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HYBRID METHODOLOGY OF DEGRADATION FEATURE EXTRACTION FOR BEARING PROGNOSTICS

METODYKA HYBRYDOWA EKSTRAKCJI CECH DEGRADACJI DO ZASTOSOWAŃ W PROGNOZOWANIU CZASU ŻYCIA ŁOŻYSK

Hybrid methodology of degradation feature extraction was presented which may enable prediction of remaining useful life of a product. In this methodology, firstly, the signal was de-noised by wavelet analysis. Then the autoregressive model was used to remove the discrete frequencies from de-noised signal. Further, the residual signal which mainly contained impulsive fault signal was enhanced by minimum entropy deconvolution filter. The kurtosis was extracted which was taken as the feature for prognostics. At last, the empirical mode decomposition was used to reduce fluctuation of feature value and to extract the trend content. A case study was presented to verify the effectiveness of the proposed method.

***Keywords**: feature extraction, degradation, signal, bearing.*

Przedstawiono hybrydową metodę ekstrakcji cech degradacji, która umożliwia przewidywanie pozostałego okresu użytkowania produktu. W tej metodyce, sygnał został najpierw odfiltrowany z wykorzystaniem analizy falkowej. Następnie, za pomocą modelu autoregresyjnego usunięto z pozbawionego szumów sygnału częstotliwości dyskretne. W dalszej kolejności, sygnał resztkowy, który zawierał głównie impulsowy sygnał uszkodzenia został wzmocniony z zastosowaniem filtru dekonwolucji minimum entropii. Obliczono kurtozę, którą przyjęto jako cechę w procesie prognozowania. Na koniec, zastosowano empiryczną dekompozycję sygnału (EMD) w celu zmniejszenia wahań wartości cechy oraz w celu ekstrakcji trendu. Studium przypadku demonstruje efektywność proponowanej metody.

***Słowa kluczowe**: ekstrakcja cech, degradacja, sygnał, łożysko.*

1. Introduction

Bearing is one of the most critical components in rotating machines and its degradation is one of the most frequent reasons which cause a machine to breakdown. In order to reduce downtime costs caused by bearing failures, condition monitoring may be conducted in which remaining useful lives (RUL) of bearings are predicted and fault bearings will be replaced before occurrence of bearing functional failures.

As for the vibration data of bearings, signal modulation effect and noise are two major challenges in incipient fault detection. The modulation effect can be overcome using envelope analysis. As fault signals are often very weak and masked by noise, de-noising and extracting the useful feature which can reflect the degradation effectively from the weak signal are crucial to RUL prediction. In addition, many vibration signals measured externally on machines are distorted by the transmission paths from the source to the transducer. A method known as minimum entropy deconvolution [10] (MED) can remove the effect of the transmission path and enhance the bearing impulsive fault signal. The MED method was applied to gear diagnostics by Endo and Randall [3], and to bearing diagnostics by Sawalhi [7]. Sometimes, the features extracted from full life cycle data of bearing often fluctuate largely which baffles the RUL prediction. These years, the time series modeling has been used to remove discrete frequency which may cause feature fluctuating. Wang and Wong employed the autoregressive (AR) filter to isolate the impulse-like effect of localized cracks in a gear tooth [8, 9]. Barszcz and Sawalhi applied AR and MED to wind turbines' bearing fault detection [1].

In order to enable the prediction of remaining useful life of bearings, a hybrid methodology of degradation feature extraction was presented in this paper. In the method, wavelet analysis was used for de-noising the original signal. AR and MED are employed for enhancing impulsive fault signal. EMD was used to reduce fluctuation of feature value and to extract the trend content.

2. Methodology

2.1. Procedure of degradation feature extraction method

The procedure of bearing degradation feature extraction is illustrated as Figure 1. There are three phases in this procedure. First, bearing signals are de-noised using Matlab's Wavelet Toolbox which eliminates wavelets whose coefficients are smaller than a certain threshold. Second, discrete frequencies are removed from the de-noised signals after applying AR filter, and the smearing effect of transfer path is also removed by MED. At last, EMD method was applied to extract the trend content from features which fluctuate with large ranges.

