Hierarchical Graph Model Based Approach for Change Detection in Bearing Degradation Process

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***Abstract*—Detection of early changes in dynamical bearing degradation process is essential for analyzing of bearing running status, residual useful life and potential fault(s). To achieve this end, this paper presents an hierarchical graph model based method. Hierarchical decomposition is firstly adopted to the collected vibration signal and graphs are then constructed for each decomposed component. Similarity scores are then calculated based on the adaptive input weight fusion taking into account the changing information in different components. A common hypothesis testing is finally employed to make the change decision. Experiment, conducted on the public XJTU-SY data set, demonstrated the effectiveness of the proposed method.**

***Index Terms*—change detection, bearing degradation, hierarchical graph model, adaptive input weights**

I. Introduction

Bearings are commonly used in industrial systems and are subject to wear in their long-term service time [1]. Detection of changes, that are from normal to abnormal in bearing running process, can provide the starting time of degradation, which helps to predict the residual useful time (RUL) [2]. Besides, once a status change is detected, pattern recognition techniques can be adopted to identify the fault type at an early stage, which helps user to take appropriate actions to avoid serious consequences [3]. To summarize, early detection of changes in dynamical bearing degradation process is essential to enhance the function of bearings.

The change detection scheme can be summarized into three stages: (1) data collection, (2) modeling construction and (3) decision making. Many techniques have been employed in data collection, i.e., using vibration, sound and temperature measurements. Among them, vibration signals are more advantageous than other measurements due to its quick interpretation of bearing health condition [4]. However the collected vibration signal is complex and non-stationary in real engineering scenarios [5], [6], which requires appropriate modeling to extract essential information that can characterize the bearing health condition. Graph modeling has been introduced and adopted to condition monitoring in recent articles [7]–[9]. However, existing methods for graph construction only analyzes the vibration signal from a single scale, which ignore the difference between frequency components. This point will lead to the loss of weak changing information. To cope with this limitation, a new and practical hierarchical graph method is proposed in this paper that can take multi scales of vibration signals into account for graph construction.

This work is supported in part by Natural Science Foundation of Shandong Province, China (ZR2019MEE063), and Young Scholars Program of Shandong University.

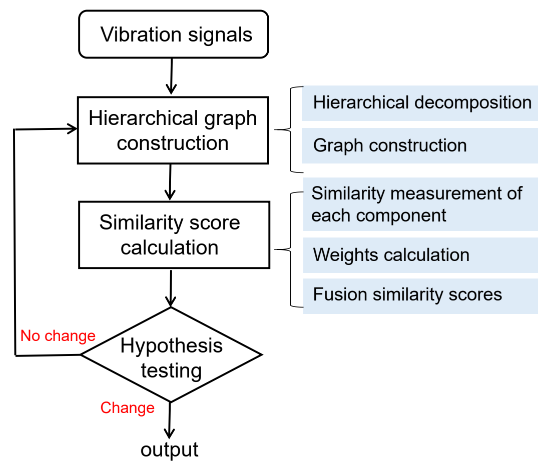

Fig. 1. Flow chart of the proposed approach.

The flowchart of the proposed method is depicted in Fig. 1. Hierarchical decomposition is first adopted to the raw vibration signal with the purpose of inspection of bearing health condition over different multiple scales. As such, a family of HGMs are constructed from each decomposed components that are resulted from hierarchical decomposition. Moreover, to consider and utilize the difference between constructed graphs, adaptive inputs weighting fusion is adopted to calculate the similarity scores to characterize the dynamical behavior of bearing health condition. A null hypothesis testing is finally employed for decision making. The method is operated periodically and continuously, such that the health condition of ongoing bearing can be inspected with an on-line and continuous manner. Experiments, conducted on the recently-released XJTU-SY (Xian Jiaotong University-Sumyoung) data set [10] [1], demonstrated the effectiveness of the method; moreover, comparison with representative competitors suggests its priority in real

[1]http://biaowang.tech/xjtu-sy-bearing-datasets/

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applications.

II. Methodology

The proposed approach includes three steps: (1) hierarchical graph construction; (2) similarity score calculation and (3) decision making, which will be described in details in the following.

