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Discrete Wavelet Transform and Energy Distribution for Effective Bearing Fault Detection and Analysis

***Abstract**. Condition monitoring and problem diagnostics have drawn more attention recently in the industrial sector. One of the most crucial parts of rotating machinery are rolling-element bearings. Bearing faults are a common cause of machinery failures. To identify failing bearings early, vibration condition monitoring of rotating machinery has emerged as the preferred technique. Several signal analysis techniques can extract useful information from vibration data. The non-stationary analysis signals that are typically associated with machine defects cannot be handled by frequency-based approaches. Non-stationary signals are analyzed effectively by applying time-frequency techniques. The use of wavelet transform has increased in bearing monitoring research for the last 20 years to obtain correlated time-frequency information. This paper presents a discrete wavelet transform (DWT) and energy distribution-based bearing defect diagnostic technique. The "db3" wavelet form of DWT is used to decompose vibration signals under both normal and faulty (inner race-fault and outer race-fault) bearing conditions at various frequency ranges. Due to the default, the energy distribution for every decomposition level is calculated to detect which frequency band contains the harmonics. The results obtained from healthy and defective bearings are compared. The wavelet coefficient with the highest value of the energy distribution is employed in the Fourier analysis to pinpoint the site of the fault. The monitoring results demonstrate that the suggested approach is effective in finding and analyzing faults.*

Streszczenie.** Monitorowanie stanu i diagnostyka problemów przyciągnęły ostatnio więcej uwagi w sektorze przemysłowym. Jedną z najbardziej kluczowych części maszyn wirujących są łożyska toczne. Usterki łożysk są częstą przyczyną awarii maszyn. W celu wczesnej identyfikacji uszkodzonych łożysk, monitorowanie stanu wibracji maszyn wirujących stało się preferowaną techniką. Kilka technik analizy sygnału może wydobyć użyteczne informacje z danych o drganiach. Niestacjonarne sygnały analizy, które są zwykle związane z uszkodzeniami maszyn, nie mogą być obsługiwane przez podejścia oparte na częstotliwości. Sygnały niestacjonarne są skutecznie analizowane poprzez zastosowanie technik czasowo-częstotliwościowych. Zastosowanie transformaty falkowej wzrosło w badaniach nad monitorowaniem łożysk przez ostatnie 20 lat w celu uzyskania skorelowanej informacji czasowo-częstotliwościowej. W niniejszej pracy przedstawiono dyskretną transformatę falkową (DWT) oraz technikę diagnostyczną opartą na rozkładzie energii. Forma falkowa "db3" DWT jest używana do dekomponowania sygnałów drganiowych w warunkach łożyska zarówno normalnego, jak i wadliwego (wewnętrznego i zewnętrznego) w różnych zakresach częstotliwości. Ze względu na domyślność, rozkład energii dla każdego poziomu dekompozycji jest obliczany w celu wykrycia, które pasmo częstotliwości zawiera harmoniczne. Wyniki uzyskane z łożysk zdrowych i uszkodzonych są porównywane. Współczynnik falkowy o największej wartości rozkładu energii jest wykorzystywany w analizie Fouriera w celu określenia miejsca uszkodzenia. Wyniki monitorowania pokazują, że proponowane podejście jest skuteczne w wyszukiwaniu i analizie uszkodzeń. (**Dyskretna transformacja falkowa i dystrybucja energii w celu skutecznego wykrywania i analizy uszkodzeń łożysk)

Keywords: discrete wavelet transform (DWT), multi-resolution analysis, energy distribution, fast Fourier transform (FFT), fault diagnosis.
Słowa kluczowe: dyskretna transformata falkowa (DWT), analiza wielorozdzielcza, dystrybucja energii, szybka transformata Fouriera (FFT), diagnostyka uszkodzeń.

Introduction

Along with the growth in manufacturing capacity, the implementation of an efficient machine condition monitoring system has become increasingly necessary to prevent machine failure and reduce operating maintenance costs [1]. Rolling bearings are one of the main machine elements in rotating equipment. One of the common causes of this sort of equipment failing is the unavoidable bearing failure. [2]. Vibration analysis has been one of the principal tools for identifying early defects [3]. It is presently frequently used to find and diagnose bearing defects in a range of components. Condition monitoring based on vibration signal recording may be analyzed in both the time and frequency domains, as well as the time-frequency domain.