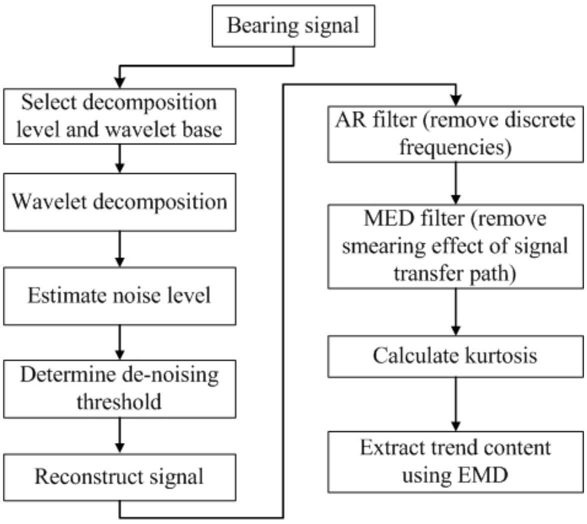

Fig.1. Procedure for degradation feature extraction

2.2. Wavelet based signal de-noising

The basic model for the noisy signal is of the following form:

$$s(n) = f(n) + \sigma\, e(n) \quad n = 0,1\ldots, N-1 \tag{1}$$

Where, $e(n)$ denotes noise. σ denotes the noise level. The objective of de-noising is to suppress the noise part $e(n)$ and to recover $f(n)$. Theoretically, this is implemented by reconstructing the signal from the noisy data such that the mean squared error between $f(n)$ and the reconstructed signal is minimized.

Wavelet de-noising is based on the principle of multi-resolution analysis [2]. By multi-level wavelet decomposition, the discrete detail coefficient and approximation coefficient can be obtained. Grossmann [4] attested that the variance and amplitude of the details of white noise at different levels decreases regularly when the level increases, yet the variance and amplitude of the wavelet transform of the available signal are not related to the change of scale. According to this property, noise can be weakened or even removed by adjusting the wavelet coefficients properly. The de-noising procedure applying in this paper includes following four steps:

- Signal decomposition. Choose a wavelet basis, and choose a level *N*. Compute the wavelet decomposition of the signal at level *N*.
- Estimate the noise level through the detail coefficients of first level.
- Determine the de-noising threshold by penalty strategy.
- Signal reconstruction. Compute wavelet reconstruction using the original approximation coefficients of level *N* and apply soft thresholding to the detail coefficients.

2.3. Fault signal enhancement using AR and MED

One of major sources which mask the relatively weak bearing signals is discrete frequency "noise" from gears or other inherent structures. Even in machines other than gearboxes, there will usually be strong discrete frequency components that may contaminate frequency bands where the bearing signal is dominant. It is generally advantageous therefore to remove such discrete frequency noise before proceeding with bearing fault detection. To this end, AR and MED are employed to enhance the detection of bearings fault, as depicted in Figure 2.

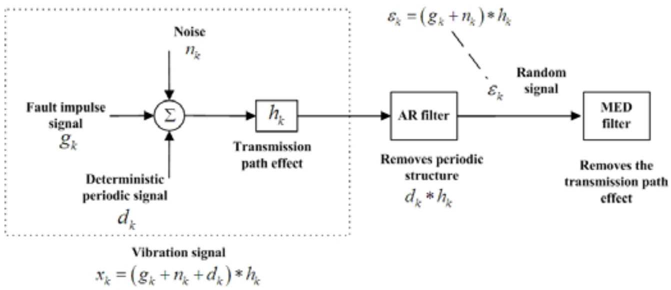

Fig. 2. The filtering process to enhance the detection of bearing faults using AR and MED technique

2.3.1. Removing discrete frequency using AR model

Linear prediction is a basic way which can obtain the model of the deterministic part (vibration of inherent structure of machine) of a signal. In the method, the next value in the series is predicted on the basis of a certain number of previous values. The residual (unpredictable) part of the signal is then obtained by subtraction from the actual signal value. It can be described by the following equation:

$$y(n) = -\sum_{k=1}^{p} a(k)x(n-k) \tag{2}$$

where the predicted current value $y(n)$ is obtained as a weighted sum of the *p* previous values. The actual current value is given by the sum of the predicted value and a noise term:

$$x(n) = y(n) + e(n) \tag{3}$$

The coefficients $a(k)$ can be obtained using the Yule-Walker equations and using Levinson-Durban recursion algorithm.