A. Hierarchical graph construction

Graph model has been proved to be a powerful tool for change detection in mechanical condition monitor in previous researches [7]–[9]. However, graph only considers the detection problem in single scale and ignores the difference between frequency components, which will result in the loss of weak changing information. To solve the problem, a new method considering bearing health condition in different scales is proposed as shown in Fig. 2, where hierarchical graphs are constructed from different frequency components for a more comprehensive analysis of bearing health condition [11].

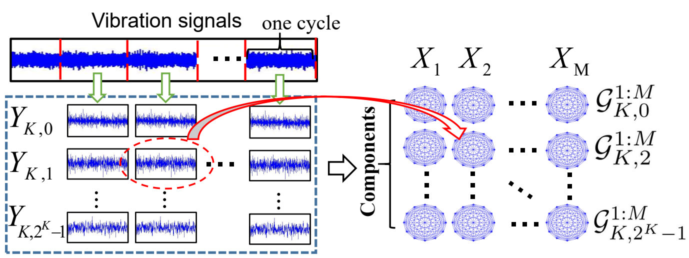

Fig. 2. Demonstration of hierarchical graph constraction.

For the time series of collected vibration signals $\mathcal{X} = \{x_t\}$, a non-overlapping sliding window T is used to divide $\mathcal{X}$ into time-sequential data segments, i.e., $\mathcal{X} = \{X_m\}, m = 1, \cdots, M$. For each segments, hierarchical graphs are constructed according to the following steps.

(1) For the mth segment, i.e., $X_m = \{x(t)\}, t = 1, 2, \cdots, T$, two operators corresponding to the low frequency component and high frequency component are defined respectively as

$$Q_0(x) = \frac{x(t) + x(t+1)}{2} \tag{1}$$

$$Q_1(x) = \frac{x(t) - x(t+1)}{2} \tag{2}$$

where Q_0 is average operator and Q_1 is difference operator. The operators Q_j for $j \in \{0, 1\}$ then can be representated as,

$$Q_j^K = \begin{bmatrix} \frac{1}{2} & \frac{(-1)^j}{2} & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \frac{1}{2} & \frac{(-1)^j}{2} & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & \frac{1}{2} & \frac{(-1)^j}{2} \end{bmatrix}_{\frac{T}{2^K} \times \frac{T}{2^{K-1}}} \tag{3}$$

where K denotes the number of hierarchical decomposition layers.

(2) According to the operators Q_j , hierarchical components of the segment X_m are defined as

$$Y^m_{K,e} = Q^K_{l_K} \bullet Q^{K-1}_{l_{K-1}} \bullet \cdots \bullet Q^1_{l_1} \bullet X_m. \tag{4}$$

where $[l_1, \cdots, l_k, \cdots, l_K] \in \{0, 1\}$ is an unique vector and e is an integer corresponding to the unique vector, i.e., $e \in [0, 2^K - 1]$, calculated by

$$e = \sum_{k=1}^{K} 2^{K-k} l_k, \tag{5}$$

(3) For each obtained frequency component $Y^m_{K,e} = \{y_t\}, t = 1, ..., T'$, discrete short-time Fourier transform (DSTFT) is employed to convert it into frequency domain by

$$p(i, n) = \sum_{t=0}^{T'-1} y[t]\phi^*[t - nN]e^{-j\frac{2\pi i}{T'}t} \tag{6}$$

where $\phi^*[\bullet]$ is window function and N is the time step of window function moving. And the periodogram is calculated as

$$P(i, n) = \frac{1}{N}|p(i, n)|^2. \tag{7}$$

(4) Frequency resolution at time index n is obtained by periodogram $\{P\{i, n\}\}$ as $F_n = \{f(i)\}$ and they are regarded as the nodes of hierarchical graph. The weight $d_{i,j}$ of the edge between $f(i)$ and $f(j)$ is then calculated by Euclidean distance. Hierarchical graph $G^m_{K,e}$ of eth component $Y^m_{K,e}$ is constructed and represented as an adjacent matrix,

$$\varphi^m_{K,e} = \begin{bmatrix} d_{1,1} & \cdots & d_{1,T'/2} \\ \vdots & \ddots & \vdots \\ d_{T'/2,1} & \cdots & d_{T'/2,T'/2} \end{bmatrix} \tag{8}$$

