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Early fault detection based on empirical mode decomposition method

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Abstract

Vibration signal analysis is a widely used condition monitoring technique. Though the extraction of information from the raw vibration signals is difficult because of its non-stationary and non-linear nature, the Empirical mode decomposition has proven to be an effective method. In this method, the raw vibration signal is decomposed into the various intrinsic mode functions. Further, the energy content of these intrinsic modes and the spectral entropy's associated with each intrinsic mode is analyzed. The method is validated with the available data sets. Based on the results obtained, this method has proven to work better for early fault detection.

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Keywords: Condition monitoring, early fault detection, empirical mode decomposition, fault diagnosis, ensemble empirical mode decomposition.

1. Introduction

Condition monitoring is one of the fast growing branch of preventive maintenance. Due to the various advancements and increased complexity of various machineries and machine tools, necessity to monitor these systems has grown with time. There are various aspects of condition monitoring. Based on the methodology and sensing tools used condition monitoring can be classified as vibration based condition monitoring, acoustic emission based, oil debris analysis etc. [1-3]. Selection of the monitoring technique is based on the application and the type of system to be monitored.

Vibration based condition health monitoring is one of the popular condition based monitoring technique [4-6]. Various engineering applications such as aviation industry, power plants, mining industries and naval industries etc. have various rotating and sliding components. If any of these moving components is subjected to a defect, it leads to increased vibration level. Eventually with time the defect may grow in size, if it is not detected. This may lead to catastrophic failure of the system. From safety and reliability point of view, detection of the defect at earlier stages becomes very important [4]. Early fault detection has always been challenging. Multiple factors contributing to the inefficient early fault detection are system complexity, restrictions to access remote locations, unavailability of the necessary sensing tools and selection of appropriate signal processing techniques etc. Currently signal processing is assumed to be the biggest challenge. Significant amount of attention should be paid to the selection of proper signal processing techniques. Discussions related to this problem are reported in the literature [6].

Vibration signals are considered to be the source of fault features. The extraction of these fault features from a raw vibration signals is a complex process. The nature of the vibration signals acquired and the noise present in practical scenario makes the signal processing tedious. If the signal acquired is non-stationary and non-linear, the selection of appropriate signal processing technique must be ensured. Over the past few years' different signal processing techniques were developed to tackle the above issue [6]. Empirical mode decomposition (EMD) is one of the widely used technique [7-8]. EMD method is capable of handling the non-linearity and non-stationarity present in the raw vibration signals.

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The other sections of the article are structured as given below: section 2 presents detailed discussion about EMD and EEMD (Ensemble empirical mode decomposition), section 3 presents fault features, section 4 presents the early fault detection, section 5 presents the results and discussion section, section 6 presents the conclusion and future work section.

2. EMD AND EEMD:

2.1. EMD:

EMD method was developed for processing of the non-linear and non-stationary signals. EMD method was initially inducted by Huang et al. [9]. EMD breaks down a multi-component signal into different mono-component signal. The mono-components obtained are termed as Intrinsic mode functions (IMF). For a signal to be classified as an IMF following two conditions should be satisfied;

a.) The difference between the number of extrema points and the number of zero crossing points must be either zero or one.

b.) The mean value of the envelops obtained by the local maxima and the local minima must be zero for any given point.

Mathematically it is expressed as [8],

$$X(t) = \sum_{i=1}^{n} c_i + R_n \tag{1}$$

where, c = Intrinsic mode function
n = Number of IMF's
R = Residue

Although EMD is known to be a reliable technique for analyzing non-linear and non-stationary signals, it has few shortcomings as well. The mode mixing is the major drawback associated with EMD method [4,10]. Mode mixing is related to appearance of the same frequency mode in two different IMF's. The mode mixing may result into aliasing. Aliasing could affect the information content of the signal. Also EMD method fails to address the end effect phenomenon [10-11]. A new methodology named as EEMD was introduced by Wu and Huang [12] to address these drawbacks. In the next sub-section, a brief discussion is made on the EEMD method.

