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Automatic damage identification of roller bearings and effects of sifting stop criterion of IMFs

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ABSTRACT

Damage identification of roller bearings has been deeply developed to detect faults using vibration-based signal processing. Empirical mode decomposition (EMD) is one of the recent techniques adapted to this purpose; it decomposes a multi-component signal into some elementary Intrinsic Mode Functions (IMFs). Although the EMD has been applied in various applications successfully, there are some drawbacks such as lack of a mathematical base, no robust stopping criterion for sifting process, mode mixing and border effect problem. One of the most relevant drawbacks in fault diagnosis is the sifting stop criterion. Although sifting as many times as possible is needed to decompose the signal, too many sifting steps will reduce the physical meaning of IMFs which are extremely important for fault diagnosis. Thus, a precise criterion is required to identify the appropriate stage to conclude the sifting process. The proposed criteria so far are: Cauchy-type convergence, Mean fluctuations thresholds, Energy difference tracking, Resolution factor, Bandwidths, and Orthogonality criterion. Effects of sifting stop criterion on damage identification performance has not studied thoroughly yet. In this study the influence of different stopping criteria on automatic fault diagnosis is investigated. Vibration signals were acquired using the test rig assembled by Dynamics & Identification Research Group (DIRG) at Department of Mechanical and Aerospace Engineering, Politecnico di Torino. Various operating conditions were considered to obtain reliable results. By extracting feature vectors for each decomposing algorithms, the accuracy of defect detection is examined by labeling the samples whether they are healthy or faulty using support vector machine (SVM).

1. Introduction

Modern rotating machines become more precise and automatic and there is a demand to increase the reliability and detect any possible faults at an early stage. Through processing of collected vibration signals and extracting significant information, it is possible to detect even small defects on bearings. There are different signal processing techniques to decompose a signal and extract informative features such as EMD and Wavelet transform. EMD introduced by Huang et al. [1,2] is a method for decomposing a multi-component signal into several elementary Intrinsic Mode Functions (IMFs) and has been widely applied to fault diagnosis of rotating machines. However, there are some drawbacks such as stopping criterion for sifting process, mode mixing and border effect problem.

The sifting process actually serves two purposes: to eliminate riding waves and to make the wave profiles more symmetric with respect to zero. In fact, one of the conditions that an IMF has to satisfy is that the mean between the upper and lower envelopes must be zero. On the other hand, too many sifting steps will reduce the IMF to be a constant amplitude frequency-modulated function, which makes the results physically less meaningful. To preserve the natural amplitude variations of the oscillations, sifting must be limited to as few steps as possible. Different kind of criteria have been proposed so far. In the Cauchy-type convergence criterion, standard deviation of two consequent sifting results is used as the criterion (SD criterion) [1]. The main flaw of this approach is that it is unrelated to the definition of IMFs. The mean fluctuations thresholds (MFT) utilize three thresholds to compare a specific defined fraction [3]. The shortcoming of MFT is that the thresholds do not adapt to the signal. The energy difference tracking (EDT) is based on the assumption that the residue and IMFs are mutually orthogonal [4]. The difference between the total energy and energy of the original signal is tracked as the sifting stop criterion. The

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resolution factor (RF) is defined by the ratio between the energy of the signal at the beginning of the sifting and the energy of the envelopes means [5]. None of the before-mentioned criteria uses the frequency or phase information of the analyzed signal. Xuan and Xie [6] designed a new stop criterion based on two types of bandwidth: instantaneous bandwidth and frequency bandwidth which is caused only by frequency changes. Based on orthogonality definition, Lin and Hongbing defined orthogonality criterion (OC) [7].

Automatic fault diagnosis is necessary in industry because manual checking of a number of bearings in rotating machinery may take an unacceptable long time and also it is advisable to allow relatively unskilled operators to make reliable decisions instead of needing for a diagnosis expert. Various techniques, such as artificial neural network (ANN) and Support vector machine have been proposed to construct a pattern from acquired signals and make a decision on the health of the machine. After training the system with the past data referred to healthy or faulty conditions of a machine they will be able to classify new acquired samples. SVM introduced by Vapnik [8], is a relatively new computational learning method based on statistical learning theory which has been applied successfully to numerous applications [9]. The main difference between ANN and SVM is in their risk minimization [10]. In the case of SVM, structural risk minimization is used to minimize an upper bound based on an expected risk whereas traditional empirical risk is used to minimize the error in the training of data, in ANN. Thus, better generalization performance is obtained for SVM. Meantime, SVM can solve the learning problem with a smaller number of samples. Taking into account the fact that acquiring sufficient faulty samples is not applicable in practice, SVM has been used in numerous fault diagnosis problems successfully [10].

