Fault Diagnosis Method Based on Kurtosis Wave and Information Divergence for Rolling Element Bearings

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Abstract: Fault diagnosis depends largely on feature analysis of vibration signals. However, feature extraction for fault diagnosis is difficult because the vibration signals often contain a strong noise component. Noises stronger than the actual fault signal may interfere with diagnosis and ultimately cause misdiagnosis. In order to extract the feature from a fault signal highly contaminated by the noise, and to accurately identify the fault types, a novel diagnosis method is proposed based on the kurtosis wave and information divergence for fault detection in a rolling element bearing. A kurtosis wave (KW) is defined in the time domain using the vibration signal, and a method for obtaining the kurtosis information wave (KIW) is also proposed based on Kullback-Leibler (KL) divergence using the kurtosis wave. A practical example of diagnosis for an outer-race defect in a bearing is provided to verify the effectiveness of the proposed method. This paper also compares the proposed method with two envelope analysis techniques, namely the wavelet transform- and the FFT-based envelope analysis techniques. The analyzed results show that the feature of a bearing defect is extracted clearly, and the bearing fault can be effectively identified using the proposed method.

Key-Words: - Fault Diagnosis, Rolling Element Bearing, Envelope Analysis, Kurtosis Wave, Information Divergence.

1 Introduction

In the case of fault diagnosis in plant machinery, utilization of vibration signals is effective in detection of faults and discrimination of fault types because the signals carry dynamic information about the machine state. Fault diagnosis depends largely on feature analysis of the vibration signals, so it is important that the signal feature is sensitively extracted at the machine's state of change. However, feature extraction for fault diagnosis is difficult because vibration signals measured at any point in the machine often contain a strong noise component. Noises stronger than the actual fault signal may interfere with diagnosis and ultimately cause misdiagnosis. In cases where a strong noise is present, quality information is not obtained, resulting in an incorrect conclusion. Therefore, it is important to remove as much noise as possible from the measured signal in order to accurately identify the fault type [1]-[5].

A rolling bearing is an important part of, and is widely used in, plant machinery. Failure of a bearing may cause breakdown in a rotating machine, leading to serious consequences. Therefore, fault diagnosis of rolling bearings is important for guaranteeing production efficiency and plant safety. While a faulty rolling bearing with is in operation, the vibration signals will present a modulation feature. Therefore, in spectrum analysis, demodulation analysis should be carried out prior to performing the FFT. Envelope detection has been widely applied to identification of bearing defects by extraction of fault-characteristic frequencies from the vibration signal of a defective bearing [6]-[12].

There have been many studies done on fault detection in rolling bearings using vibration signals. In [3]-[5], a condition diagnosis method for a bearing and rotating machinery was proposed based on the fuzzy neural network method, by which the condition of a machine was automatically judged. Reference [6] demonstrated why usually when theoretical mathematical models are used to compute the frequencies corresponding to a faulty rolling bearing a deviation is obtained between the computed values and the real frequencies emitted by such a device. In [7], vibration and acoustic measurement methods for detection of defects in rolling element bearings were reviewed. In [8], a method of fault feature extraction was proposed based on an intrinsic mode function envelope spectrum in order to overcome the limitations of the conventional envelope analysis method. Several envelope detection (ED) methods, namely, wavelet-based ED, logarithmic-transformation ED, and first-vibration-mode ED, were proposed in laboratory conditions for fault diagnosis in bearings [10]-[12]. Statistical analysis methods were used for detection of bearing failure in a simple test rig [13] [14]. In [15], several autoregressive modeling techniques were compared for fault diagnosis in rolling element bearings. In [16], a method was proposed for analysis of vibration signals resulting from bearings with localized defects using the wavelet packet transform as a systematic tool. In [17], the effectiveness and flexibility of wavelet analysis and envelope detection were investigated for fault diagnosis in rolling element bearings used in motor-pump driven systems. In [18], comprehensive case studies for defect diagnosis of rolling element bearings were reported by vibration monitoring and spectral analysis used as a predictive maintenance tool; bearing outer-race defects only were successfully diagnosed in the fan motor and centrifugal pump systems. In [19], four approaches based on bispectral and wavelet analysis of signals were investigated as signal processing techniques for application in diagnosis of induction motor roller bearing faults. In [20] [21], bearing fault diagnosis with wavelet-based methods was reported.