Finally, the hierarchical graphs of mth segment are constructed as $X_m := \{G^m_{K,0}, ..., G^m_{K,2^K-1}\}$. Perform the hierarchical graph construction for each segment, the collected vibration signals is represented as $\mathcal{X} := \{G^m_{K,0}, ..., G^m_{K,2^K-1}\}, m = 1, ..., M$. For subsequent similarity calculation, the hierarchical graphs are rearranged as $\mathcal{X} := \{\mathcal{G}^{1:M}_{K,0}, ..., \mathcal{G}^{1:M}_{K,2}, ...\mathcal{G}^{1:M}_{K,2^K-1}\}$, where $\mathcal{G}^{1:M}_{K,e} = \{G^1_{K,e}, ..., G^M_{K,e}\}$.

B. Similarity score calculation

Hierarchical graph model provides a more effective method for evaluation of bearing health condition, which considers the characteristics of signal from different scales. Sequentially, similarity score calculation, as an important tool to measure the similarity of hierarchical graphs, is discussed in this section to provide a reliable indicator for decision making. Similarity measurement of each frequency component is firstly calculated, where median graph is adopted to model the normal bearing working condition by extracting the useful information of observed graphs into a single median graph [12]. Similarity scores are subsequently obtained by calculating the weights of each component according the amount of change information.

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According to the observed hierarchical graphs of eth frequency component, i.e., $\mathcal{G}_{K,e}^{1:M} = \{G_{K,e}^1, ..., G_{K,e}^M\}$, the similarity score of $M+1$th hierarchical graph is calculated by

$$S_{K,e}^{M+1} = L(G_{K,e}^{M+1}, \bar{G}_{K,e}^{1:M}) \tag{9}$$

where $\bar{G}_{K,e}^{1:M}$ is the median graph of the former m graphs, calculated by solving the minimization optimization,

$$\bar{G}_{K,e}^{1:M} = \arg \min_{G \in \mathcal{G}_{K,e}^{1:M}} \sum_{m=1}^{M} L(G, G_{K,e}^m) \tag{10}$$

Here, it is noted that $L(\bullet)$ used in Eq. 9 and Eq. 10 is a metric for graph similarity measurement. Considering the hierarchical graph constructed in this paper is undirected weighted graph, difference of edge-weight values [13] of the graph is calculated as L, which is

$$L(G, G') = \begin{cases} \sum_{i=1}^{T/2} \sum_{j=1}^{T/2} \frac{|d_{i,j} - d'_{i,j}|}{\max\{d_{i,j}, d'_{i,j}\}}, & i \neq j; \\ 0, & i = j. \end{cases} \tag{11}$$

Similarity score of eth frequency component is final calculated as $\{S_{K,e}^1, ..., S_{K,e}^M, S_{K,e}^{M+1}\}$. Performing the similarity scores calculation for each frequency component, we can obtain all the similarity scores as $\{S_{K,e}^1, ..., S_{K,e}^M, S_{K,e}^{M+1}\}, e = 1, ..., 2^K - 1$.

Based on the calculated similarity scores, an effective fusion strategy is adopted by assigning the weight to each component according to their importance. Variance, as an indicator of data fluctuation, has been proved in [9] that it plays an important role in weight calculation, i.e., a small variance is more importance for change decision making. Therefore, the weight of eth component is calculated according variance as

$$w_{K,e} = \frac{1}{\sigma_{K,e}^2 \sum_{e=1}^{2^K-1} \frac{1}{\sigma_{K,e}^2}} \tag{12}$$

where $\sigma_{K,e}$ is the variance of eth component, which is calculated as $\sigma_{K,e}^2 = \frac{1}{M+1} \sum_{m=1}^{M+1} (S_{K,e}^m - \overline{S}_{K,e})^2$. Moreover, $\overline{S}_{K,e}$ is the mean, calculated by $\overline{S}_{K,e} = \frac{1}{M+1} \sum_{m=1}^{M+1} S_{K,e}^m$.

The fusion similarity score is then calculated by weights as

$$\mathcal{S}_m = \sum_{e=1}^{2^K-1} w_{K,e} S_{K,e}^m \tag{13}$$

Finally, a series fusion similarity scores are obtained, i.e., $\{\mathcal{S}_1, \mathcal{S}_2, \cdots, \mathcal{S}_{M+1}\}$. Similarity score calculation method proposed in this paper provides an powerful indicator for change decision making, where median graph is constructed by modeling a series graphs into a single graph to reflect the normal bearing condition and variance is used in weight calculation aiming to combine all the components according to their importance. Based on the calculated fusion similarity scores, hypothesis testing is carried out for change evaluation.

