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Machine Speed Condition Monitoring using Statistical Time-Domain Features Modeled with Graph

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***Abstract*—The most important part of speed condition monitoring for industrial machinery is to find the structural changes in dynamic running status. The existing detection methods mainly rely on the time-domain or frequency-domain analysis of the collected operation signals to detect the change. In this paper, the time-domain features and the structural graph similarity are combined to detect the dynamic speed conditions. For the condition signal, we firstly divide it into time-sequential segments. Secondly, extract statistical features from each segment, and modeled as graph to characterize the dynamic behavior of machine speed condition. A common hypothesis testing based on the 3σ criterion is finally used to make the change decision. We have investigated the proposed method based on an experimental setup. Experimental results show that compared with the time-domain features, the precision and F_{score} are improved by more than 10%, which shows the effectiveness of our method.**

Keywords—speed condition monitoring, change detection,time domain feature, graph

I. INTRODUCTION

The rotating speed has an important indication function for the running state and load condition of industrial machines [1]. The running status of ongoing machinery can be thus monitored by detecting the change of speed in its successive operations [2]. As such, it is of great significance for making operation plan or maintenance in advance, preventing equipment failure and ensuring the reliability and safety of the machine. [3].

In real scenarios, however, considering the actual operating conditions and environmental limitations of the machine, it is impossible to directly measure the speed of the machine with the speed sensor [4]. Vibration signal, as an alternative measurement, is therefore widely used to acquire speed information [5]. Once the vibration signal is collected, appropriate features such as root mean square (RMS), are extracted from the original data to form an index that can characterize the dynamic running state of the machine. However, the vibration signals are easily submerged by the strong background noise [6], and the changing information at the early stage cannot be described sufficiently using these indexes, making the change decision require to be further assured [7].

Graph theory has already been used to vibration signal analysis in machine condition monitoring [8–9]. Taking merits of graph modeling (GM), topological and structural information hidden in the original data can be found, making it very useful to analyze complex vibration signals. GM is advantageous due to its higher computational efficiency and more robustness to noise, which has been proved to be useful for capturing the long-range correlation (LRC) of non-stationary vibration data that are involved in the machine conditions. In addition, GM has been also demonstrated to be very helpful in statistics to absorb the high noise in raw vibration data. So in this paper, graph theory is applied to detect the speed change from collected vibration signals.

In this work, the time-domain statistical features and the structural graph similarity are combined to obtain a high-level dynamic index that can characterize the machine running status. In this work, as depicted in Fig. 1, for a given vibration signal, we first divide it into time-sequential segments to make the signal stable. The length of the segments is determined by experiment set up. Next, a set of employed time-domain features are extracted from each segment to extract key information. Furthermore, graph is constructed from the vector of extracted features for each segment to represent it. Finally, the metric of differences in edge-weight values (DEWV) [10] is employed to assess the similarity of two neighboring graphs, supporting an online decision making by hypothesis test.

The performance of the proposed method is assessed at the experimental setup as used in [11]. Comparisons the proposed method and time-domain statistical features methods and their improved forms. Experimental result shows that the new method achieved the best test result among all compared methods. This methods has the latency to improve the existing speed monitoring techniques, what's more, its performance could be further increased when more features are considered in the future.

In the rest of this paper, Section II introduces the details of the proposed method; Section III provides the results of our experiment; Section IV concludes all the paper with important remarks.

II. METHODOLOGY

In summary, the raised method performs three steps for continuous monitoring of collected vibration signals: 1) time domain feature extraction, 2) graph modeling, and 3) hypothesis testing for decision making. The detail description of our method will be given below.

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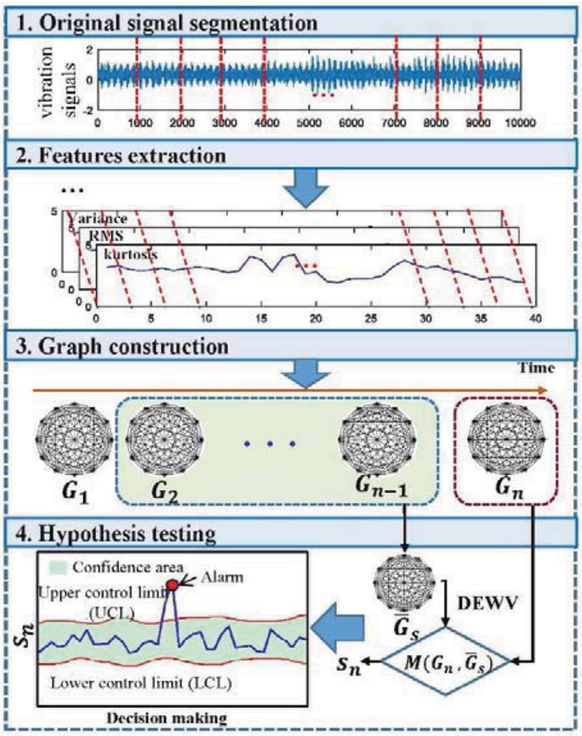

Fig. 1. The flowchart of the new method.