Although many studies have tried to develop a method for detecting faulty bearings, some studies were condition under the ideal conditions in the laboratory. Most of these works focus on bearings used in general rotating machinery rather than in reciprocating machinery with high noise levels. Fault diagnosis using the vibration method for reciprocating machinery (such as diesel engines, vibration separators, etc.) is more difficult than in general rotating machinery such as electric motors. This is because the signals measured in reciprocating machinery contain a strong noise component and higher vibration levels, even under normal conditions.

For the above reasons, this paper proposes a novel diagnosis method based on the kurtosis wave and information divergence for fault detection in a rolling element bearing. The diagnosis process is carried out as follows. First, the reference and diagnosis signals are measured simultaneously. Second, the kurtosis information wave (KIW) is obtained based on KL divergence in the time domain using filtered and normalized signals. Next, the envelope signal is obtained from the absolute values of the KIW, and the spectrum of the envelope KIW is transformed using the FFT technique. Lastly, by comparing the fault characteristic frequencies in the envelope spectrum with the pass-frequencies of the bearing, the bearing fault types are identified. In this case, the bearing outer-race defect should be successfully identified in order to verify the effectiveness of the proposed method. To illustrate the effectiveness of the proposed method for bearing fault diagnosis, the paper also compares this method with the conventional FFT-based envelope analysis and wavelet-transform-based envelope analysis.

2 Definition of Kurtosis Wave

In the case of fault diagnosis, statistical feature parameters calculated from the signals are normally used to identify the machinery condition because they express information indicated by a signal measured for diagnostic purposes. Statistical feature parameters are commonly classified into two types, namely, the non-dimensional feature parameters and the dimensional feature parameters. The former, such as the mean value and the peak value, express the magnitude of a signal. The latter, such as skewness, shape of wave, and kurtosis, reflect the shape of a signal.

Many statistical feature parameters have been defined in the pattern recognition field [22]. Kurtosis has been applied with limited success for detection of localized defects [13]-[14], and is defined as follows:

$$Kur = \frac{\sum_{i=1}^{N}(x_i - \mu)^4}{N\sigma^4} \tag{1}$$

where μ and σ are the mean and the standard deviation of the signal series x_i (i=1-N), respectively.

To acquire the features of the vibration signal in the time domain, a new time waveform, called the "Kurtosis Wave (KW)" is proposed. In order to facilitate understanding of the derivation of the kurtosis wave, a simple illustration is shown in Fig.1.

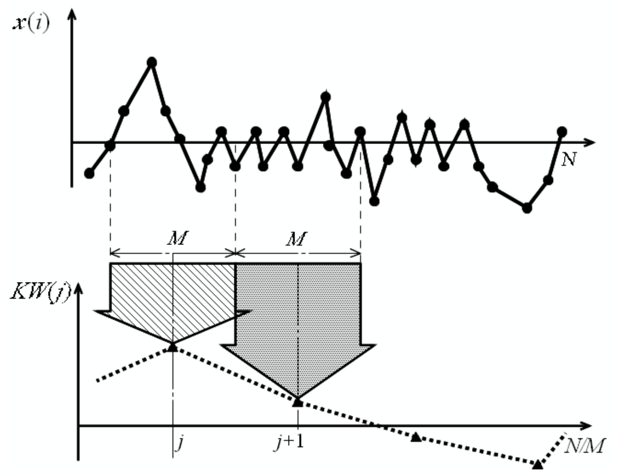

Fig. 1. An illustration to obtain the kurtosis wave

As shown in Fig. 1, the entire data signal x_i (i=1-N) is divided into smaller regions. The values of the kurtosis can be calculated by (1) using the data in those smaller regions. The points of the kurtosis are connected to derive the kurtosis wave $KW(j)$. Obviously, the kurtosis wave varies with time and can retain the features of the time domain.

The calculation formula of the kurtosis wave is given as follows:

$$KW(j) = \frac{\sum_{i=(j-1)*M+1}^{j*M} (x_i - \mu_j)^4}{M\sigma_j^{\ 4}} \qquad (2)$$

where μ_j and σ_j are the mean and standard deviation of the signal series x_i in the jth small region, respectively. M is the number of data in a smaller region, and j=1-L, $L = M / N \le f_S / f_A$, and f_S and f_A are the sampling frequency and the analysis frequency, respectively.