2.2. EEMD:

To address the shortcomings of the EMD method a new method was introduced named as EEMD. EEMD is known to be a noise assisted signal processing method. A white Gaussian noise is added to the raw signals in order to populate the original signal uniformly. The white Gaussian noise added has different components scale, which will establish a reference background for the different scales in the original signal. In the process of mean calculation, the white Gaussian noise series added in the raw signal cancels out each other [12]. The EEMD algorithm is shown in Fig. 1.

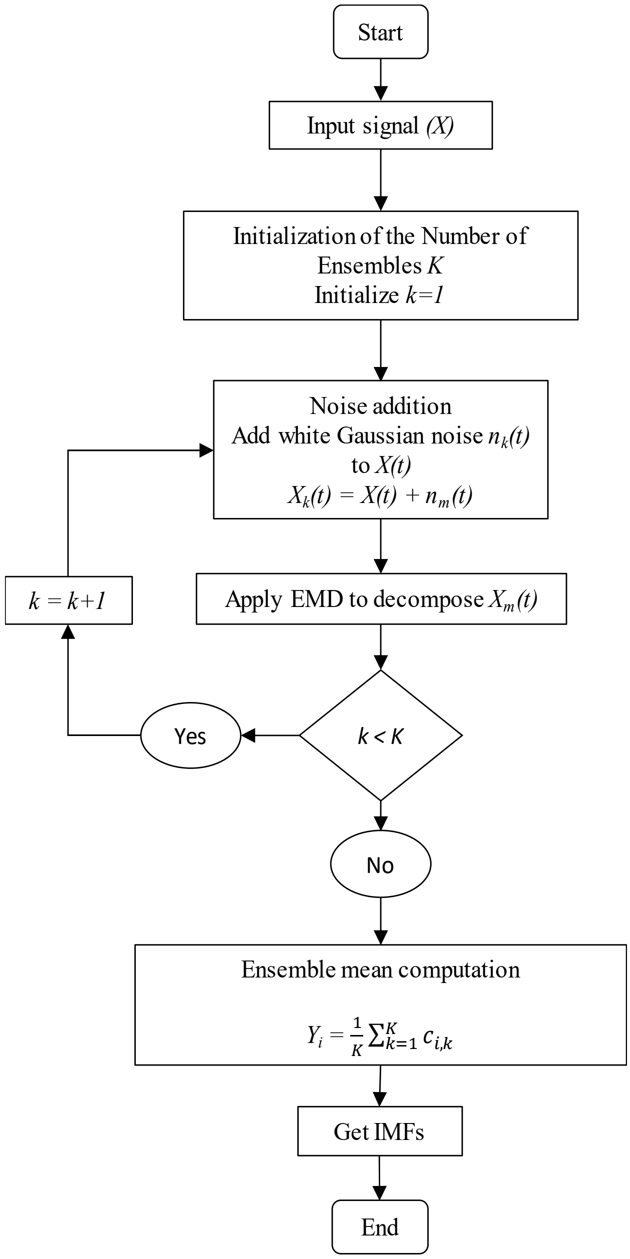

Fig. 1. EEMD flowchart.

3. Fault features:

Feature extraction is considered as the crucial step in the fault diagnosis. For extracting the information content from a vibration signal features are computed.

3.1. Energy

Energy of a signal can be computed as follows,

$$Energy = \sum_{i=1}^{k} \left| X_i \right|^2 \tag{2}$$

where, X is the input signal.

3.2. Entropy

Entropy is the randomness associated with a given signal. Mathematically entropy is expressed as,

$$Energy = \sum_{i=1}^{k} X_I . \log(X_I) \quad (3)$$

where, X is input signal.

3.3. Energy-entropy ratio

It is the ratio of the two quantities, energy of the signal and entropy of a signal.

$$Energy\text{-}entropy\ ratio = \frac{Energy}{Entropy} \quad (4)$$

As mentioned earlier entropy is associated with the randomness. When there is a defect in the system, the randomness associated with system is disturbed. Also, when a defect is initiate the energy level of the vibration signal also increases. Same principle is applicable for the early fault detection. The Energy-entropy ratio is computed as a parameter for early fault detection. Bearing data set from the Prognostics Center of Excellence [13] has been utilized for validation. The data set contains life test data of the four bearings. At the end of test corresponding to set-1, bearing-1 undergoes failure. The data set is pre-processed with EEMD method and based on the selection criteria mentioned in [14] sum of first six intrinsic mode functions is utilized as input signal. The Energy-entropy ratio is computed for the same.