In time domain analysis, the metrics kurtosis, RMS, skewness, peak, and crest factor will be heavily utilized [4]. For analyzing stationary signals, the Fast Fourier Transform (FFT), which transforms time-domain data into frequency-domain data, has been the most popular method. Due to the properties of non-stationary vibration signals, time-frequency analysis has been investigated to analyze them. Several techniques exist in the time-frequency domain, including Empirical Mode Decomposition (EMD), Short Time Fourier Transform (STFT) [5], Hilbert Huang Transform (HHT), Wigner-Ville Distribution (WVD) [6], and Wavelet Transform (WT) [7]. Hence, the wavelet transform has a characteristic called "multi-scale analysis", which comprises the discrete wavelet transform (DWT) and the continuous wavelet transform (CWT). The DWT provides time-scale information about vibration signals, allowing for the extraction of effective features that change over time. Simple features, such as energy distribution or impulses, are computed in a given way to return particular signal characteristics.

There is a tremendous quantity of literature on fault detection and analysis. According to Wu et al. [8], a DWT strategy that incorporates energy spectrum feature selection and fault classification using a neural network that evaluates fault signals in order to rectify defects without sacrificing the original quality. Veerasamy et al. in [9] describe a method that employs DWT and an adaptive neuro-fuzzy inference system to identify and categorize high impedance faults in medium voltage (MV) distribution networks (ANFIS). In Addition, Tse et al. [10] propose a coupled FFT and wavelet analysis for machine fault diagnosis. Otherwise, Rai et al. [11] incorporate the frequency Fourier transform (FFT) of intrinsic mode functions (IMFs) from Hilbert–Huang Transform (HHT) process to utilize the efficiency of HT in the frequency domain. In [12], Chen et al. introduced a convolution neural network (CNN) and DWT-based method for diagnosing failure states in planetary gearboxes. However, Yan et al. [13] give an overview of current wavelet applications with a focus on rotary machine fault diagnosis.

In the present paper, Daubechies wavelets have been applied in DWT decomposition to decompose the bearing vibration signals. This approach for bearing defect identification is based on time-domain analysis. The energy distribution has been calculated to indicate the desired level of resolution and extract fault features. Also, to get the location of the fault, the Fourier analysis was performed using the higher energy output from DWT. The study includes normal and defective data.

The paper is structured as follows: Section II goes through the bearing dataset. Section III outlines the fault diagnostic approach. Section IV contains the monitoring findings and conversations. The paper is concluded in the final portion.

1. Bearings fault data acquisition

In the studies included in this research, the vibration data collected from the Case Western Reserve University Bearing Data [14] was used. The vibration information was gathered using an accelerometer, as shown in Figure 1. The experimental system was used to collect vibration data under various bearing states, including (1) normal state, (2) Inner Race Fault (IRF), (3) Outer Race Fault (ORF), and (4) Ball Fault (BF). Each vibration signal lasted for 10 seconds, and the data was collected at a frequency of 12000 Hz. SKF bearings were used for the 0.18, 0.36, and 0.53-mm diameter faults. Data on vibration was obtained for motor loads ranging from zero to three horsepower at rotational speeds between 1720 and 1797 revolutions per minute.

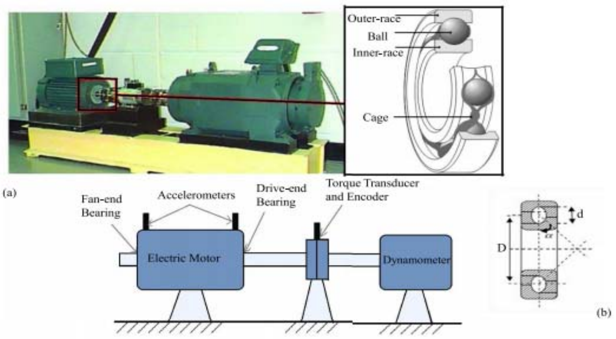

Fig.1. (a) Bearing test rig and (b) its cross-sectional view [14],[15]