3 Feature Extraction by Kullback-Leibler Divergence

3.1 Derivation for Kurtosis Information Wave (KIW)

In this section, the method of feature extraction is presented based on the Kullback-Leibler (KL) divergence information theory [23]. KL divergence plays a central role in the theory of statistical inference and is introduced, in brief, as follows [24].

Let P_1 and P_2 be two probability distributions. If P_1 and P_2 have probability density functions $p_1(x)$ and $p_2(x)$ over $\boldsymbol{R}^k$, respectively, the information of KL divergence from P_1 to P_2 is defined by

$$KL(P_1, P_2) = \int p_1(x) \log \frac{p_1(x)}{p_2(x)} dx \qquad (3)$$

Two fundamental properties of KL are:

•Non-negativity: $KL(P_1,P_2) \ge 0$ with equality if and only if $P_1 = P_2$.

•Asymmetry: $KL(P_1,P_2) \ne KL(P_2,P_1)$.

Smaller values of the information quantity $KL(P_1,P_2)$ mean that the distance between the two distributions is smaller. That is, the larger the distance between the two distributions, the larger the difference between the two distributions. Therefore, the distance between the two distributions can indicate the difference between the two distributions.

In the case of fault diagnosis, KL information has been applied to comparison of the unknown distribution to be diagnosed with a known reference distribution, which is then used for the simple diagnosis of machinery [25]-[27]. In the present work, we define the diagnosis feature variable and the reference feature variable, instead of the diagnosis distribution and the reference distribution, and apply these feature variables using KL divergence. The diagnosis feature variable KW_D is a kurtosis wave that is calculated with the diagnosis signal measured in the diagnostic location (such as the bearing housing). The reference feature variable KW_R is a kurtosis wave that is calculated with the reference signal measured in the reference location. The reference location is near the assembly base of a machine and far from the diagnostic location.

The distance between KW_D and KW_R can be quantitatively described by the value of the information divergence. The KL information quantity is calculated from the expectation value of the reference feature variable and is defined by

$$KL = \int_0^T KW_R(t) \log \frac{KW_R(t)}{KW_D(t)} dt \qquad (4)$$

To extract the feature of the fault signals, an information waveform of a kurtosis wave, shortened to the "Kurtosis Information Wave (KIW)", is proposed based on the KL information quantity.

The calculation formula of the KIW is defined as follows:

$$KIW(t) = KW_R(t)\log\frac{KW_R(t)}{KW_D(t)} \qquad (5)$$

An illustration for the derivation of the discrete KIW is shown in Fig. 2. Practical diagnosis examples via the KIW are discussed in Section 4.

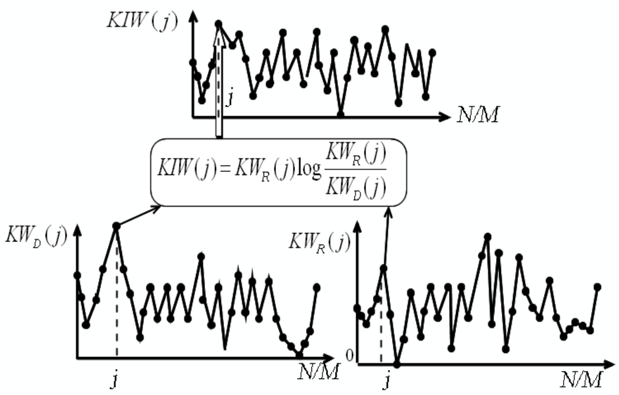

Fig. 2. An illustration for the derivation of the discrete KIW

3.2 Spectrum Analysis for Kurtosis Information Wave

The signal analysis technique is one of the most important methods used for fault diagnosis, with the goal of finding a simple and effective transform of the original signals. In this way, the important information contained in the signals can be shown, and the dominant features of signals can be extracted for fault diagnosis. Frequency-domain analysis or spectral analysis is based on the transformed signal in the frequency domain. The advantage of frequency-domain analysis over time-domain analysis is its ability to easily identify and isolate certain frequency components of interest. FFT-based spectral analysis has the advantage that it is able to detect the location of the fault and is the most widely used approach for fault diagnosis of rotating machinery.