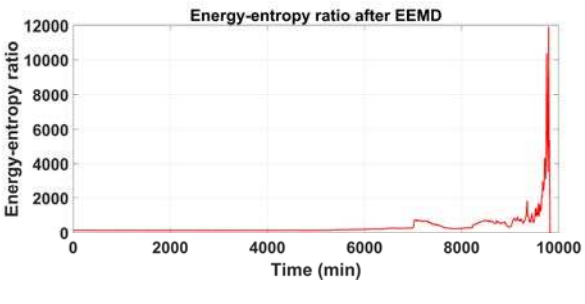

Fig. 2. Energy-entropy ratio.

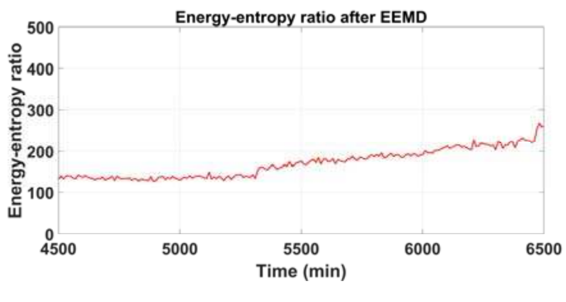

Fig. 3. Zoomed Energy-entropy ratio (4500-6500 min).

4. Early fault detection:

Early fault detection can be termed as a state of system during which the operating characteristics of the system deviates from the normal operating condition. In the present case, when the vibration levels are deviated from the normal operating condition initiation of the defect in the system may be identified. With the early detection of the defect the preventive maintenance activities can be planned accordingly.

Fig. 3. Show that there is a noticeable variation in the Energy-entropy ratio, but still the exact point of variation is unknown. To identify the variation in the data set an algorithm based on penalized contrast method is implemented. This method is proposed by Lavielle [15] based on a global approach, in order to identify the different change points within a dataset simultaneously. In this method, the change point is calculated by minimizing the penalized contrast function. It is a combination of two different functions namely, the contrast function and the penalty function. Mathematically, it given as [15],

$$H(n) = J(n,x) + \beta . pen(n) \quad (5)$$

Where $J(\tau, x)$ is the Contrast function, $pen(\tau)$ is the Penalty function and β is the penalization parameter [15] for signal of length n, σ is the standard deviation.

$$\beta = 2\sigma^2 (\log n) / n \quad (6)$$

4.1. Contrast function

Contrast function is related to identifying change in the statistical property of the given data set. Mathematically [15],

$$J(\tau, x) = \frac{1}{n} \sum_{k=1}^{K} n_k \log(\hat{\sigma}_k^{\,2}) \quad (7)$$

Where n is the signal length, τ is set of integers and gives the change point instances, $n_k = \tau_{k-1} - \tau_k$ is the length of segment k, K is the number of segments and is the empirical mean of X_1, X_2, ……… X_n, X is the input signal.

$$\hat{\sigma}_k^{\,2} = 1/n_k \sum_{i=\tau_{k-1}+1}^{\tau_k} \left(X_i - \overline{X}\right)^2 \quad (8)$$

Eq. 8. is the empirical variance computed on segment k

4.2. Penalty function

Penalty function is associated with identifying the number of change points within the data set. $pen(\tau)$ represents the Penalty function. The Penalty function selected is based on the Schwarz criterion [15].

$$pen(\tau) = K(\tau) \tag{9}$$

where $K(\tau)$ is estimated segments function.

5. Results and Discussion

The algorithm based on Penalized contrast method is applied to the Energy-entropy ratio. As discussed earlier, there is a noticeable variation for the time range 4000 - 8000 min. The change points for the range 4000-8000 min were computed.