2.3.2. Enhancing impulsive fault signal using MED

The MED method is designed to reduce the spread of impulse response functions (IRFs), in order to obtain signals closer to the original impulses. It was first proposed by Wiggins to sharpen the reflections from different subterranean layers in seismic analysis. The basic idea of the method is to find an inverse filter which can counteracts the effect of the transmission path, by assuming that the original excitation was impulsive, and then the signal will have high kurtosis. The name of the method derives from the fact that increasing entropy corresponds to increasing disorder, whereas impulsive signals are very structured, requiring all significant frequency components to have zero phase simultaneously at the time of each impulse. Maximizing the structure of the signal corresponds to maximizing the kurtosis of the inverse filter output (corresponding to the original input to the system). According to the Randall's opinion, the method can be also called "maximum kurtosis deconvolution" because the criterion used to optimize the coefficients of the inverse filter is maximization of the kurtosis (impulsiveness) of the inverse filter output. The detailed algorithm can be found in paper of Wiggins [10].

The Figure 2 illustrates the basic idea. The signal $g_k + d_k + n_k$ passes through the structural filter h_k whose output is x_k. The AR filter produces output ε_k, which removes the periodic signal d_k. The inverse (MED) filter produces output y_k, which has to be as close as possible to the fault impulse signal g_k. The MED filter can be modeled as a finite impulsive response filter with L coefficients such that

$$y(k) = \sum_{l=1}^{L} f(l)v(k-l) \tag{4}$$

where f has to invert the system IRFs h such that

$$f * h(k) = \delta\,(k - l_m) \tag{5}$$

The delay l_m is such that the inverse filter can be causal. It will displace the whole signal by l_m but will not change pulse spacing. This method is applied through maximizing the kurtosis of the output signal y_k, by varying the coefficients of the filter f. The kurtosis is taken as the normalized fourth order moment given by

$$O(f) = \frac{\sum_{n=0}^{N-1} (y(k))^4}{\left[\sum_{n=0}^{N-1} (y(k))^2\right]^2} \tag{6}$$

And the maximum is obtained by finding the value of f for which the derivative of the objective function is zero, i.e.,

$$\frac{\partial O(f)}{\partial f} = 0 \tag{7}$$

2.4. EMD based trend component extraction

Empirical mode decomposition (EMD) which is wildly used in nonlinear non-stationary data analysis may be used to extract the content which has some uptrend [5]. It decomposes a raw signal into a set of complete and almost orthogonal components called intrinsic mode functions (IMFs). IMFs represent the natural oscillatory modes embedded in the raw signal. They work as the basis functions which are determined by the raw signal rather than by pre-determined functions. When the trend component is complex which may contain non-period, linear, polynomial, or exponential components, traditional trend component extraction method will be not applicable. For this case, however, the EMD can be used for trend component extraction. According to the EMD, the signal $s(n)$ can be decomposed as:

$$s(n) = \sum_{i=1}^{n} c_i + r_n \tag{8}$$

In the equation, $c_i\,(i = 1, 2, \cdots, n)$ is IMFs, r_n is the residual component. If $s(n)$ denotes the signal which contains the mixture trend component, r_n will be the trend component. The performance of EMD method is shown in the following case study. After applied EMD to features of 7 bearings, the features will be de-noised as shown in Figure 7. It can be seen that all the features progress with time and the trends are very obvious. Also, the trend can reflect the early degradation process which is more significant to RUL prediction.

3. Case Study

A case study was conducted in order to show the performance of the proposed method. The study used PHM 2012 challenge data [6], which is real experiment data characterizing the degradation of ball bearings along their whole operational life. In the experiment, two accelerometers were mounted on the external race of bearing. The first one was placed on the vertical axis and the second was placed on the horizontal axis. Because the radial force was applied on the tested bearing along the horizontal direction, the horizontal sensor can acquire the more effective signals. In this paper, we only analyze the signals collected from horizontal sensor.

