Mechanical Systems and Signal Processing 100 (2018) 827–845

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

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

Average combination difference morphological filters for fault feature extraction of bearing

Jingxiang Lv, Jianbo Yu *

School of Mechanical Engineering, Tongji University, Shanghai 201804, China

ARTICLE INFO

Article history:
Received 27 March 2017
Received in revised form 25 June 2017
Accepted 9 August 2017

Keywords:
Bearing
Fault feature extraction
Impulsive feature
Morphological filter
Teager energy kurtosis

ABSTRACT

In order to extract impulse components from vibration signals with much noise and harmonics, a new morphological filter called average combination difference morphological filter (ACDIF) is proposed in this paper. ACDIF constructs firstly several new combination difference (CDIF) operators, and then integrates the best two CDIFs as the final morphological filter. This design scheme enables ACIDF to extract positive and negative impacts existing in vibration signals to enhance accuracy of bearing fault diagnosis. The length of structure element (SE) that affects the performance of ACDIF is determined adaptively by a new indicator called Teager energy kurtosis (TEK). TEK further improves the effectiveness of ACDIF for fault feature extraction. Experimental results on the simulation and bearing vibration signals demonstrate that ACDIF can effectively suppress noise and extract periodic impulses from bearing vibration signals.

1. Introduction

Vibration signal analysis is an effective method for bearing fault diagnosis and condition-based-monitoring. If a localized defect occurs in a rolling bearing, an impulse of short duration will be generated and this excites resonance of the bearing and other components of the machine, which enables the vibration signals to present the feature of amplitude modulation [1]. The impulses are periodically produced in the rotation of the bearings, i.e., the rolling elements, inner and outer races. Thus, the vibration signals collected from bearings are ordinarily non-stationary and non-linear, and the fault information contained in the periodicity of impacts is inevitably affected by the strong background noise [2]. Therefore, the fault feature extraction from the bearing vibration signals immersed in heavy noise becomes an important issue.

Signal processing has gone through the development of time domain, frequency domain and time-frequency analysis. Time and frequency domain analysis only can be applied to stationary and linear signals. To deal with non-stationary signals, the time-frequency analysis method that can extract local features in both time and frequency domains simultaneously has been used widely for machinery fault diagnosis. The regular time-frequency analysis methods include short time Fourier transform (STFT), Wigner-Vill distribution (WVD), wavelet transform (WT), empirical mode decomposition (EMD), etc. However, each of these methods has its own limitations [3,4]. For instance, STFT is governed by Heisenberg uncertainty principle. WVD can describe the energy distribution of a signal but it would cause cross-term interference when dealing with multi-component signals. WT has variable time-frequency window but its mother wavelet should be predefined well. EMD is based on the local time scales of a signal and has achieved great progress recently. However, these still exist some deficiencies (e.g., end effects, mode mixing) to be overcome.

* Corresponding author at: School of Mechanical Engineering, Tongji University, 4800 Caoan Road, Shanghai 201804, PR China.
E-mail address: jianboyu.bob@gmail.com (J. Yu).

http://dx.doi.org/10.1016/j.ymssp.2017.08.020
0888-3270/

Different from these regular time-frequency analysis methods, morphological filter (MF) [5,6] is a nonlinear analysis method, which aims to modify the geometry of a signal by its intersection with structure element (SE). Thus, only the morphological features of the signal that are matched with those of SE can be extracted effectively. In recent years, MF has been used for impact feature extraction of vibration signals. They generally focus on the construction of morphological operators and selection of SE. In order to separate compound faults from rolling bearings, Li et al. [7] used the MF with sparse component analysis to ensure the signals to meet the sparseness requirement and to extract modulation features. Meng et al. [8] proposed a hybrid fault diagnosis method using MF-translation invariant wavelet and ensemble empirical mode decomposition (EEMD). Hu et al. [9] employed morphological gradient (MG) operator to pick up both positive and negative impulses and to extract the harmonic waveform from vibration signals. Dong et al. [10] introduced the average operator (AVG) in the impulse components extraction, where the length of SE was determined by an indicator called signal noise ration (SNR). Particle swarm optimization (PSO) was used to obtain the optimal SE in the morphological operator [11]. However, these morphological operators generally suffer from the different output bias and SE selection problems.

Because the vibration signals collected from rolling bearings always suffer from the noise and harmonics interference, we propose a new morphological operator named average combination difference morphological filter (ACDIF) to extract both positive and negative impulses. In this study, the four basic operators (i.e., erosion, dilation, opening and closing) are classified into two categories according to their filtering characteristics. Then several new combination difference (CDIF) operators are constructed by a combination of two basic operators. Finally, the average of the best two CDIF operators is used as the final morphological filter. Meanwhile, a Teager energy kurtosis (TEK) [12]-based indicator is utilized to determine the length of SE in ACDIF. Therefore, the major contributions and innovations of this paper include: (1) A new morphological operator (i.e., ACDIF) that integrates four basic operators is proposed to extract both positive and negative impulses in the vibration signals. (2) A new indicator (i.e., TEK) is developed for determining the length of the SE to further improve the performance of ACDIF. The results on simulation and vibration signals illustrate that ACDIF is capable of suppressing noise and extracting periodic impacts from the vibration signals.

The rest of this paper is organized as follows. The new morphological filter (i.e., ACDIF) with TEK is proposed in Section 2. In Section 3, the proposed method is validated on the simulation signals. Vibration signals collected from two detective bearings with inner and outer race defect, respectively are further used to verify the effectiveness of ACDIF in Section 4. Finally, the conclusions are given in Section 5.

2. Average combination difference morphological filter

2.1. Morphological filter

Mathematical morphology (MM) based on set theory was initially proposed as an image processing method by Serra [13,14]. In recent years, MM was often used as a demodulation method in the bearing fault diagnosis [15,16]. There are four basic morphological operators, i.e., erosion, dilation, opening and closing. Let $f(n)$ be the original 1-D discrete signal that is the function over a domain $F = (0, 1, \ldots, N-1)$. Let $g(m)$ be the SE that is the discrete function over a domain $G = (0, 1, \ldots, M-1)(M \leqslant N)$. The four basic operators can be defined as follows:

Erosion:

$$(f\Theta g)(n) = \min\{f(n+m) - g(m)\}\{1 \leqslant n \leqslant N; 1 \leqslant m \leqslant M\} \tag{1}$$

Dilation:

$$(f \oplus g)(n) = \max\{f(n-m) + g(m)\}\{1 \leqslant n \leqslant N; 1 \leqslant m \leqslant M\} \tag{2}$$

Opening:

$$(f \circ g)(n) = (f\Theta g \oplus g)(n) \tag{3}$$

Closing:

$$(f \bullet g)(n) = (f \oplus g\Theta g)(n) \tag{4}$$

where Θ, $\oplus$, $\circ$ and $\bullet$ denote the erosion, dilation, opening and closing operator, respectively. The discrete dilation and erosion operators are equivalent to the maximum and minimum filter of the discrete function in a sliding window, respectively.

Morphological filters are composed of the four basic operators and employed for suppressing noise and extracting impulsive features of the signal. Several main morphological filters [17–19] are introduced as follows:

Morphological gradient (MG):

$$MG(f(n)) = (f \oplus g)(n) - (f\Theta g)(n) \tag{5}$$

MG, a union of dilation and erosion, can be used for transient information detection and impulse location.

Difference filter (DIF):

$$DIF(f(n)) = (f \bullet g)(n) - (f \circ g)(n) = ((f \bullet g)(n) - f(n)) + (f(n) - (f \circ g)(n)) \tag{6}$$