The bearing fault frequencies associated with the defective inner and outer races may be estimated as follows:

$$(1)\quad BPFI = \left(\frac{n}{2}\right) f_r\left(1 + \left(\frac{d}{D}\right) cos\alpha\right)$$

$$(2)\quad BPFO = \left(\frac{n}{2}\right) f_r\left(1 - \left(\frac{d}{D}\right) cos\alpha\right)$$

where BPFI represents the inner-race ball pass frequency, BPFO represents the outer-race ball pass frequency, n represents the number of rolling elements, f_r is the shaft speed, d represents the rolling element diameter, D represents the bearing pitch diameter, and α is the contact angle.

This study includes three cases: normal condition, IRF, and outside race fault with a diameter of 0.53 mm. The data was obtained with no load at a rotational speed of 1797 rpm. Each signal has 4096 data points. The vibration signals of the normal condition, the IRF, and the ORF are shown in Figures (2a), (2b), and (2c, respectively).

According to calculation formulas (1) and (2), the fault frequencies of the inner race and the outer race are 162 Hz and 107 Hz.

2. Fault Diagnosis Strategy

2.1 Discrete wavelet transforms

The Wavelet Transform is an adaptive transform that has overcome the resolution problem of the STFT.

When translating and dilating a basic function known as the "mother wavelet," wavelets are produced (3) [16].

$$(3)\quad \psi_{a,b}(t) = \psi\left(\frac{t-b}{a}\right) \qquad a>0$$

where a is the scale factor, and b is the shift translation factor.

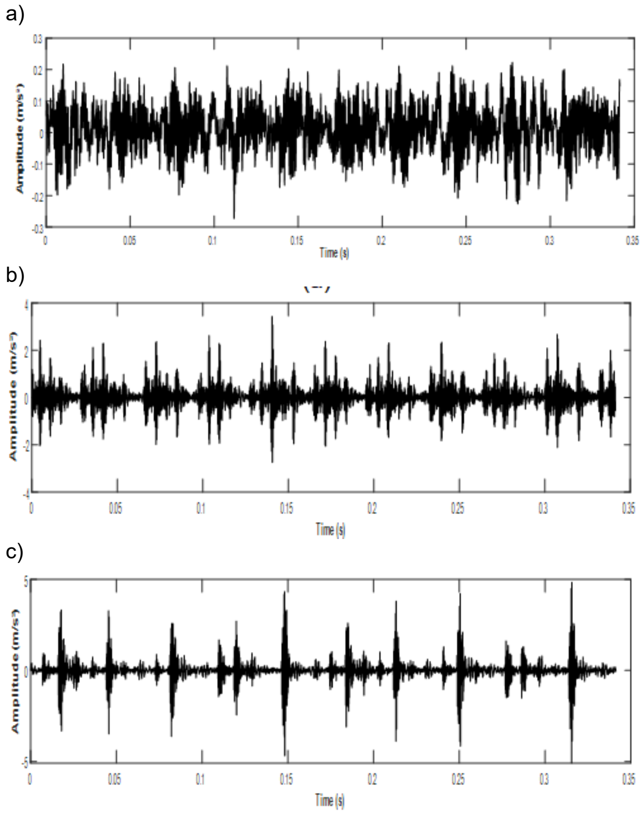

Fig.2. Vibration Signals: (a) normal state, (b) inner race fault, and (c) outer race fault

The CWT is defined as:

$$(4)\quad CWT_{(a,b)} = \frac{1}{\sqrt{2}} \int_{-\infty}^{+\infty} f(t)\, \psi^{*}\left(\frac{t-b}{a}\right) dt$$

Where * denotes complex conjugate.

The DWT is obtained by discretizing $CWT_{(a,b)}$ as:

$$(5)\quad DWT_{(j,k)} = 1/\sqrt{2^j} \int_{-\infty}^{+\infty} f(t) \psi\left(\frac{t-2^j k}{2^j}\right)$$

With $a=2^j$, and $b=2^j.k$, where j represents the decomposition level, and k is the translation factor.