Each bearing element has a characteristic rotational frequency. With the presence of a defect on a particular bearing element, an increase in vibrational energy may occur at this element's rotational frequency. The components that often fail in a rolling element bearing are the outer race, the inner race, the rollers, and the cage. Such failures generate a series of impact vibrations in short time intervals, which occur at the bearing characteristic frequencies. However, the signal from a defective bearing is a typical vibration with amplitude modulation. This phenomenon of amplitude modulation arises because a high-frequency carrier signal is varied by a low-frequency modulating signal. Thus, the modulated signal could be the product of the modulating signal with the carrier signal. Moreover, the modulating signal represents the impact caused by bearing defects and could be represented by bursts of exponentially decaying vibration. Its spectrum would be expanded in a frequency band, making it difficult to find the characteristic frequency of the modulating signal. Therefore, demodulation analysis should be carried out prior to performing the FFT. FFT-based envelope detection has been widely applied to identification of bearing faults occurring at the characteristic frequencies [8]-[12].

In the present work, the envelope wave is obtained from the absolute values of the kurtosis information wave, and is shown as follows:

$$|KIW(j)| = \left|KV_R(j)\log\frac{KV_R(j)}{KV_D(j)}\right| \qquad (6)$$

The envelope spectrum of the kurtosis information wave, $Q(f_i)$, can be acquired by the FFT technique. Here, f_i is a frequency of the spectrum. Practical diagnosis examples using the envelope spectrum of the KIW are given in the next section.

4. Practical Application

Practical examples of fault diagnosis for a bearing used in a diesel engine are given to verify the effectiveness of the proposed method. To illustrate this, we also compared this method with the conventional FFT-based envelope analysis and with wavelet transform-based envelope analysis.

4.1. Experimental System

The experimental setup used for bearing fault diagnosis, including the diesel engine (Yanmar L40ASS), bearings, and inspection locations, is shown in Fig. 3.

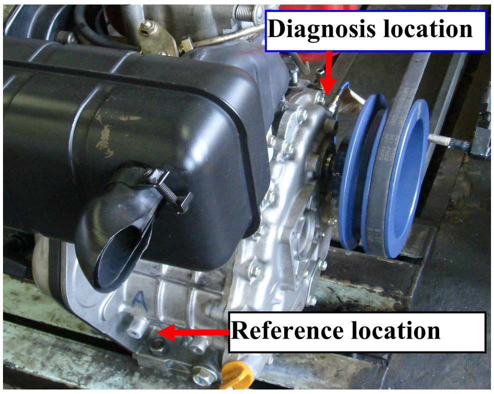

Fig. 3 Experimental setup and inspection locations

In this case, a bearing outer-race defect should be successfully identified in order to verify the effectiveness of the proposed method. The defective bearing is shown in Fig. 4, and the defect was artificially induced with a wire-cutting machine. Specifications for the test bearing, the size of the fault, and other necessary information are listed in Table 1.

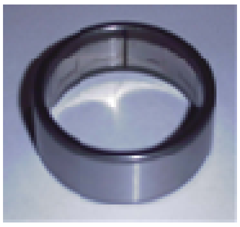
Fig. 4 Bearing outer-race defect

Table 1. Bearing information

Contents	Parameters
Bearing specification	NTN205
Bearing outer diameter	52 mm
Bearing inner diameter	25 mm
Bearing width	15 mm
Bearing roller diameter	7 mm
The number of the rollers	13
Contact angle	0 rad
Flaw width	0.8 mm.
Flaw depth	0.8 mm.

In this work, two accelerometers (PCB MA352A60) with bandwidth from 5 Hz to 70 kHz and a 10 mV/g output were used for inspection of the vibration signals. As shown in Fig. 3, one sensor was mounted on the engine housing (diagnosis location) at the output of the shaft for inspection of the diagnosis signal. The other was fixed in the reference location far from the diagnostic location and near the assembly base of engine.

In order to fully analyze signal features by searching out the frequency areas of high S/N, we chose the larger sampling frequency for acquiring more comprehensive information for research on the fault diagnosis. Because the accelerometer (PCB MA352A60) had a bandwidth from 5 Hz to 70 kHz, the sampling frequency of the vibration signals was set at 200 kHz. The sampling time was 20 sec, and the rotating speed of the machine was 1000 rpm.

4.2. Pass-frequency of a Bearing

Faults that typically occur in rolling element bearings are usually caused by localized defects in the outer race, the inner race, and the roller. Such defects generate a series of impact vibrations every time a running roller passes over the surfaces of the defects. These vibrations occur at bearing characteristic frequencies, which are estimated based on the geometry of the bearing, its rotational speed, and the location of the defect [17]. By identifying the type of the reoccurring bearing characteristic frequency, the cause of the defect can be determined.