Fig. 4. Shows the early fault detection plot for the Energy-entropy ratio. The first variation point in the data can be clearly observed at around 5330th min. For verification purpose discrete wavelet transform (DWT) is utilized. DWT is also popularly used signal processing technique for bearing fault diagnosis. The wavelet transform is the decomposition of the signal into basis functions known as wavelets. The wavelets are characterized by varying scale and translations. DWT expression is given as [16],

$$DWT_{(i,j)} = \frac{1}{\sqrt{2^i}} \int_{-\infty}^{\infty} X(t).\psi^* \left(\frac{t - 2^i j}{2^i} \right) dt \tag{10}$$

Where, $X(t)$ is the signal input, ψ^* is the mother wavelet function, 2^i is scaling variable, $2^i j$ is a shifting variable. The DWT is the multi-resolution analysis technique. The DWT

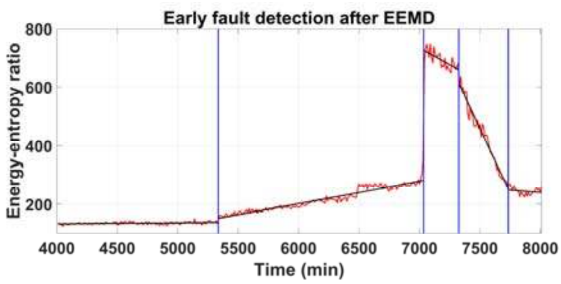

Fig. 4. Early fault detection for Energy-entropy ratio after EEMD.

analyses the given vibration signal by means of discretization at different resolutions or scales. For the proper decomposition, mother wavelet to be selected plays very important. For bearings it is proposed to use Daubichies (db) wavelet of 4th order (db4) [16]. Also it is better to decompose the vibration signal at 3rd or 4th level [16].

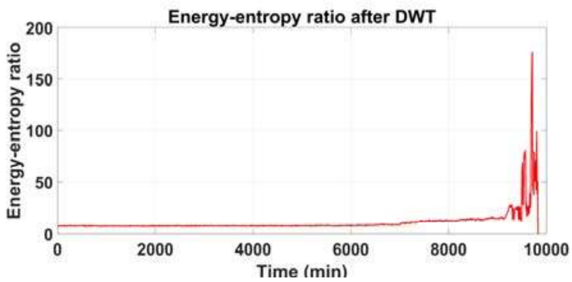

Fig. 5. Energy-entropy ratio after DWT on raw signal.

Here the mother wavelet used is db4. Input signal is decomposed up to 4-level of decomposition, since many of the fault frequencies fall within the range of 0-500 Hz.

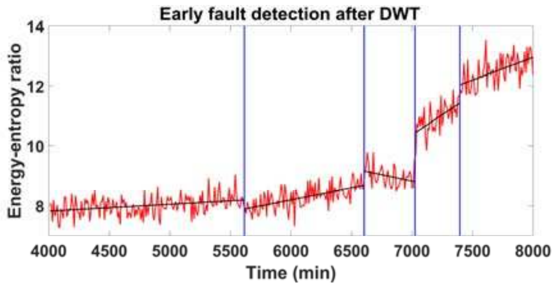

Fig. 6. Early fault detection for Energy-entropy ratio after DWT.

Fig. 6. Shows the early fault detection plot for the Energy-entropy ratio after DWT. The first variation point in the data can be clearly observed at around 5615th min. By observing the Fig. 4. and Fig. 6. it may be concluded that the variation in the Energy-entropy ratio after EEMD is detected much earlier than that of the Energy-entropy ratio after DWT. The difference in time between the early fault detection for EEMD and DWT is around 285 min (4.75 Hrs.). The time gap suggests the capability of the method to detect early faults in the system. The available time window shows the importance of the early fault detection.

6. Conclusion and Future scope

The results show that the penalized contrast method gives better early fault detection resolution for Energy-entropy ratio after EEMD as compared with the Energy-entropy ratio after DWT. If the faults are detected at the early stages, then the inventory and the maintenance activities may be planned accordingly.

Future plans include the validation of above method for online fault detection. In that case, the system will be monitored continuously and prediction of the defect at early stages will be attempted.

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