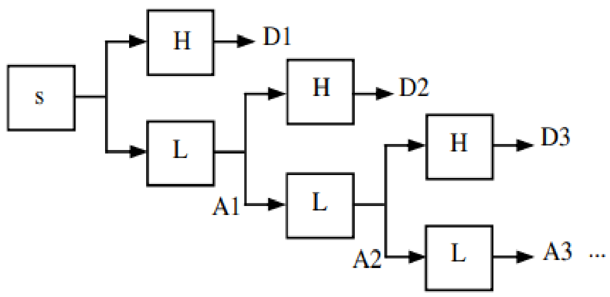

Fig.3. Structure of Wavelet decomposition

The notion of multi-resolution analysis (MRA) was invented by Mallat [17]. High-pass (wavelets) and low-pass filters (scaling functions) are used to implement MRA. A multi-resolution analysis often breaks down the signal into two parts: a smoothed version of the input signal (approximation) and a collection of extensive explanation at several scales. Detail coefficients (D) and approximation coefficients(A), respectively, are the terms for the high- and low-frequency components [18]. To analyze the signal, the high-frequency components will indeed be investigated in this paper.

2.2 Features analysis of data

Based on Parseval's theorem, the amount of energy of the signal f(t) in the wavelet domain for an m-level DWT decomposition equals the energy of the approximation coefficient (EA_m) plus the energies of the detail coefficients (ED_j), this can be described by [16]:.

$$\sum_1^N |f(t)|^2 = EA_m + \sum_j^m ED_j \quad (6)$$

Where: $EA_m = \sum_1^N |A_m|^2$, $ED_j = \sum_1^N |D_j|^2$, N is the number of samples, while m denotes the highest wavelet decomposition level.

Wavelet energy distribution is used to recognize the local characteristic variations at different levels. The band's energy content is the sum of the scale and detail components' energies [19]. Hence, the energy distribution is computed to obtain the most useful information from the various resolution levels. It comes from:

$$P_a = \sum_1^{N/2^m} |A_m|^2 / N_m \quad (7)$$

$$P_d = \sum_1^{N/2^j} |D_j|^2 / N_j \qquad \text{j=1,2,1,3,…m} \quad (8)$$

As found in the literature, for time-series signals, Haar, Daubechies, and Symlets wavelets are widely used [18]. To identify fault frequencies in the current study, we employ the Daubechies wavelet of order 3 (db3).

