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Rolling bearing diagnosing method based on Empirical Mode Decomposition of machine vibration signal

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ABSTRACT

Rolling bearing faults are one of the major reasons for breakdown of industrial machinery and bearing diagnosing is one of the most important topics in machine condition monitoring.

The main problem in industrial application of bearing vibration diagnostics is the masking of informative bearing signal by machine noise. The vibration signal of the rolling bearing is often covered or concealed by other structural vibrations sources, such as gears. Although a number of vibration diagnostic techniques have been developed over the last several years, in many cases these methods are quite complicated in use or only effective at later stages of damage development. This paper presents an *EMD*-based rolling bearing diagnosing method that shows potential for bearing damage detection at a much earlier stage of damage development.

By using *EMD* a raw vibration signal is decomposed into a number of Intrinsic Mode Functions (*IMF*s). Then, a new method of *IMF*s aggregation into three Combined Mode Functions (*CMF*s) is applied and finally the vibration signal is divided into three parts of signal: noise-only part, signal-only part and trend-only part. To further bearing fault-related feature extraction from resultant signals, the spectral analysis of the empirically determined local amplitude is used. To validate the proposed method, raw vibration signals generated by complex mechanical systems employed in the industry (driving units of belt conveyors), including normal and fault bearing vibration data, are used in two case studies. The results show that the proposed rolling bearing diagnosing method can identify bearing faults at early stages of their development.

1. Introduction

Rolling element bearings, also known as rolling bearings, are widely used in rotary machinery systems. Rolling bearings fall out of service for various reasons, such as unexpected heavy loads, unsuitable or inadequate lubrication and ineffective sealing. The components that often fail in rolling bearings are the rolling elements, the inner race and the outer race. Rolling bearings' diagnostics is important for guaranteeing machine safety and production efficiency. The damage of a bearing may cause the breakdown of a rotary machine, leading to serious consequences. One of the key issues in rolling bearing diagnostics is to detect the defect at its early stage and alert the machine operator before it develops into a catastrophic damage. Contrary to oil condition and thermal state monitoring methods that detect damages of bearings at very late stages of their development (close to catastrophic stages), vibroacoustic analysis detect most of the damages yet at much earlier stages of bearings' technical degradation.

Rolling bearing is a complex vibration system whose components (e.g. rolling elements, outer race, inner race and cage) interact to generate complex vibration signal. When a fault on one surface of a bearing element strikes another surface, an impact is generated. The successive mechanical impacts (which are the result of the passage of the fault through the load zone) produce a series of impulses observed in a bearing signal. These mechanical impacts modulate the bearing signal at characteristic frequencies depending on the localization of the defect, such as: Fundamental Train (Cage) frequency (f_{FTF}), Ball Spin Frequency (f_{BSF}), Ball Fault Frequency ($f_{BFF} = 2{\cdot}f_{BSF}$), Ball Pass Frequency Outer Race (f_{BPFO}) and Ball Pass Frequency Inner Race (f_{BPFI}) [1,2]. Calculations of the characteristic frequencies assume that the rolling elements do not slide, but roll over the race's surfaces. There is always some slip and real characteristic frequencies differ from calculated characteristic frequencies by about a few percent [3].

There are two main groups of diagnosing techniques using vibration signals: time-domain and frequency-domain analysis techniques. Traditional time-domain analysis calculates characteristic

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features from vibration signal waveform, such as root mean square, skewness, kurtosis or crest factor and they have been applied with limited success for rolling bearing diagnosing [4]. Kurtosis of vibration signal can be used to detect bearing faults at early stages of their development [5]. The kurtosis is a statistical parameter based on the fourth and the second moments of a signal, which is close to 3 for Gaussian noise and other stationary signals, but large for impulsive signals containing series of impulses, such as a signal generated by damaged bearing. However, precise nature of the fault cannot be defined by the kurtosis analysis and for such information it is necessary to use a more sophisticated diagnostic method. The advantage of frequency-domain analysis, based on the transformation of a signal in the frequency domain, is its ability to easily identify certain spectral components of the signal. With high frequency resonance analysis (also known as envelope analysis) it is possible to identify not only the occurrence of the bearing's fault, but also identify this fault, like damage in the outer race or in the rolling element [1]. In short, the conventional Hilbert-transform-based envelope detection is based on amplitude demodulation and consists of band-pass filtering and the Hilbert transform. Defects in rolling bearings can be detected and localized by discovering spectral components of vibration signal with the frequencies (and their harmonics) typical for the fault.

Usually, bearing vibration signal is collected with an accelerometer installed on the bearing housing where the vibration sensor is often subject to collecting active vibration sources from other mechanical components of the machine. The vibration signal from a bearing at an early stage of defect development may be masked by machine noise, making it difficult to detect the fault by vibration analysis techniques [1,6]. Therefore, a method of diagnostic signal extraction is needed to provide useful information regarding the bearing condition. A number of techniques are described for the separation of bearing signals from background signals which mask it [7–10]. For some specific requirements (e.g. time-triggered signal acquisition), not all of them can be always applied in industrial reality. Moreover, the effectiveness of some techniques depends in essential degree on proper values of a given technique's parameters (e.g. convergence factor, filter order), which must be determined in an empirical study.