3.1. Traditional feature extraction

Investigation on bearing fault prognostics has been implemented recent years. A key to the success of using vibration data for bearing lifecycle prognostics is to develop a relationship between bearing damage and the fault features extracted from the original sensor signals. There are many traditional features such as kurtosis, root mean square (RMS), and the peak value.

As shown in the Figures 3–5, the degradations of bearing 2 and bearing 4 are similar; and the bearing 1 and bearing 3 may have similar characteristic of degradation. However, the peak values and RMS values of bearing 5, bearing 6 and bearing 7 do not increase with bearing's working time. This presents a complex situation where traditional features may not be applicable to predict the RUL of bearing. In order to extract the features which progress with time, AR and MED method will be used in this data analysis which can enhance the fault signal of bearing. However, in the case that the signals have not periodical impulsive which can be seen obviously from the wave, the effectiveness of AR and MED will be significantly influenced by noise. This is because the MED will enhance the some impulsive like noise and signals without de-noising process will be still masked by noise. Therefore, de-noising is very important step in the proposed method, which can be demonstrated through analyzing the end file of bearing 1 as illustrated by Figure 6.

3.2. Feature extraction using the proposed method

The proposed method of feature extraction contains four steps: denoising, AR filtering, MED filtering and kurtosis calculation. Using the method, the features of 7 bearings can be obtained as shown in Figure 7. It can be seen from Figure 7 that all the features are non-stationary which fluctuate with large ranges. Therefore, it is very difficult to predict the RUL in this situation. The characteristics of signals commonly exist in many real cases of condition monitoring and RUL prediction. In order to deal with the problem, it is necessary to extract trend components from non-stationary features. There are many methods which can be used for trend component extraction, such as. linear trend component extraction, power function trend component extraction, exponential trend component extraction, period trend component extraction, and mixture trend component extraction.

In this paper, EMD is employed to de-noise for the features of bearings. De-noised features of 7 bearings based on EMD are shown in