C. Change decision making

According to the fusion similarity scores, i.e., $\{\mathcal{S}_1, \mathcal{S}_2, \cdots, \mathcal{S}_{M+1}\}$, a null hypothesis testing is performed for change decision making.

$$\begin{aligned} H_0: &\text{ no change}: & |\mathcal{S}_{M+1} - \mu'_M| &\leq 3\sigma'_M \\ H_A: &\text{ change occurs}: & |\mathcal{S}_{M+1} - \mu'_M| &> 3\sigma'_M \end{aligned} \tag{14}$$

where μ'_M and σ'_M are the mean and standard deviation of the former similarity metrics $\{\mathcal{S}_1, \mathcal{S}_2, \cdots, \mathcal{S}_M\}$, respectively calculated by $\mu'_M = \frac{1}{M} \sum_{i=1}^{M} \mathcal{S}_i$ and $\sigma'_M = \sqrt{\frac{1}{M} \sum_{i=1}^{M} (\mathcal{S}_i - \mu_M)^2}$.

The above hypothesis testing is based on the assumption of Gaussian distribution. This assumption would be unfeasible in some real cases. For these situations, alternative such as Gaussian Mixture Model [14] and non-Gaussian approaches [15], [16] can be used to improve the proposed method. However, as the focus of our study is on the data modeling, we avoid to make additional discussion in this paper.

III. Experiment

Experiments are conducted on the recently-released XJTU-SY data set to validate the proposed method.

This data set is collected by the setup shown in Fig. 3, where accelerated degradation experiments is conducted for data collection. Finally, 15 testing data are collected including three operating conditions, i.e., 35Hz/12kN, 37.5Hz/11kN and 40Hz/10kN. The sampling rate is 25.6 kHz. More details of dataset are shown in Table I

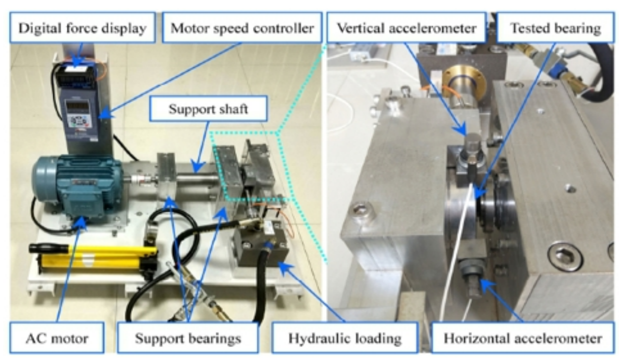

Fig. 3. Experimental setup for collection of XJTU-SY data set.

Detection results of the proposed method in XJTU-SY dataset is shown in Fig. 4. Here, it is noted that the original data of bearings 3-1, 3-2 and 3-4 with a down-sampling rate of 1:50 and others with 1:10 considering their different data length for the purpose of computing efficient improvement. From the results, it can be seen that all the changes can be detected successfully except bearing 3-2. The main reason is the signal of bearing 3-2 does not show a discriminative health status compared with other tested bearings. Moreover, there are two types of the successful detection, which are (1) slowly degradation process including bearings 1-1, 1-2, 1-3, 1-5, 2-2, 2-3, 2-4, 2-5 and 3-5: there are one or two changes detected

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TABLE I
DATA SETS PROVIDED BY XJTU-SY.

Operation condition	Bearing dataset	Fault element
Condition1 (35 Hz/12 kN)	Bearing 1-1	Outer race
	Bearing 1-2	Outer race
	Bearing 1-3	Outer race
	Bearing 1-4	Cage
	Bearing 1-5	Inner race and outer race
Condition2 (37.5 Hz/11 kN)	Bearing 2-1	Inner race
	Bearing 2-2	Outer race
	Bearing 2-3	Cage
	Bearing 2-4	Outer race
	Bearing 2-5	Outer race
Condition3 (40 Hz/10 kN)	Bearing 3-1	Outer race
	Bearing 3-2	Ball, cage, inner and outer race
	Bearing 3-3	Inner race
	Bearing 3-4	Inner race
	Bearing 3-5	Outer race

TABLE II
SUMMARY OF DIFFERENT METHODS WITH XJTU-SY DATA SET.