In this study we will investigate the influence of different proposed criteria on automatic fault diagnosis (using SVM) to understand if stopping criteria can affect the result of fault detections.

2. EMD algorithm

The EMD method decomposes a complex signal into a number of intrinsic mode functions (IMFs) which is designated by the following definitions [1,2]:

(1) In the whole data set, the number of extrema and the number of zero crossings must either equal or differ at most by one.
(2) At any point, the mean value of the envelopes defined by local maxima and the envelope defined by the local minima is zero.

The decomposition consists of the following steps:

(1) To identify all the local extrema, and then connect all the local maxima by an interpolation method to produce the upper envelope. Repeat the procedure for the local minima to produce the lower envelope.
(2) To determine the difference between the signal $x(t)$ and m_1 which is the mean of upper and lower envelopes to obtain the first component, h_1.

$$x(t) - m_1 = h_1 \tag{1}$$

If h_1 is an IMF, then h_1 would be the first component of $x(t)$. Otherwise, h_1 is treated as the original signal and step (1)–(2) are repeated:

$$h_1 - m_{11} = h_{11} \tag{2}$$

in which, m_{11} is the mean of upper and lower envelope value of h_1. After repeated sifting, up to k times (based on sifting stop criterion), h_{1k} becomes an IMF, that is

$$h_{1(k-1)} - m_{1k} = h_{1k} \tag{3}$$

Then it is designated as the first IMF component of the data: $c_1 \equiv h_{1k}$. The sifting process can be stopped by any preselected criterion which will be discussed in the next section.

(3) To separate IMF (c_1) from the original signal $x(t)$ to obtain the residue r_1:

$$r_1 = x(t) - c_1 \tag{4}$$

(4) To consider r_1 as the new data and repeat the above described process for n times, so that n-IMFs of signal $x(t)$ can be obtained. Then:

$$\begin{aligned} &r_1 - c_2 = r_2 \\ &\dots \\ &r_{n-1} - c_n = r_n \end{aligned} \tag{5}$$

(5) To stop the decomposition process when r_n becomes a monotonic function from which no more IMF can be extracted. By summing up Eqs. (4) and (5), we finally obtain:

$$x(t) = \sum_{j=1}^{n} c_j + r_n \tag{6}$$

Thus, a signal $x(t)$ can be decomposed into n-empirical modes and a residue r_n, that could be interpreted as the mean trend of the signal.

3. IMF sifting stop criteria

3.1. Cauchy-type convergence (SD)

Huang et al. [1] proposed a criterion where the size of the standard deviation of two consequent sifting results (h_n, h_{n-1}) should be limited and when it reaches a certain predefined value, sifting must stop:

$$SD = \sum_t \frac{[h_{n-1}(t) - h_n(t)]^2}{h_{n-1}^2(t)} < \varepsilon \tag{7}$$

3.2. Mean fluctuations thresholds (MFT)

Rilling et al. [3] introduced a new criterion based on three thresholds ($\theta_1, \theta_2, \alpha$) aimed at guaranteeing globally small fluctuations in the mean while taking into account locally large excursions. For $(1-\alpha)$ fraction of data, sifting will be continued when $\sigma(t) < \theta_1$ and for remaining fraction when $\sigma(t) < \theta_2$:

$$\sigma(t) = \left| \frac{m(t)}{a(t)} \right| \tag{8}$$

where $a(t) = (e_{\max}(t) - e_{\min}(t))/2$, $m(t) = (e_{\max}(t) + e_{\min}(t))/2$, $e_{\max}(t)$ and $e_{\min}(t)$ are the envelopes.

3.3. Energy difference tracking (EDT)

If h_1 is an orthogonal component of $x(t)$, the sum of its energy and those of the residual signal (E_{tot}) is equal to the original signal energy E_x. Otherwise, there is a difference denoted as E_{err} [4]. Hence, E_{err} is tracked and when it reaches a certain minimum and the mean value of envelope becomes small enough, sifting process is completed and the obtained IMF component is orthogonal to the original signal.