For a bearing with a stationary outer race, the outer-race defect is revealed at the outer-race pass frequency (f_O) given by [28]:

$$f_O = \frac{zfr}{2}\left(1 - \frac{d}{D}\cos\alpha\right) \tag{7}$$

where z is the number of rolling elements, f_r is the rotating frequency (Hz), d is the diameter of rolling elements (mm), D is the pitch diameter (mm), and α is the contact angle of the rolling element (rad).

This equation is based on the assumption of a pure rolling motion. However, in practice, some sliding motion may occur, which causes slight deviation in the characteristic frequency locations. Therefore, this equation should be regarded as an approximation only. In the present work, the calculated pass-frequency of the outer-race defect is 83.1 Hz.

4.3. Verification and Discussion

Original diagnosis signals measured at the diagnosis location and original reference signals measured at the reference location are shown in Figs. 5 and 6, respectively, under the normal state and outer-race flaw state.

It can be seen from the original signals that there are strong impulses in the vibration signal of each state due to the reciprocating mechanism, and the magnitudes of the signals are high even in the normal state. It also shows, in the case of fault diagnosis for a diesel engine, that the signal waveforms in the normal state and the fault state are similar; time intervals of impacts in those states are approximately equal, and the machine condition cannot be judged as “normal” or “abnormal” in a qualitative way from the these signal waveforms in the time domain.

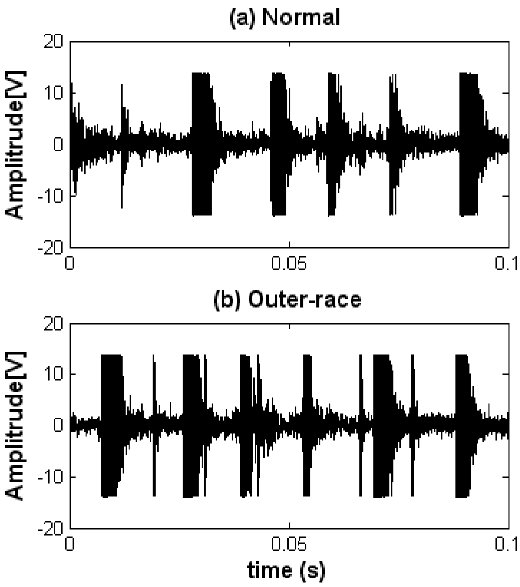

Fig. 5 Original diagnosis signals in each state (a) Normal state, (b) Outer-race flaw state

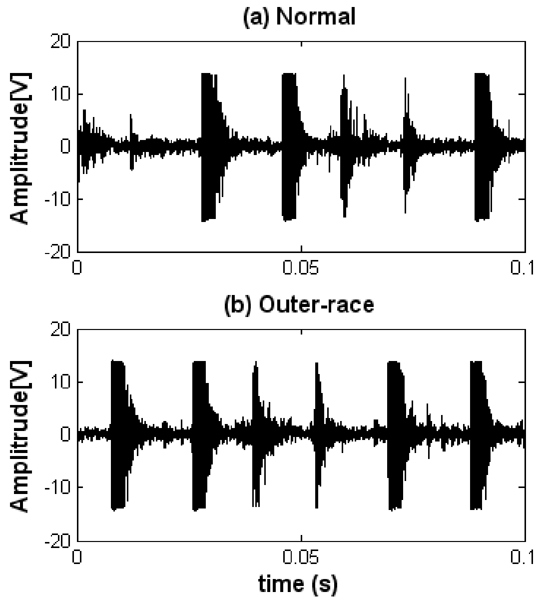

Fig. 6 Original reference signals in each state (a) Normal state, (b) Outer-race flaw state

4.3.1 Diagnosis by the conventional FFT-based envelope analysis

As mentioned in the previous section, the signal from a defective bearing is a typical vibration with amplitude modulation. Envelope detection is usually applied for processing vibration signals with amplitude modulation. The envelope signal can be obtained from the absolute value of the original signal. FFT-based envelope analysis for derivation the signal envelope spectrum has the advantage of high computational speed. Therefore, FFT-based envelope analysis is adaptable to online signal analysis and is most commonly used [10]-[12]. It is indicated that the resonances of the bearing are not significantly altered, and these natural frequencies are usually higher than 5 kHz [7].