A. Statistical feature extraction

Feature extraction is of great importance for condition identification [12]. It is thus extremely important to find an appropriate method to extract effective features from vibration signals. An effective tool is to quantify the temporal stationary from those time-sequential segments that are obtained from the given vibration signal [8]. To achieve this end, in this work we divide the raw vibration signal X into time-sequential segments denoted as $\{X_1, X_2, ..., X_n\}$ where n is the number of resulting segments, to make the signal stationary. Here it is noted that, many factors such as experiment setting and sampling frequency, need to be considered in determination of the length of divided segments. In this work, considering the experimental environment, we set the segment empirically with a length of 500 data points.

After data segmentation, a set of time-domain features are extracted from the vibration signal, and then arranged as a time series of features to describe the machine conditions. It is obvious that the data of vibration signal emerges strong symmetry and periodicity. For time series with symmetric distribution, two terms standard deviation and mean are often considered as important measures. Other statistical features, such as variation, skewness, and shape factor, are also used to provide useful information about time series. Totally, twelve features of *{standard deviation, variation, RMS, absolute maximum, skewness, kurtosis, crest factor, margin factor, shape factor, impulse factor, A factor and B factor}* are considered as features to represent the vibration data in [13].

B. Graph modeling

In the above section, we have extracted a set of features to represent the collected vibration data. In the following Section III B, we will conduct an experiment to confirm which of these features will provide the key role in characterization of machine speed conditions. Based on the selected informative features, graphs are constructed from each segment in order to quantify the anomaly of time series. A graph G consists of a finite nonempty set of nodes V, and a finite set of edges E, where an edge is an ordered pair of nodes in V indicating a link between them. In other words, the graph can be defined as $G= \{V, E\}$ where $V = \{v_1, v_2, ...\}$ and $E = \{e_1, e_2, ...\}$.

Let us suppose$F_k = [f_1^k, f_2^k, ..., f_m^k]^T, k \in [1,2, ..., n]$ is the set of selected features for the kth vibration segment, where m is the number of features we selected. A graph G_k corresponding to this segment is then constructed as follows:

- Regard each feature as a nodev_i, $i \in \{1,2, ..., m\}$, and connect each two nodes v_a and v_b and obtain an edge $l_{\{a,b\}}$.
- Compute weight $d_{\{a,b\}}$ for each edge, where $d_{\{a,b\}}$ is computed as the Euclidean distance between the value of features corresponding to v_a and v_b.
- Represent the graph G_k using its adjacent matrix ε_k, i.e., $\varepsilon_k = \begin{bmatrix} d_{11} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{n1} & \cdots & d_{nn} \end{bmatrix}$, which is symmetric and square.

We perform the above-described graph construction in each vibration segment. So that the raw vibration data X is now represented by a time series of resulting graphs, i.e., X : = Γ $= \{G_1, G_2, ..., G_n\}$.

Due to the interference of background noise, there are inevitably data fluctuations in those constructed graphs even in steady speed conditions. The so-called median graph is thus extracted so can absorb such fluctuations. Given a graph set Γ $= \{G_1, G_2, ..., G_n\}$, the median graph $\overline{G}_s$ is calculated by the following formula as,

$$\overline{G}_s = \arg\min_{G \in \Gamma} \sum_{k=1}^{n} M(G, G_k) \quad (1)$$

where $M(\cdot, \cdot)$ is a distance metric, used as the DEWV in this study, i.e.,

$$DEWV\{G, G'\} = \sum_{a=1}^{n} \sum_{b=1}^{n} \left| d_{a,b} - d'_{a,b} \right| \quad (2)$$

$$M\{G, G'\} = \sum_{a=1}^{n} \sum_{b=1}^{n} \Delta_{a,b} \quad (3)$$

where $\Delta_{\{a,b\}}$ is computed as,

$$\Delta_{a,b} = \begin{cases} \dfrac{|d_{a,b} - d'_{a,b}|}{\max\{d_{a,b} - d'_{a,b}\}}, & a \neq b \\ 0, & a = b \end{cases} \tag{4}$$

From (1), it is found that the calculation of $\overline{G}_s$ needs a full search of past graphs, which will takes large time cost in real implementation. To reduce the computation burden, we use a local searching extent to speed up the calculation. That is, we only use four graph before the current inspection time to calculate the median graph in the experiment.