	HGM	Graph	Kurtosis	RMS	Skewness	Histogram	Bispectrum
Bearing 1-1	4	4	1	3	7	4	1
Bearing 1-2	1	3	2	7	6	4	5
Bearing 1-3	1	2	3	7	4	5	6
Bearing 1-4	1	1	7	4	5	1	5
Bearing 1-5	2	5	2	1	7	2	6
Bearing 2-1	1	1	1	7	1	6	1
Bearing 2-2	1	2	2	4	6	4	7
Bearing 2-3	1	2	3	4	4	4	4
Bearing 2-4	1	1	7	1	6	1	1
Bearing 2-5	2	1	3	5	3	5	7
Bearing 3-1	3	1	5	6	7	4	1
Bearing 3-2	4	1	2	2	6	5	6
Bearing 3-3	1	5	6	7	1	1	1
Bearing 3-4	1	1	7	3	6	5	3
Bearing 3-5	3	1	1	5	4	7	6
Average rank	**1.80**	2.07	3.47	4.40	4.87	3.87	4.00

for that the degradation process of bearing has multi-stages; (2) abrupt fault detection including bearings 1-4, 2-1, 3-1, 3-3 and 3-4: changes can be detected accurately.

In order to demonstrate the priority of the proposed method, comparison experiments are conducted with representative methods, i.e., kurtosis, root mean square (RMS), skewness, histogram and bispectrum. Examples of comparison experiments are given in Fig. 5. From the comparison results, we can see that the proposed method and graph method can detect changes successfully and accurately and the others have many false alarms. Moreover, graph method has a large detection delay than our method, which demonstrates the effectiveness and priority of the proposed method in this paper.

Table II shows the comparison results based on "method of rank", where all methods are ranked according their detection results. In particular, the methods with less false alarm and a small detection delay are highly ranked. From the comparison results, it is clearly that the proposed method achieves the promising detection performance.

IV. CONCLUSION

A new method has been proposed in this paper to detect the dynamical bearing degradation process. The method considers the characteristics of vibration signal from different scales, aiming to conduct a more precise description of bearing health condition. Hierarchical graphs are firstly constructed by decomposing the vibration signals into different components. Weights of each component are then calculated to assemble all constructed graphs, such that the similarity scores are produced to characterize the dynamical behavior of bearing health condition. Finally, a common hypothesis testing is performed for change decision making. Experiment conducted on the XJTU-SY dataset suggests that the proposed method achieves the promising detection performance. Moreover, comparison with representative competitors demonstrates its effectiveness and priority in real applications.