In this case, the procedure for envelope detection can be implemented in two steps. First, a high-pass filter with a 5 kHz cut-off frequency is applied to the normalized signal. Secondly, a demodulated signal can be obtained from the absolute value of the high-passed signal. The envelope spectra of each state obtained by the FFT are shown in Fig. 7.

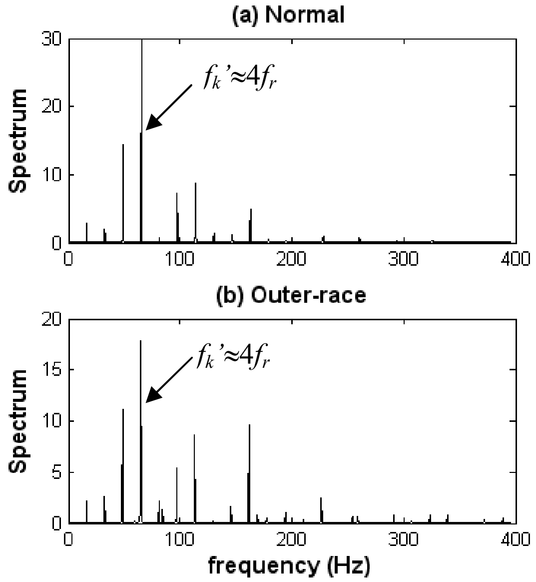

Fig. 7. Envelope spectra of diagnosis signals in each state: (a) Normal state, (b) Outer-race flaw state

There are two pistons in the engine, and the shock frequency (f_k) caused by the piston can be calculated as follows:

$$f_k = 4 f_r \tag{8}$$

where f_r is a rotating frequency.

The signals are measured at 1000 rpm, so that f_k is about 66.7 Hz. Obviously, the impact frequency (f_k') in each state where the energy is maximal is the shock frequency of the piston, as shown in Fig. 6. Because the machine contains a strong noise component, the fault characteristic frequencies caused by the defective bearing and its harmonics are buried and difficult to detect in the corresponding spectrum, where the type of bearing characteristic frequency should be located. Therefore, the bearing outer-race fault cannot be identified by the conventional FFT-based envelope analysis technique.

4.3.2. Diagnosis by wavelet transform-based envelope analysis

Wavelet transform (WT) methods, such as the discrete wavelet transform (DWT), have been applied to fault diagnosis in rotating machinery and have attracted increasing amounts of attention during the past decade [2] [29]-[31]. Here, we show that the DWT is difficult to apply to fault diagnosis of bearings used in a diesel engine.

The continuous wavelet transform (CWT) of $x(t)$ is a time-scale method of signal processing that can be mathematically defined as the sum over all time of the signal multiplied by scaled and shifted versions of the wavelet function $\psi(t)$ [2]. Mathematically,

$$\mathrm{CWT}_x\ (a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t)\psi(\frac{t-b}{a})dt \tag{9}$$

$$a, b \in R$$

where $\psi(t)$ denotes the mother wavelet or basic wavelet, its Fourier transform is $\hat{\psi}(\omega)$, a is a parameter related to scale, and b is a parameter related to time.

The discrete wavelet transform (DWT) analysis is more efficient and just as accurate. It is derived from the discretization of CWT (a, b), and the most common discretization is dyadic, given by

$$\mathrm{DWT}\ (\mathrm{j,k}) = \sum_{\mathrm{j}} \sum_{\mathrm{k}} \frac{1}{\sqrt{2^j}} x(k)\psi(\frac{t-2^j k}{2^j}) \tag{10}$$

$$j, k \in N$$

where, a and b are replaced by 2^j and $2^j k$. An efficient way to implement this scheme using filters was developed in 1989 by Mallat [32].

The original signal passes through two complementary filters and emerges as low frequency [approximations (A)] and high frequency [details (D)] signals. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that a signal can be decomposed into many lower-resolution components. By using reconstruction filters, we can reconstruct the signal constituents at each level of the decomposition [2].

There are a broad variety of mother wavelet functions available for different purposes, such as the Harr, Daubechies, Gaussian, Meyer, and Morlet functions. For the purpose of comparison with the proposed diagnosis method, the selection of mother wavelet function is not discussed in this paper. In this study, the Daubechies (db9) wavelet [30] is chosen as a mother wavelet function.