C. Decision making

Based on the median graph $\overline{G}_s$ given in the above, we can measure the anomaly of a new graph G_{n+1} and detect the potential change by hypothesis test.

- Anomaly measure: it is a common practice to measure the anomaly of current inspection time for change decision making. The anomaly is to quantify how much the currently monitored G_{n+1} deviates from the normal model by calculating the distance between G_{n+1} and $\overline{G}_s$, which is calculated as,

$$s_{n+1} = M(G_{n+1}, \overline{G}_s) \tag{5}$$

where *M(· , ·)* is also the DEWV as used in (1).

- Hypothesis testing: we use the common 3σ criterion to test a null hypothesis for change decision. The 3σ control chart is conducted based on the Gaussian distribution where an upper control limit (UCL) and a lower control limit (LCL) are used to determine a confidence area. The point beyond the scope of the confidence area is considered as a change. This procedure is drawn up as,

$$\begin{aligned} &H_0: \quad no \quad change: s_{n+1} \in A \\ &H_A: speed \quad change: s_{n+1} \notin A \end{aligned} \tag{6}$$

where A=[$\mu_n - 3\sigma_n$, $\mu_n + 3\sigma_n$] is the confidence area, μ_n is the mean value, σ_n is the standard deviation of all past anomalies, computed as:

$$\mu_n = \frac{1}{n}\sum_{i=1}^{n} s_i \tag{7}$$

$$\sigma_n = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(s_i - \mu_i)^2} \tag{8}$$

The above described decision making is operated continuously, so that the considered machinery can be monitored with an on-line manner.

D. Processing

To summarize, the processing of proposed speed change detection method is given as below.

a) Divide the raw signal into time-sequential segments;

b) Calculate statistical features in time domain for each segment, and construct a graph based on the features;

c) Extract the medium graph from the past graphs;

d) Test a null hypothesis for change decision. If one change is detected, there will be an alarm; otherwise, go to step b) update the median graph and then continues the change detection.

III. EXPERIMENTAL RESULTS

In this part, we investigated the proposed method based on an experimental setup.

A. Testing data and experiment implementation

To discuss the performance of the new method, we collect testing data on the experimental setup used in [11]. This setup, as shown in Fig.2, include a servo motor drives the whole experimental platform, a programmable brake simulates the load, and a planetary gearbox is connected with the motor and the brake respectively through the bearings on both sides. The vibration signals are acquired by an acceleration sensor fixed on the gearbox, and then sent to a PC for storage.

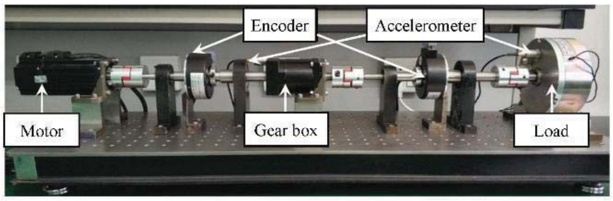

Fig. 2. Experimental setup.

TABLE I. DETAILS OF THE TESTING DATA（RPM）

Δv/v	300	350	400
50	300→300+50	350→350+50	400→400+50
100	300→300+100	350→350+100	400→400+100
150	300→300+150	350→350+150	400→400+150
200	300→300+200	350→350+200	400→400+200

Firstly we set the speed of the motor as v and then change the speed as $v + \Delta v$ in data collection. Details of v and Δv as shown in TABLE I, where v={300,350,400}*rpm* and Δv ={50,100,150,200}*rpm*. Therefore, from the TABLE I， we can obtain 12 12 different combinations of speed changes, and then we repeat the data collection at 5 times. Finally, 60 testing data sequences containing changes are used to analyze the performance of various features.