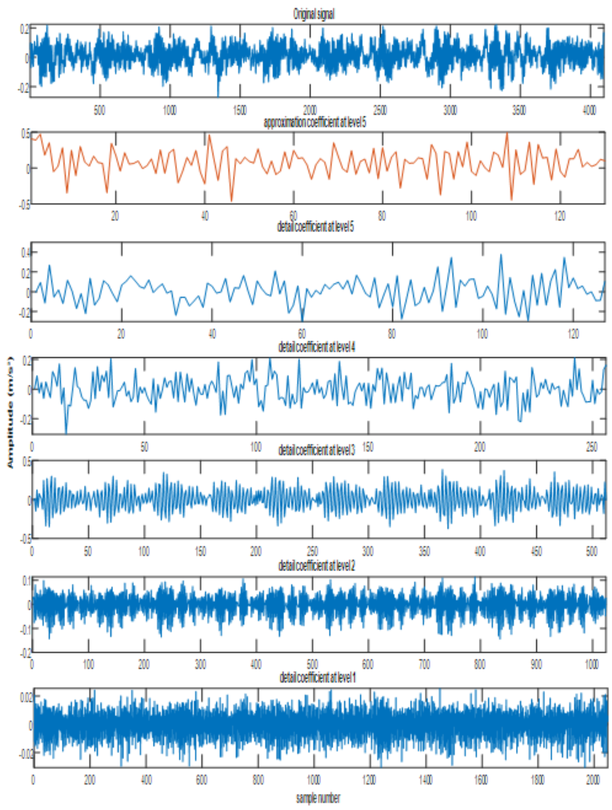

Fig.4. Wavelet decomposition of normal state

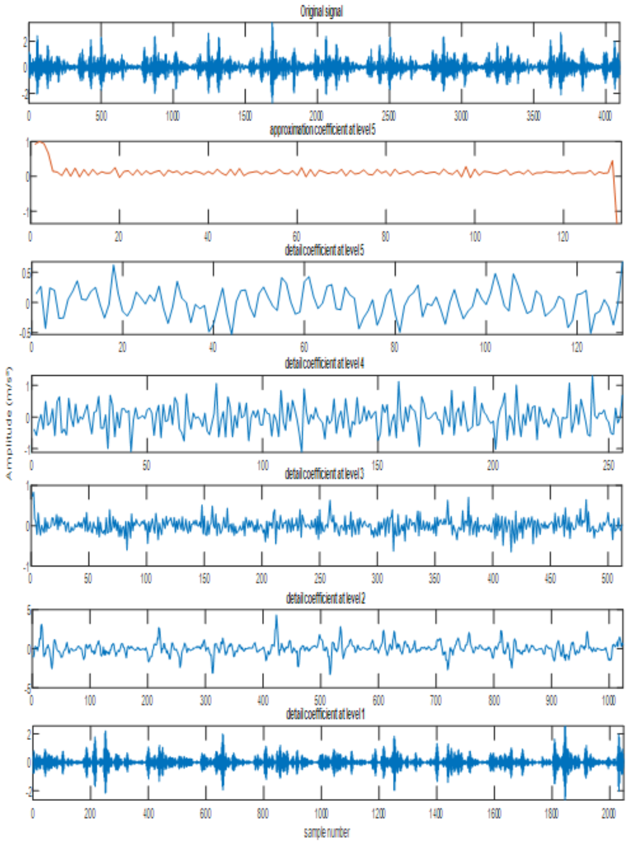

Fig.5. Wavelet decomposition of inner race fault

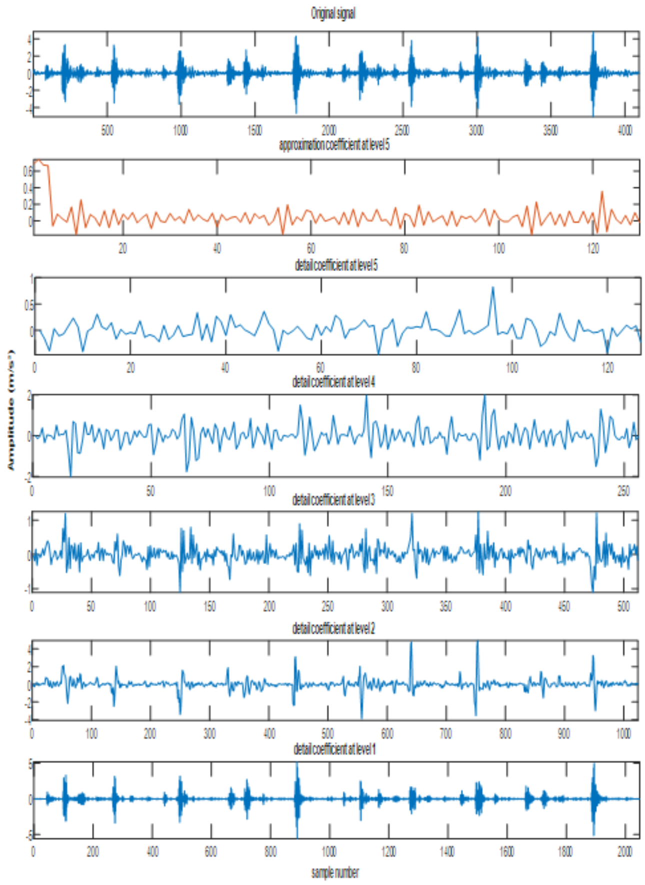

Fig.6. Wavelet decomposition of outer race fault

3. Results and discussions

The multi-scale analysis is performed on the vibration data for normal and abnormal SKF bearings at a speed of 1797 rpm (30 Hz). The vibration signals are decomposed up to 5 levels by using db3. From the 5 levels of decomposition, we obtained the detail coefficients from 1 to 5 (cD1 to cD5) and one approximation coefficient (cA5).