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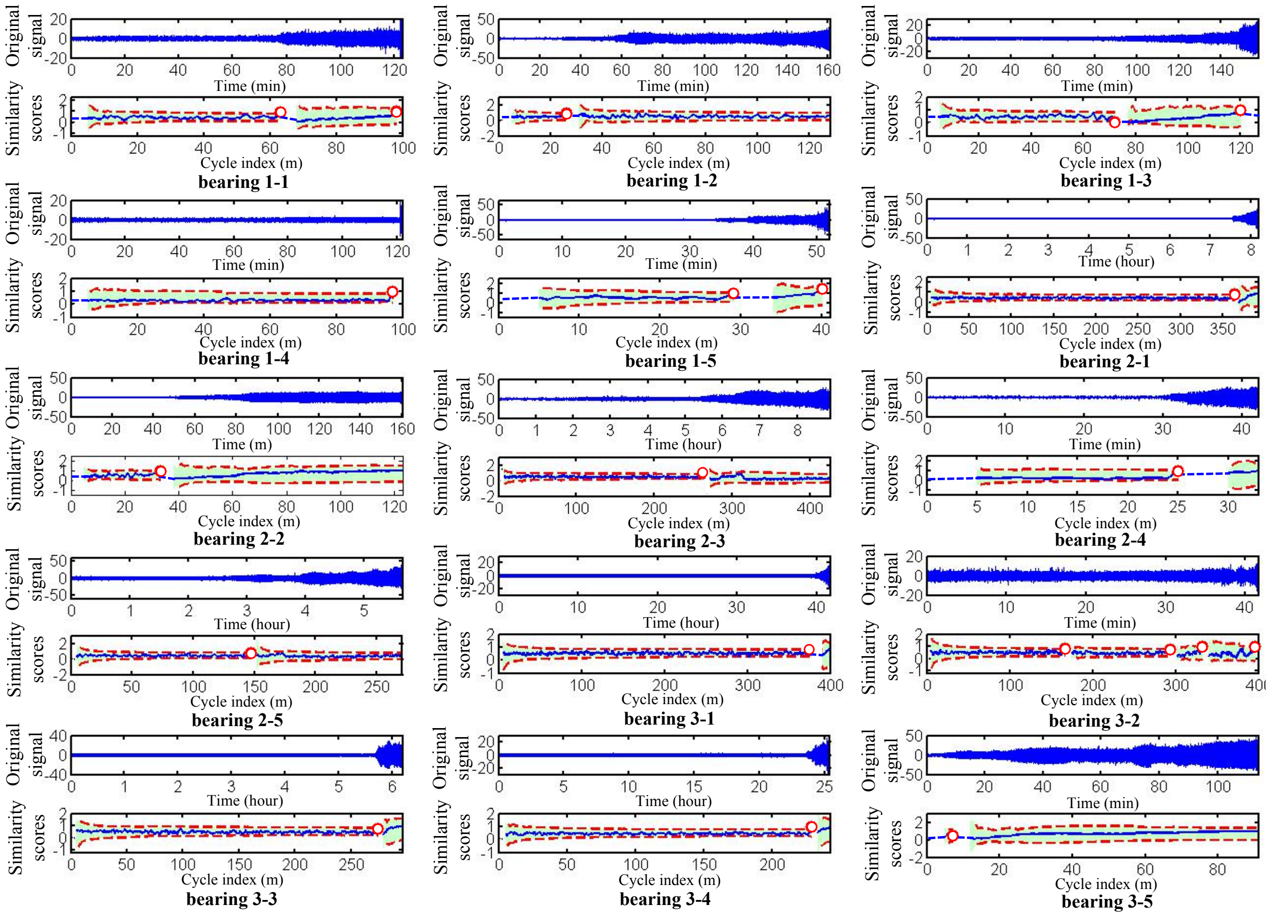

Fig. 4. Experiment results of XJTU-SY data set.

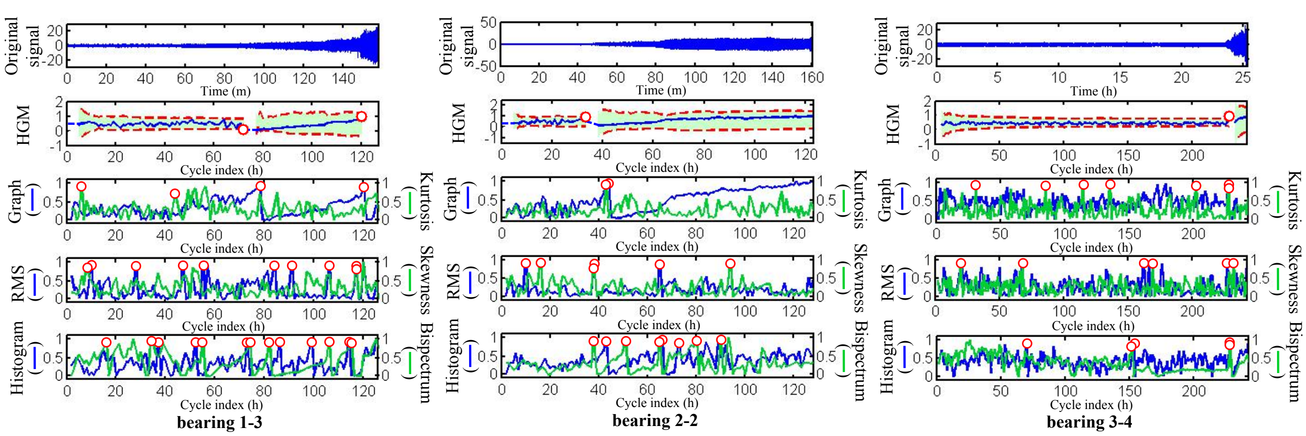

Fig. 5. Examples of detected results by our method and competitors on XJTU-SY data set.

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