The resonance frequencies of the bearing are usually higher than 5 kHz [6]. Therefore, we have decomposed the signals into six levels (the frequency range of Level D_6 is 3.125~6.25 kHz), in order to extract the feature signals of the defective bearings. The frequency region of each level is shown in Table 2.

Table 2. Frequency region of each level

Low-frequency (A)	Range of frequency (kHz)	High-frequency (D)	Range of frequency (kHz)
Level A_1	0~100	Level D_1	100~200
Level A_2	0~50	Level D_2	50~100
Level A_3	0~25	Level D_3	25~50
Level A_4	0~12.5	Level D_4	12.5~25
Level A_5	0~6.25	Level D_5	6.25~12.5
Level A_6	0~3.125	Level D_6	3.125~6.25

The diagnosis approaches using the wavelet-transform-based envelope analysis are shown as follows. First, the original diagnosis signal measured in the outer-race defect state is decomposed into six levels, in low- and high-frequency regions, by the db9 wavelet function. Secondly, after the use of the wavelet reconstruction function, the signal constituents at each level of the decomposition are reconstructed in the time domain. The resonance frequencies of the bearing and the mechanical system generally appear in the high-frequency region; therefore, only the signals in high-frequency levels are analyzed. Lastly, envelope signals are acquired from the absolute values of the reconstructed signals, and envelope spectra are obtained using the FFT technique. Envelope spectra of each high-frequency level under the condition of the outer-race defect are shown in Fig. 8.

From Fig. 8, the impact frequency (f_k') is approximately 65.6 Hz, and is close to the shock frequency of the piston at 66.7 Hz; thus, it is caused by the reciprocation of pistons. The fault characteristic frequencies caused by the bearing outer-race defect and its harmonics are buried in the strong noise spectra and cannot be observed from those envelope spectra. Therefore, in this case, a bearing outer-race fault cannot be diagnosed by the envelope analysis based on the DWT technique.

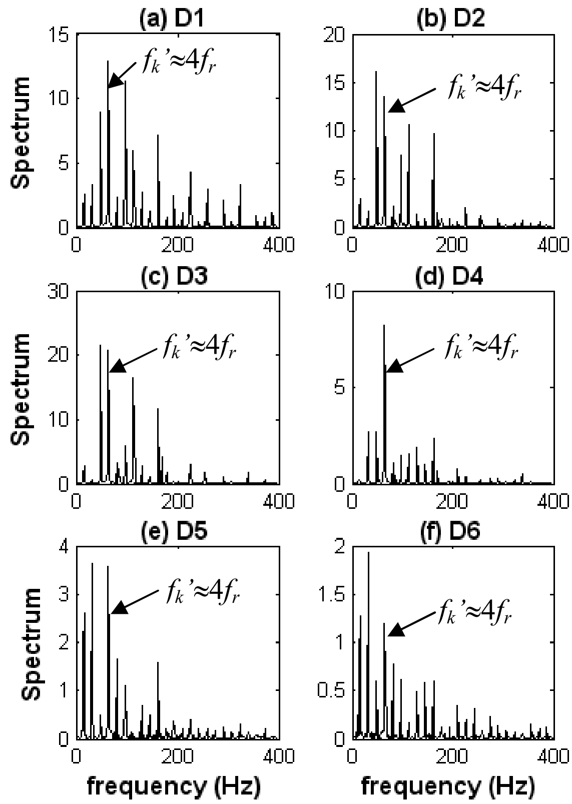

Fig. 8. Envelope spectra of each high-frequency level: (a) D1 level, (b) D2 level, (c) D3 level, (d) D4 level, (e) D5 level, (f) D6 level

4.3.3. Diagnosis by the proposed method

The diagnostic process using the proposed method in this paper is given as follows.

First, the kurtosis waves KW_D and KW_R were derived by (2), using the diagnosis signal and the reference signal in the condition of the outer-race defect, respectively. Fig. 9 shows the kurtosis waves KW_D and KW_R. Secondly, the kurtosis information wave (KIW) was obtained by the approach proposed in Section 3.1. After obtaining the envelope wave from the absolute values of the kurtosis information wave, the spectrum of the envelope wave was acquired. Fig. 10 shows the waveform of the absolute values of the KIW. The extracted envelope spectrum of KIW is shown in Fig. 11. Lastly, we diagnosed the conditions of the bearing using the pass-frequency of a bearing from the extracted feature spectrum.

