Measurement 94 (2016) 794–805

Contents lists available at ScienceDirect

Measurement

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

The morphological undecimated wavelet decomposition – Discrete cosine transform composite spectrum fusion algorithm and its application on hydraulic pumps

Jian Sun, Hongru Li *, Baohua Xu

Mechanical Engineering College, Shijiazhuang 050003, China

ARTICLE INFO

Article history:
Received 29 February 2016
Received in revised form 8 September 2016
Accepted 13 September 2016
Available online 14 September 2016

Keywords:
Degradation feature extraction
MUWD
DCS
Hydraulic pump

ABSTRACT

Degradation feature extraction of hydraulic pumps is a key step of the condition-based maintenance. In this paper, a novel method based on MUWD-DCS fusion algorithm is proposed. In order to decrease noises and disturbances, the method for obtaining detail components by the Morphological Undecimated Wavelet Decomposition (MUWD) with the selected parameters is presented firstly. Multi-channel vibration signals are proposed by the MUWD and the detail components containing sensitive information are achieved. Furthermore, on the basement of the earlier Composite Spectrum (CS), the DCS fusion algorithm is proposed to make fusion of the obtained detail components for improving the feature performance. The DCS entropy is extracted to be the degradation feature. Analysis of application on the hydraulic pump degradation experiment demonstrates that the proposed algorithm is feasible and it is effective to reveal the performance degradation of the hydraulic pump.

1. Introduction

Feature extraction is one of the key steps of fault diagnosis. Plenty of researches have been conducted in the extraction of failure mode features, which are widely used in many fields. Varied from the failure mode features, the degradation features require high sensitivity to identify various degradation stages. Meanwhile, the degradation experiment costs long time and the vibration signals during the degradation are very complex. Therefore, fewer contributions are made in this filed. Wang et al. [1] and Tran et al. [2] extracted features by the analysis of the monitoring signal in time domain to realize the recognition and prognostic of bearing degradation. Zhao [3] applied the Empirical Mode Decomposition (EMD) in vibration signal analysis and extracted the approximate entropy as the degradation feature. Dong [4] chose the non-extensive wavelet feature scale entropy to be the feature for degradation evaluation. These methods have achieved some expected purposes. However, most extracted features are based only on the single monitoring signal. Without information fusion, it can hardly fulfill the multi-sources requirement and the integrity of feature information, leading to the influences on features sensitivity. Furthermore, unlike the rolling bearing, the structure of the hydraulic pump is complex. Its vibrations are mainly caused by the shocks of pistons and the inherent mechanism such as bearing [5]. The liquid compressibility and the coupling effect between fluid and solid may also contribute to the abrasion of piston and swash plate. Therefore, the feature information in vibration signals during degradation is too weak to be extracted efficaciously [6]. Consequently, an effective method is required for extracting the degradation feature of hydraulic pumps.

The basement of the feature extraction is the signal pre-processing for obtaining sensitive failure information. Common methods are the wavelet analysis algorithm, the Empirical Mode Decomposition (EMD) algorithm and the Local Characteristic-scale Decomposition (LCD) algorithm. The wavelet analysis algorithm is able to divide the signal into various frequency bands and to obtain useful information [7,8]. However, selection of both thresholds and the wavelet basis can hardly be solved. EMD is capable of dividing the signal into several components and searching for useful fault information in each component [9,10]. Since the mode fixing and the end effect are severe, the sensitive information may not be accurately extracted by EMD sometimes. LCD can adaptively partition a complex signal into several intrinsic scale components [11]. Compared with EMD, LCD has advantages in iterations and the restraining of end effect [12]. Limited by the three spline function fitting, the mode mixing in LCD algorithm still exists, which may introduces the disturbances of noise and some useless components. Being one of the late proposed algorithms for signal

* Corresponding author.
E-mail addresses: hehetcs1@163.com (J. Sun), lihr168@sohu.com (H. Li), xbh8237@163.com (B. Xu).

http://dx.doi.org/10.1016/j.measurement.2016.09.024
0263-2241/

preprocessing, Morphological Undecimated Wavelet Decomposition (MUWD) omits the sampling operation during the decomposition and reconstruction, which avoids the distortion [13]. Meanwhile, based on the morphological operator, the mode mixing has been effectively reduced. It becomes easier to achieve the sensitive information [14]. Related studies have shown that the preprocessing result of MUWD has close connections with the related parameters, such as the number of decomposition layers and the initial length of the structure element [13–15]. However, there has been no scientific and systematical solution for optimal parameters selection of MUWD. Consequently, a method for achieving the detail components containing sensitive information based on MUWD with the selected parameters is required.

Furthermore, in order to improve the feature performance, the fusion algorithms are introduced to deal with the detail components obtained from multi-channel signals, such as the weighted fusion, Kalman filtering and wavelet analysis. However, it seems difficult to select appropriate fusion weights for the weighted fusion algorithm [16,17]. Kalman filtering algorithm lacks of strict filtering functions for nonlinear systems [18,19]. During the sampling operation in the wavelet analysis fusion algorithm, some sensitive feature information may be lost [20]. As a novel fusion algorithm, the Composite Spectrum (CS) is able to realize information fusion of various signals by calculating the correlative index and the mutual power spectrum of neighboring signals [21]. It is also capable of taking advantages of detail information and extracting useful feature information [22]. Influenced by the multiplication of Fourier coefficient and its complex conjugate, it seems to be easy to lose some feature information. To solve this problem, some modification has to be made. Being the spread of the Fourier transform, Discrete Cosine Transform (DCT) has the property of energy aggregation [23]. Its coefficients are sensitive enough to energy changing [24]. Therefore, it is reasonable to present the DCT – Composite Spectrum (DCS) algorithm based upon the replacement of Fourier transform by DCT. On this basement, the obtained detail components could be better fused for improving feature sensitivity to degradation.