Figures 4, 5, and 6 show the results of the db3 decomposition, accordingly.

a)

b)

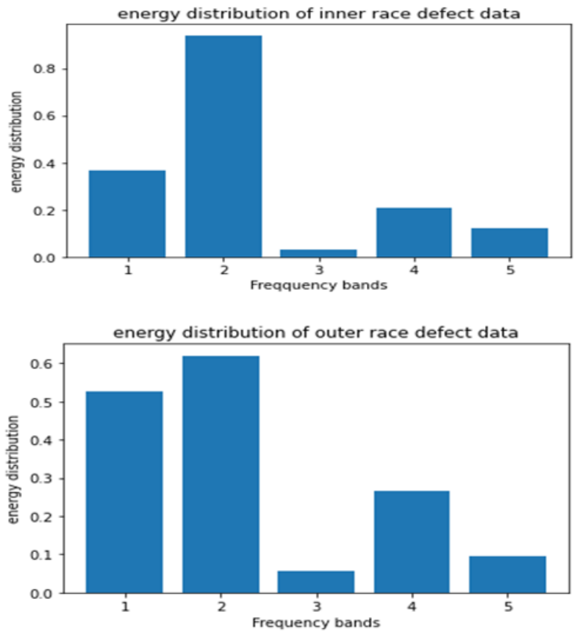

Fig.7. Energy distribution:(a) inner race fault and (b) outer race fault.

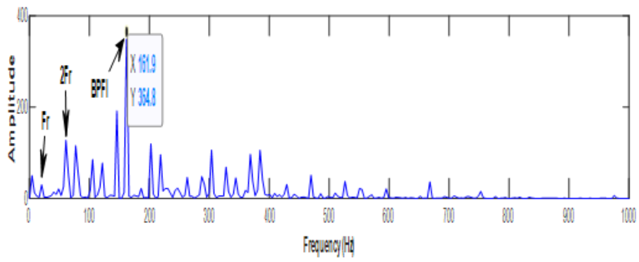

Fig.8. FFT spectrum of signal D2 sub-bands of inner race

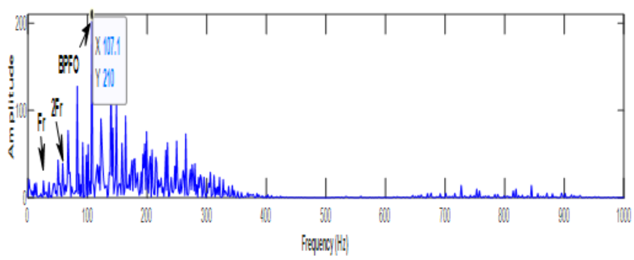

Fig.9. FFT spectrum of signal D2 sub-bands of outer race

The first step in a diagnosis of a rolling bearing condition is to identify the existence of defects, then identify its location. If a bearing is unhealthy, the percentage of energy present at the higher frequencies is large, otherwise, it is small. From figure 4, the standard vibration data shows no significant changes in magnitude. However, for defective data, there are essential changes in all sub-bands of DWT decompositions. In Figures 5 and 6, it is also possible to observe the maximum magnitude changes in sub-band D2, which belongs to a higher frequency. That suggests concentrating on the D2 sub-band. Further, the energy distribution is calculated for each sub-band, and it can be seen that there are abnormal changes in the energy distribution at level 2, as shown in figure 7. That demonstrates that the D2 sub-band contains a multitude of fault-related data

Figure 7 displays the energy distribution at each level of inner race and outer race faults.

The FFT on the D2 signal of the IRF and ORF is performed to determine the fault location from the selected level.

Figures 8 and 9 show the FFT spectrum of D2 for the IRF and ORF, respectively. The obtained frequencies correspond to the IRF (162 Hz), the ORF (107 Hz), and their harmonics, which are diagnostic of a damaged bearing.

4. Conclusion

This paper presents an improved method based on multiresolution analysis using discrete wavelet transform and energy distribution for the effective extraction of defects' features. In this work, the nature of the vibration signals used for bearing fault diagnosis is non-stationary, which is why we apply DWT analysis. The proposed approach was modified to employ wavelet decomposition to collect many datasets at different resolutions and determine energy distribution using Parseval's theorem. The presence of faults was determined by the DWT node energy, which increases significantly in faulty bearings. Finally, the fault's location is easily found through the fast Fourier transform method. Thus, this approach is a successful tool for vibration monitoring and fault diagnosis.

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