root mean square (RMS) of vibration acceleration signal. With the advantages of low computational complexity and no need to tuning parameters, HDD method can be applied to practical engineering effectively.

1. Introduction

Rolling bearing failure is one of the leading causes of aviation accidents. In order to maintain aero-engine uptime at the highest possible level and reduce maintenance costs, maintenance should be carried out in a proactive way. It means a transformation of maintenance strategy from the traditional fail-and-fix practices (diagnostics) to a predict-and-prevent methodology (prognostics) [1]. However, predict-and-prevent methodology is based on effective condition monitoring technology.

Condition monitoring data are very versatile, including vibration data, acoustic data, oil analysis data, etc. Vibration data collection is a widely used approach for fault detection [2–4]. However, the sensitivity of various original features that are characteristics of bearing performance may vary significantly under different working conditions [5]. Hence, it is critical to devise an evaluating indicator that provides a useful and automatic guidance on using the most effective features for bearing degradation assessment without human intervention.

* Corresponding author.
E-mail address: cgzyx@263.net (G. Chen).

https://doi.org/10.1016/j.ymssp.2018.01.009
0888-3270/

Generally, fault detection and condition monitoring of the aero-engine rolling bearings should be considered as a data domain description problem (also called one-class classification), in view of that the fault samples are hard to be acquired in engineering. That is, when nothing about the outlier distribution can be assumed, only a description of the boundary of the target class can be made [6]. Since the on-line monitoring of aero-engine rolling bearing can be regarded as a data domain description problem, it is necessary to study the distribution of multidimensional feature vectors in space in order to establish a more accurate model by greater using the prior knowledge. The distribution of feature vectors cannot be visualized because the dimensionality of feature vectors is usually more than three, but its two-dimensional (2-D) projection can be easily study. If the projection on each 2-D feature plane tends to an ellipse, we can infer that the distribution of feature vectors in high-dimension space tends to a hyper-ellipsoid. When different features are chosen, length and direction of the hyper-ellipsoid principal axis may change. Hence a strongly nonlinear algorithm is needed for describing such a complicated distribution. Different methods have been developed to solve this problem such as SVDD [7–9], SOM [10–12], gaussian mixture model (GMM) [5,13], etc, and have been proved effective in experiments. However, these methods have a deficiency of high computational complexity when training. The bearing detection model is envisioned to reside in the engine controller and operates on-board. The engine controller has to carefully prioritize and distribute computing resources among multiple processes to ensure the safety of the critical tasks such as flight and engine controls. Therefore, a simple fusion model is strongly preferable to a computationally complex one [14].

According to above analysis, the limited computing resources in engineering and the complexity of the model constitute a contradiction. The reason why the models of high computational complexity are chosen is because the described boundary is complicated. So if it is possible to improve the spatial distribution of feature vectors, then it is possible to greatly simplify the algorithm describing the boundary of the data domain. Based on this, a novel method called hyper-spherical distance discrimination (HDD) is proposed. Compared with some typical data domain description like SVDD, SOM etc., HDD has the advantages of low computational complexity and no need to tuning parameters during the training stage. In this study, we implemented HDD on aero-engine rolling bearing monitoring.

The remaining part of the paper is organized as follows. Section 2 introduces the multi-dimensional features used in following sections and briefly describes how to extract these features. In Section 3, two kinds of experiments (including experiment 1: rolling bearing fault simulation experiment and experiment 2: run-to-failure test) were carried out and the distribution of original feature vectors is discussed in detail. The discussion reveals a potential approach for simplifying the distribution. Section 4 proposes a novel method for bearing fault detection and degradation assessment. Section 5 shows the results of two experiments. The performance of proposed method under different operating conditions and different measurement points is compared with SVDD and SOM. Section 6 discusses some problems in detail. Finally, conclusions are made in Section 7.

2. Feature extraction

2.1. Time-domain features

Six dimensionless time-domain features used in this study are summarized in Table 1, including shape indicator T_{SI}, crest indicator T_{CI}, impulse indicator T_{MI}, clearance indicator T_{CLI}, kurtosis T_{KU} and skewness T_{SK}, where y_i is raw waveform data, $y_{\mathrm{p}i}$ is the maximum absolute value of each section where the raw waveform data is divided into 10 sections.

2.2. Frequency-domain features

Three dimensionless frequency-domain features used in this study are summarized in Table 2, including frequency center F_{FC}, mean square of frequency F_{MSF} and variance of frequency F_{VF}, where $S(f_i)$ is the spectral amplitude at frequency f_i.

Table 1
Dimensionless time-domain features.

Shape indicator	Crest indicator	Impulse indicator	Clearance indicator	Kurtosis	Skewness
$T_{\mathrm{SI}} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i^2)}}{\frac{1}{N}\sum_{i=1}^{N}\lvert y_i\rvert}$	$T_{\mathrm{CI}} = \frac{\sum_{i=1}^{10}y_{\mathrm{p}i}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i)^2}}$	$T_{\mathrm{MI}} = \frac{\sum_{i=1}^{10}y_{\mathrm{p}i}}{\frac{1}{N}\sum_{i=1}^{N}\lvert y_i\rvert}$	$T_{\mathrm{CLI}} = \frac{\sum_{i=1}^{10}y_{\mathrm{p}i}}{\left[\frac{1}{N}\sum_{i=1}^{N}\sqrt{\lvert y_i\rvert}\right]^2}$	$T_{\mathrm{KU}} = \frac{\frac{1}{N}\sum_{i=1}^{N}y_i^4}{\left(\frac{1}{N}\sum_{i=1}^{N}y_i^2\right)^2}$	$T_{\mathrm{SK}} = \frac{\frac{1}{N}\sum_{i=1}^{N}y_i^3}{\left(\frac{1}{N}\sum_{i=1}^{N}y_i^2\right)^{\frac{3}{2}}}$

Table 2
Dimensionless time-domain features.

Frequency center	Mean square frequency	Variance of frequency
$F_{\mathrm{FC}} = \frac{\sum_{\mathrm{i}=0}^{n}f_iS(f_i)}{\sum_{\mathrm{i}=0}^{n}S(f_i)}$	$F_{\mathrm{MSF}} = \frac{\sum_{\mathrm{i}=0}^{n}f_i^2S(f_i)}{\sum_{\mathrm{i}=0}^{n}S(f_i)}$	$F_{\mathrm{VF}} = \frac{\sum_{\mathrm{i}=0}^{n}(f_i-F_{\mathrm{FC}})^2S(f_i)}{\sum_{\mathrm{i}=0}^{n}S(f_i)}$