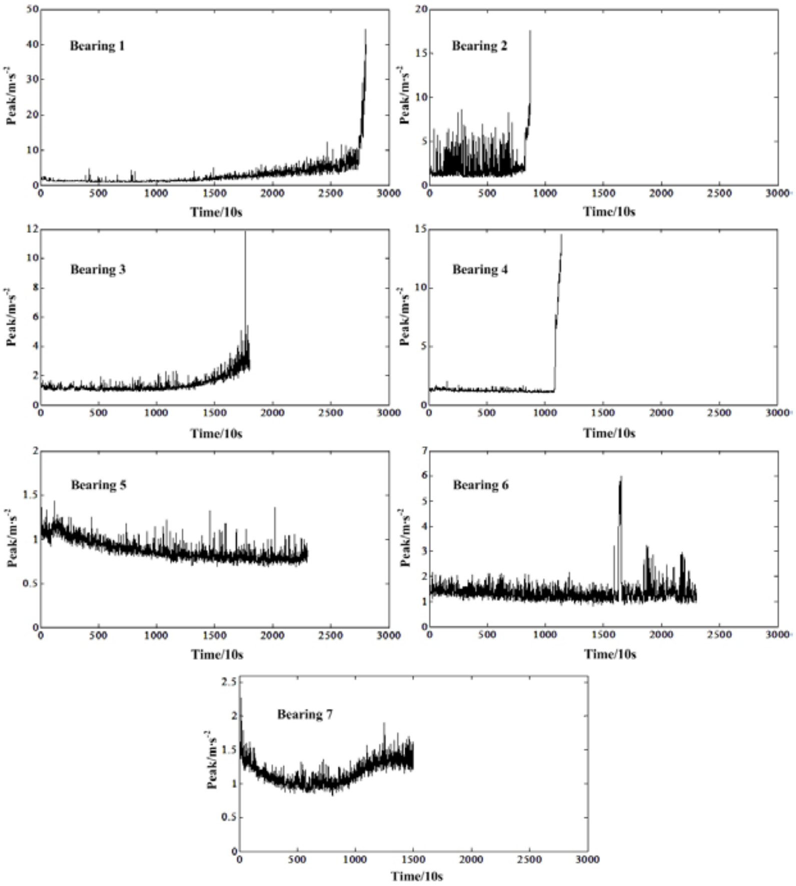

Fig. 3. The peak value of 7 bearings' life vibration under condition 1

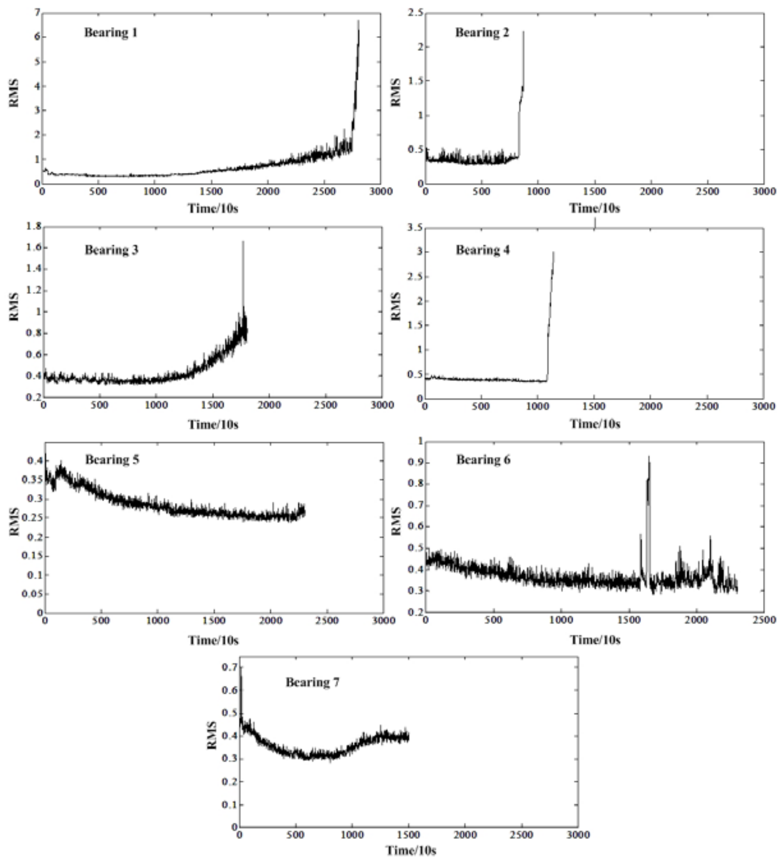

Fig. 4. The RMS value of bearings' vibration under condition 1

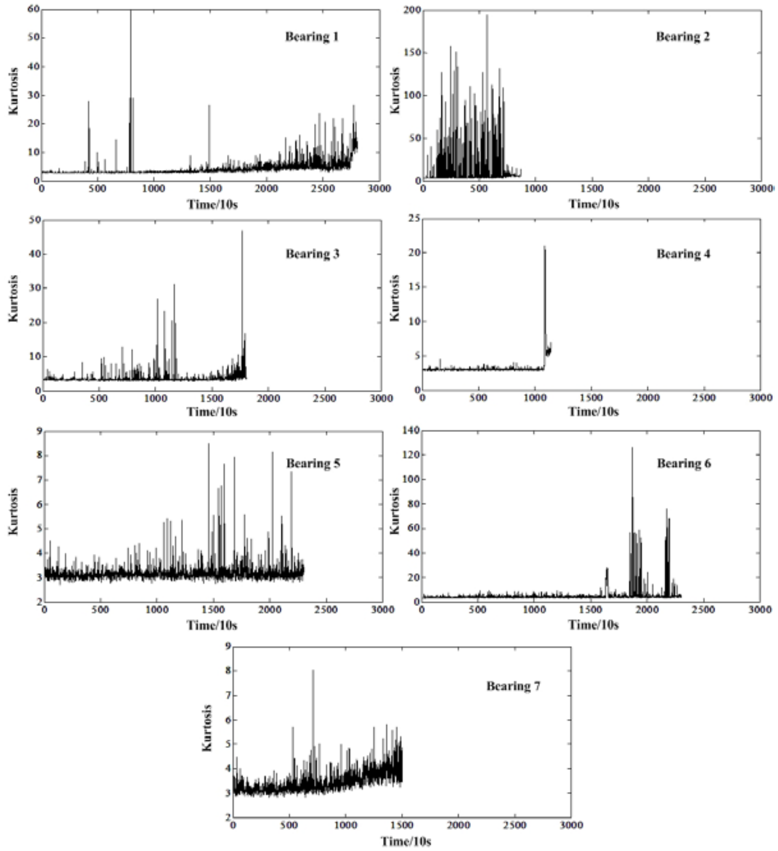