Consequently, a novel method for the degradation feature extraction of hydraulic pumps based on MUWD-DCS is proposed. Contributions of this article are summarized hereinafter. In Section 2, a method for detail components decomposed from original signals based on MUWD is presented. The parameters selection for MUWD is also demonstrated. Meanwhile, the proposed method is applied in the simulation signals analysis; in Section 3, DCS fusion algorithm is proposed and the degradation feature extraction by MUWD-DCS is indicated in detail; in Section 4, we confirm the results through the hydraulic pump degradation experiment; while in Section 5, we draw some conclusions.

2. Detail components obtaining by MUWD

2.1. MUWD algorithm

Assume that the collections of V and W respectively mean the i_{th} signal space and the i_{th} detail space. $T()$ denotes the morphological operator. The framework of the conventional MUWD is describe by Eqs. (1)–(3) [25].

$$x_{i+1} = \varphi_i^{\uparrow}(x_i) = T(x_i) \tag{1}$$

$$y_{i+1} = \omega_i^{\uparrow}(x_i) = (id - T)(x_i) \tag{2}$$

$$\psi_i^{\downarrow}\left(\varphi_i^{\uparrow}(x_i), \omega_i^{\uparrow}(x_i)\right) = \varphi_i^{\uparrow}(x_i) + \omega_i^{\uparrow}(x_i) = id(x_i) \tag{3}$$

where Eq. (1) means using the signal analysis operator $\varphi_i^{\uparrow}$ to decompose the signal from V_i to V_{i+1}. Eq. (2) means using the detail analysis operator $\omega_i^{\uparrow}$ to decompose the signal from V_i to V_{i+1}. Eq. (3) shows the wavelet reconstruction and pyramid principle for the composition operator $\psi_i^{\downarrow}$ and the analysis operators [26,27].

In the framework of MUWD, the key operator is $T()$, such as the mean combination operator, the morphological difference operator, the morphological gradient operator and the hybrid operator [28–30]. Considering the structural characters of hydraulic pumps, the morphological difference operator is applied in this article. It contains both black and white Top-Hat for extracting signal pulses. The basic operations of MUWD are shown in Eqs. (4)–(6) [31].

$$x_{i+1} = \varphi_i^{\uparrow}(x_i) = f(x_i) \bullet (i+1)g - f(x_i) \circ (i+1)g \tag{4}$$

$$y_{i+1} = \omega_i^{\uparrow}(x_i) = id(x_i) - [f(x_i) \bullet (i+1)g - f(x_i) \circ (i+1)g] \tag{5}$$

$$\psi_i^{\downarrow}(\varphi_i^{\uparrow}(x_i), \omega_i^{\uparrow}(x_i)) = \varphi_i^{\uparrow}(x_i) + \omega_i^{\uparrow}(x_i) = id(x_i) \tag{6}$$

where $f(n)$ is the initial signal and g is the flat structural element. '$\circ$' and '$\bullet$' denote the morphological opening operation and the morphological closing operation. $(i+1)g$ means the i_{th} swelling operation on g.

Assume that X_1-X_3 respectively denote vibration signals probed by $sensor_1$–$sensor_3$. The number of the decomposition layer is N. The initial length of the structural element is L. According to Eqs. (4)–(6), X_1-X_3 are decomposed by MUWD. Based on the operator $\varphi_i^{\uparrow}$, the feature information could be extracted from the former layer x_i and restored in the current approximate signal y_{i+1}. In order to extract the sensitive information by the morphological operations effectively, the approximate signals $MUWD_{1\text{-}N}$, $MUWD_{2\text{-}N}$, $MUWD_{3\text{-}N}$ in the N_{th} layer are considered as detail components.

2.2. Parameters selection

According to the theory of MUWD, two parameters are involved. One is N, which denotes the number of decomposition layers. The other is L, which means the initial length of the flat structural element.

- If N is too large, available information in the former layer x_i will be limited and the ingredient in the approximate signal y_{i+1} almost stays invariant.
- If N is too small, information in the former layer x_i will be too rich, leading to the disturbances of feature information.
- If L is too large, the extracted pulses will decrease and some sensitive feature information may be lost.
- If L is too small, noises may be retained in the approximate signal y_{i+1}.

Therefore, the mean feature energy factor (MFEF) is presented to be the index for evaluating the performance of MUWD. It is defined as the reciprocal of the mean percentage between the partial energy of the prior h doubling frequency of the feature frequency and the total energy in the frequency domain of each detail component. Its expression is described by Eq. (7).

$$\begin{cases} MFEF = \dfrac{m}{\sum_{l=1}^{m} FEF_l} \\ FEF_l = (E_{l1} + E_{l2} + \ldots + E_{lh})/E \end{cases} \tag{7}$$

where m denotes the number of detail components. Since three-dimensional vibration signals are applied for research in this article, we take $m = 3$. E_{lh} denotes the energy of the h_{th} feature frequency in the l_{th} ($l = 1, 2, 3$) detail component. E means the sum of E_{lh}, and we usually take $h = 3$. Obviously, MFEF is able to reveal sensitive information in all detail components. The smaller the MFEF is, the more sensitive information is achieved. Procedures for parameters selection are detailed as follows.