As shown in Fig. 11, the impact repetition frequency, f_O, at 84.5 Hz and its harmonics ($2\times f_O$ is about 169 Hz) can be clearly observed. The frequency f_O is very close to the calculated pass-frequency of the bearing outer-race defect at 83.1 Hz; hence, it was identified as the outer-race defect. It is evident that the outer-race defect of the bearing can be detected easily from the extracted envelope spectrum.

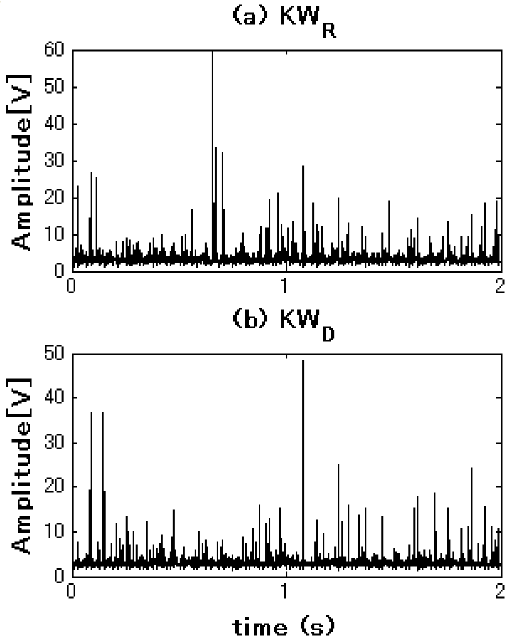

Fig. 9. Kurtosis waves: (a) KW_R, (b) KW_D

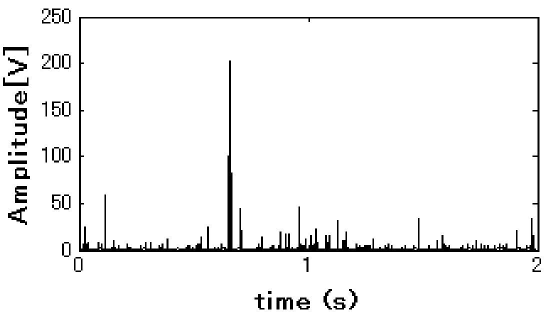

Fig. 10. Waveform of the absolute values of KIW

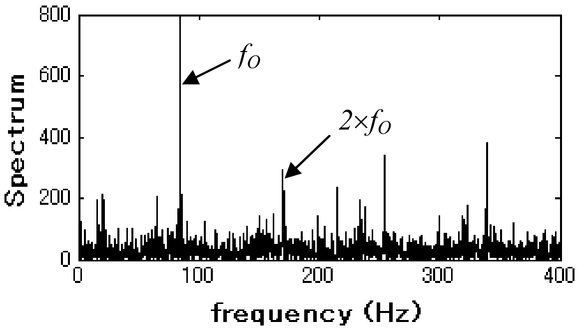

Fig. 11. The extracted feature spectrum using the proposed method

According to the analyzed results, the fault in a bearing was effectively identified by the proposed diagnostic method. However, the bearing fault was difficult to detect using the FFT- envelope analysis and wavelet-transform-based envelope analysis techniques. These results verified the effectiveness of the proposed diagnostic method for detection of faults in a bearing used in a diesel engine.

5 Conclusions

In order to extract a fault signal highly contaminated by noise and to enable the fault diagnosis of a bearing, this paper proposed a diagnosis method based on the kurtosis wave and information divergence for fault detection in a rolling element bearing. The main conclusions are described as follows:

(1) A method used to obtain the kurtosis wave (KW) was defined in the time domain using the time series signal.

(2) A kurtosis information wave (KIW) was also proposed on the basis of the Kullback-Leibler (KL) divergence using a kurtosis wave for feature extraction of a fault signal.

(3) Practical examples of diagnosis for a bearing used in a diesel engine have verified the effectiveness of the proposed method.

(4) A comparison was made between the proposed method, the conventional FFT-based envelope analysis, and wavelet-transform-based envelope analysis. The analyzed results showed that the bearing faults had been effectively identified by the proposed method. However, those faults could not be detected by either of the techniques with which it was compared.

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