Fig. 5. The Kurtosis value of 7 bearings' vibration under condition 1

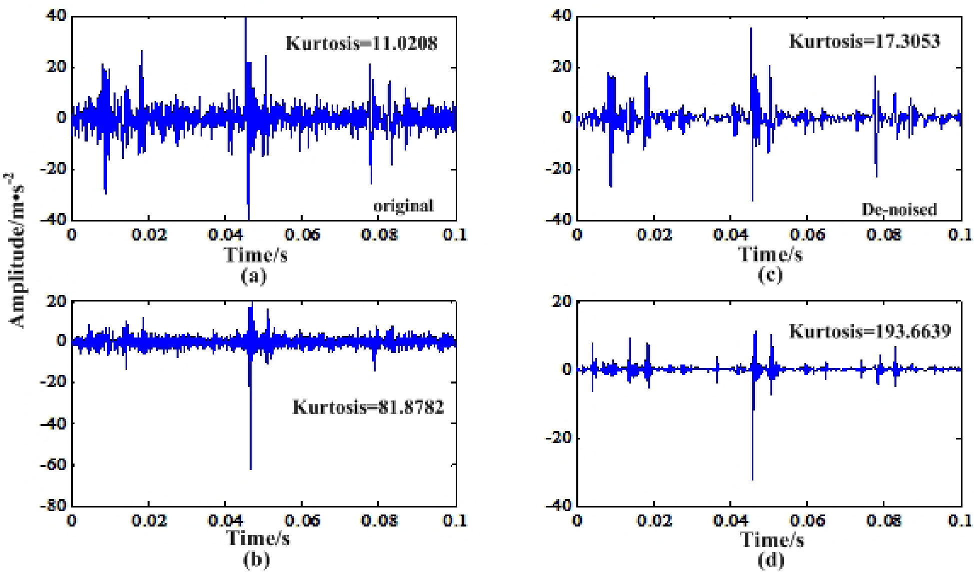

Fig. 6. (a) Original signal; (b) The result of applying AR and MED to original signal; (c) De-noised signal; (d) The result of applying AR and MED to de-noised signal