There are also more advanced techniques related to time frequency methods [11], especially wavelets [12] and dedicated approaches for signal enhancement using signal modeling [13,14] or deconvolution technique [15]. Relatively new interesting approach is related to algorithms for searching for informative frequency band [31,33]. Diagnostics under non-stationary load and operating speed condition is discussed in recent papers given by different authors [9,11,21,30,32].

Empirical Mode Decomposition (*EMD*) has attracted attention in recent years due to its ability to self-adaptive decomposition of non-stationary signals. Recent publications on *EMD* [16–21] show its advantages for non-stationary signals processing and confirm its effective application in many diagnostic tasks.

In this paper, an *EMD*-based approach for rolling bearing diagnostics is investigated. By using *EMD* a raw vibration signal is decomposed into a number of Intrinsic Mode Functions (*IMF*s). Then, a new method of *IMF*s aggregation into three Combined Mode Functions (*CMF*s) is applied and finally the vibration signal is divided into three parts of signal: noise-only part, signal-only part and trend-only part. To further bearing fault-related feature extraction from resultant signals, the spectral analysis of the empirically determined local amplitude is used. To validate the proposed method, raw vibration signals generated by complex mechanical system employed in the industry (driving units of belt conveyors), including vibration data of damaged and undamaged bearings, are used in two case studies. The results show that the proposed rolling bearing diagnosing method can identify the bearing faults at early stages of their development.

2. A brief look into Empirical Mode Decomposition (*EMD*)

Empirical Mode Decomposition (*EMD*) has been proposed by Huang et al. [22]. This self-adaptive decomposition method decomposes any signal into empirical modes which represent different oscillation modes embedded in the signal. Based on the *EMD* algorithm, any original signal $x_o(t)$ can be reconstructed by a linear superposition of empirical modes:

$$x_o t) = \sum_{i=1}^{n} c_i(t) + r_n(t), \quad (1)$$

where $c_i(t)$ is i-th empirical mode and $r_n(t)$ is the final residue after the extraction of n empirical modes. Each empirical mode $c_i(t)$, called Intrinsic Mode Function (*IMF*), fulfills the following two conditions [22]: (1) in the whole empirical mode, the number of mode local extremes and the number of mode zero-crossings are equal or differ at most by one and (2) at any point, the local average of upper and lower envelope is zero.

The algorithm for the extraction of *IMF*s from original signal $x_o(t)$ is called sifting process and it consists of the following steps [23]:

Step 1: Define $x(t) = x_o(t)$ and $r_0(t) = x_o(t)$.
Step 2: Define the maximum number of extracted *IMFs*.
Step 3: Identify all the local extremes (maxima and minima) of $x(t)$.
Step 4: Connect all the local maxima (respectively minima) with a line known as the empirically determined upper envelope $E_{max}(t)$ (respectively the lower envelope $E_{min}(t)$).
Step 5: Construct the mean of empirically determined upper and lower envelope $m(t) = 0.5\cdot(E_{min}(t) + E_{max}(t))$.
Step 6: Define the detail (proto-*IMF*) as $d(t) = x(t) - m(t)$ and replace $x(t)$ by $d(t)$.
Step 7: Repeat steps 3–6 until $d(t)$ meets the *IMF* conditions and the stoppage criterion of the sifting process is fulfilled, then derive i-th *IMF* from $d(t)$ and replace $x(t)$ by $r_i(t) = r_{i-1}(t) - d(t)$.
Step 8: If the stoppage criterion of the signal's decomposition is fulfilled then finish the decomposition process; otherwise, go to step 3.

The second *IMF* condition is too rigid to use, so it is necessary to change it to implement the *EMD*. The local average of upper and lower envelope must be close to zero according to some criterion. The evaluation (how small it is) of the amplitude of the local average may be done in comparison with the amplitude of the corresponding mode. In [24] authors introduce a new criterion based on the local mode amplitude $a(t) = 0.5\cdot(E_{max}(t) - E_{min}(t))$ and the evaluation function $\sigma(t) = |m(t)/a(t)|$. In this paper, $d(t)$ meets the second *IMF* condition, when $max(\sigma(t)) < \theta$ (the coefficient θ was equal to 0.2).

A critical part of the *EMD* procedure is the stoppage criteria of the sifting process and decomposition process. The stoppage criterion of the sifting process determines the point when sifting is complete and a new *IMF* has been found. Two different stoppage criteria of the sifting process were considered.

The first stoppage criterion of the sifting process is determined by using a Cauchy type of convergence test [22]. If the two details (proto-*IMFs*) from successive iterations are close enough to each other, it is assumed that the last extracted detail is an *IMF*. The normalized squared difference SD_k between two successive details $d_{k-1}(t)$ and $d_k(t)$ during k-th iteration is defined as: