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Diagonal slice spectrum assisted optimal scale morphological filter for rolling element bearing fault diagnosis

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ABSTRACT

This paper presents a novel signal processing scheme, diagonal slice spectrum assisted optimal scale morphological filter (DSS-OSMF), for rolling element fault diagnosis. In this scheme, the concept of quadratic frequency coupling (QFC) is firstly defined and the ability of diagonal slice spectrum (DSS) in detection QFC is derived. The DSS-OSMF possesses the merits of depressing noise and detecting QFC. It can remove fault independent frequency components and give a clear representation of fault symptoms. A simulated vibration signal and experimental vibration signals collected from a bearing test rig are employed to evaluate the effectiveness of the proposed method. Results show that the proposed method has a superior performance in extracting fault features of defective rolling element bearing. In addition, comparisons are performed between a multi-scale morphological filter (MMF) and a DSS-OSMF. DSS-OSMF outperforms MMF in detection of an outer race fault and a rolling element fault of a rolling element bearing.

1. Introduction

Mathematical morphology (MM) was originally put forward by Matheron in the fundamental of integral geometry [1]. Later, Serra and Vincent [2,3] and Maragos and Schafer [4,5] gave a deep and detailed analysis of morphological filtering in terms of mathematical theoretical framework, properties and relations with linear filters. From then on, MM theory was rapidly developed. Nowadays, increasing attentions have been aroused in applying MM for fault diagnosis of rolling element bearings [6–12].

The main idea of morphological signal processing can be described as follows: it firstly selects a data set called a structure element (SE); then, morphological operations are performed between the raw signal and the selected SE in order to modify signal geometric shape for the purpose of removing noise and extracting useful information.

Classic morphological filter performs a single-scale analysis in which a SE with fixed length is utilized [6–8]. However, the impulsive features of rolling element bearings often distribute over multiple scales; one scale where the SE is good to extract the fault symptoms for some signal segmentations may be inadequate for other segmentations [9]. Therefore, the single-scale MM method may suffer from the lack of completeness in the extracted impulsive features. Multi-scale morphological filter (MMF) performs the morphological transforms multiple times with a different lengths of SE at each time

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and then calculates the average value of filtering results from all scales. It is demonstrated in Ref. [10] that the multi-scale morphology analysis of bearing vibration signals is more effective than the single-scale analysis in terms of fault diagnosis.

Although the multi-scale morphology analysis is an interesting attempt to examine the signals in different resolutions, the averaging of the results from all scales as used in [10–14] may likely be non-optimal. As the filtered signal processes by a scale far away from the theoretical central scale is often heavily polluted, it is hard to reflect the factual features. An optimal scale may exist that can reflect the characteristics of fault better than the averaging of multiple scales and it is reasonable to find out this optimal scale for fault detection.

The repetitive transients resulting from a local fault of the rotating machinery exhibits both impulsiveness and cyclostationarity signatures [15]. Multiple methods, such as wavelet assisted independent component analysis [16], infogram [17] and its improved method multiscale clustered gray infogram [18], were developed to detect the impulsiveness and cyclostationarity of a vibration signal for fault diagnosis. In the present paper the third-order cumulant diagonal slice (TCDS) [19] and its corresponding frequency spectrum, namely diagonal slice spectrum (DSS) [19], are employed to find the optimal scale in morphology analysis and improve the performance of MMF. Because of the greatest impulsiveness and cyclostationarity should be related to the optimal informative scale in theory [20].

The fault symptoms of bearings are often obscured by the presence of noise. Gaussian noise is one of the most common noises in bearing vibration signals. If the noise is extremely strong and consequently the fault-generated impulses are submerged by noise, the performance of feature extraction would deteriorate. Luckily, TCDS is theoretically zero for Gaussian noise [21]. The vibration signal of rolling element bearings with fault is basically a non-Gaussian signal. If a non-Gaussian vibration signal is embedded by additive Gaussian noise, a transform to TCDS will eliminate the noise [22]. What's more, it is demonstrated in this paper that the DSS peaks only at frequency pairs coupled in frequency. The concept of quadratic frequency coupling (QFC) is defined and the property that DSS can effectively detect QFC is proved in this paper. This property can greatly remove the fault unrelated components in frequency domain and show fault characteristics more clearly.

The organization of the rest of this paper is as follows: Section 2 introduces the fundamentals of MMF; Section 3 describes TCDS and DSS analysis; QFC is proposed and the ability of DSS in detection of QFC is proved in Section 4; In Section 5, the DSS improved OSMF (DSS-OSMF) method is proposed, and the advantage of it over the MMF approach is demonstrated by using a simulated vibration signal; Section 6 applies the proposed technique to test rig signals of rolling element bearings and demonstrates the detection ability of DSS-OSMF for three types of faults respectively: an outer race fault, an inner race fault and a rolling element fault; Conclusions are drawn in Section 7.

2. Multi-scale morphological filter

2.1. Basic theories on mathematical morphology

The basic morphological filtering operators include those for dilation, erosion, opening and closing [3]. Supposing the input sequence $f(n)$ and the selected SE $g(m)$ are discrete data sets defined in $F=(0, 1, \dots, N-1)$ and $G=(0, 1, \dots, M-1)$ $(N \geq M)$, respectively, then dilation and erosion are expressed as:

$$(f \oplus g)(n) = \max\,[f(n-m) + g(m)] \tag{1}$$

$$(f \ \Theta \ g)(n) = \min\,[f(n+m) - g(m)] \tag{2}$$

where $\oplus$ denotes the dilation operator and Θ represents the erosion operator.

The opening and closing operators are constructed based on the dilation and erosion operators. They are defined as:

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

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

where o stands for the opening operator and $\bullet$ for the closing operator. The opening operation can inhibit positive impulses but preserve negative impulses, while the closing operation can preserve positive impulses but inhibit negative impulses. By combining the opening operator and the closing operator, two kinds of mathematical morphology filters, namely, open-close (OC) filter and close-open (CO) filter, can be expressed based on the above four operators:

$$F_{oc}(f(n)) = (f \mathrm{o} g \bullet g)(n) \tag{5}$$

$$F_{co}(f(n)) = (f \bullet g \mathrm{o} g)(n) \tag{6}$$

Either of OC and CO filters can remove both positive impulses and negative impulses. However, due to the existence of statistic bias [23], using OC or CO filter alone cannot get a satisfactory filtering performance. A difference filter which combines OC and CO filters can achieve a better performance. The difference filter is expressed as follows:

$$y(n) = F_{co}(f(n)) - F_{oc}(f(n)) \tag{7}$$