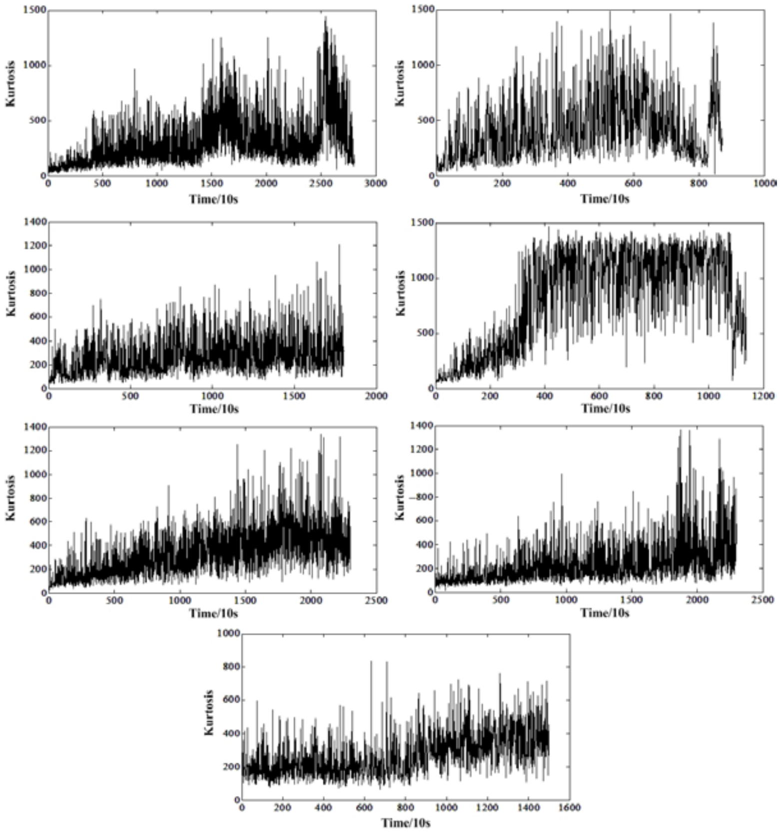

Fig. 7. Features based on AR and MED of 7 bearings

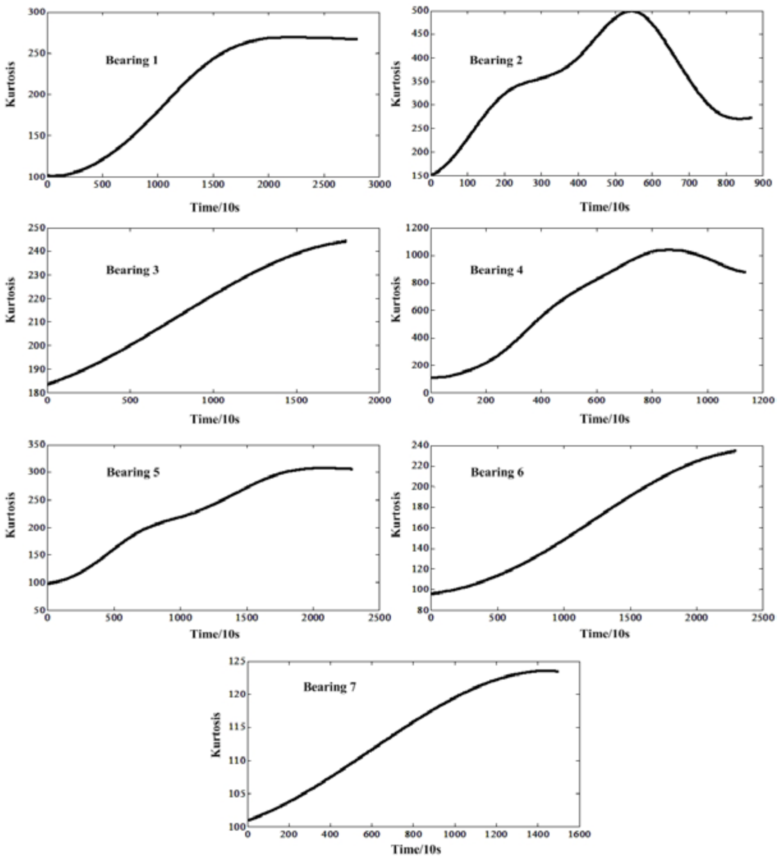

Fig. 8. De-noised features of 7 bearings based on EMD

Figure 8. It can be seen that the extracted signal features clearly show the degradation trend of bearings and enhance considerably the quality of bearing feature extraction. By comparing the de-noised features with RMS and kurtosis values of the bearings (as shown in Figure 4 and Figure 5), inflexion points in the curves of de-noised kurtosis come earlier than those of RMS and kurtosis. It may be inferred that the kurtosis processed using the proposed method can be taken as a leading indicator to evaluate the health condition of bearing, and make a conservative estimation of bearing RUL.

4. Conclusion

In this paper, a hybrid methodology of degradation feature extraction was presented where AR, MED and EMD are employed to enhance the quality of bearing feature extraction and enable bearing prognostics. A case study based on PHM 2012 challenge data was presented to show the performance of the proposed method. In the case study, the features extracted by traditional method fluctuate largely, which can be the barrier for prognostics. It is seen from the case study that the hybrid methodology is effective in degradation feature extraction from bearing vibration signals. Especially, it is applicable to the case that vibration signals fluctuate largely and mask the trend of bearing degradation.

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