In our experiment, we have selected 12 time domain feature factors. They are shown in TABLE II. We use three common

TABLE II . INVESTIGATED STATISTICAL FEATURES

where T is 'mean' calculated by $T=\sum_{n=1}^{N} x(n)/N$ and $x(n)$ is the observed vibration value at time n

Feature	***Equation***	***Feature***	***Equation***
Standard deviation	$\sqrt{\frac{\sum_{n=1}^{N}(x(n)-T)^2}{N-1}}$	Crest factor	$\mathrm{T7}=\frac{T4}{T3}$
Variance	$\left(\frac{\sum_{n=1}^{N}\sqrt{\lvert x(n)\rvert}}{N}\right)^2$	Margin factor	$\mathrm{T8}=\frac{T4}{T2}$
RMS	$\sqrt{\frac{\sum_{n=1}^{N}(x(n))^2}{N}}$	Shape factor	$\mathrm{T9}=\frac{T3}{\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert}$
Absolute maximum	$\max\lvert x(n)\rvert$	Impulse factor	$\mathrm{T10}=\frac{T4}{\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert}$
Skewness	$\frac{\sum_{n=1}^{N}(x(n)-T)^3}{(n-1)T_1^3}$	A factor	$\mathrm{T11}=\frac{T4}{T.T2}$
Kurtosis	$\frac{\sum_{n=1}^{N}(x(n)-T)^4}{(N-1)T_1^4}$	B factor	$\mathrm{T12}=\frac{T6.T7}{T}$

TABLE III . DETECTION PERFORMANCE BY SOLE FEATURES

Feature	***Precision***	***Recall***	***Fscore***	***Feature***	***Precision***	***Recall***	***Fscore***
Standard deviation	76.19%	88.89%	82.05%	Crest factor	40.54%	41.67%	41.10%
Variance	74.42%	88.89%	81.01%	Margin factor	25.93%	19.44%	22.22%
RMS	46.30%	69.44%	55.56%	Shape factor	42.11%	44.44%	43.24%
Absolute maximum	46.00%	63.89%	53.49%	Impulse factor	38.46%	41.67%	40.00%
Skewness	37.50%	25.00%	30.00%	A factor	13.51%	13.89%	13.70%
Kurtosis	47.62%	55.56%	51.28%	B factor	6.90%	5.56%	6.15%

indicators, i.e., *precision, recall* and F_{score} to evaluate the proposed method . They are calculated as,

$$Precision=\frac{\text{Number of Correct Detections of Changes}}{\text{Number of Detections of Changes}} \quad (9)$$

$$Recall=\frac{\text{Number of Correct Detections of Changes}}{\text{Number of True Changes}} \quad (10)$$

$$F_{score}=\frac{2\times Recall\times Precision}{Recall+Precision} \quad (11)$$

Precision represents the probability that a detection is a real change; *Recall* is the probability that a real change can be detected; F_{score} is a comprehensive indicator including the above two indicators. Obviously, a higher value of F_{score} indicates a better detection performance, and vice versa.

B. Investigation of sole features for detection

In this experiment, we will investigate each sole feature to show which of them will provide the key role in characterization of machine speed conditions. Once each feature is extracted, we directly feed it to the 3σ control chart for change decision making. Their detection performances are given in TABLE III. We can see that, the feature of *standard deviation* achieves the best performance but it is only 82.05% in term of F_{score}. Since the proposed method proposes to combine statistical features and graph similarity to produce a high-level dynamic index, we will investigate different feature combinations in the following experiment.

C. Investigation of ranking-based feature combination

In this experiment, we firstly select several top-ranking features from TABLE III and then combine them to construct graphs. Two examples using different number of selected top-ranking features that is from 2 to 7 are given in Fig. 3. We can clearly see that, for the first testing data, the use of two top-rankings features (i.e., *standard deviation and variance*) did not detect the change at all but produce false alarms in the second testing data; the use of three top-rankings features (i.e., *standard deviation, variance* and *RMS*) can detect the change for those two testing data; other combinations failed to detect the change for the second testing data. Comprehensive results are given in TABLE IV, where we can find that, the combination using three top-ranking features achieves the best performance in the term of F_{score} among all combination options based on the ranking selection. But it has only a result of 83.33% in term of *Recall* which is even lower than that by sole features e.g., using *standard deviation* and *variance*. This observation implies that there is a potential improvement by other available combination in the proposed method.

D. Investigation of information-based feature combination

From TABLE III, we can clearly see that the detection performance by using *shape factor* is much lower than that by the features of *standard deviation* and *variance*. However, two interesting examples are given in Fig.4. We can find that, the features of *standard deviation* and *variance* can find the changes for both of testing data, although they produce false alarms for

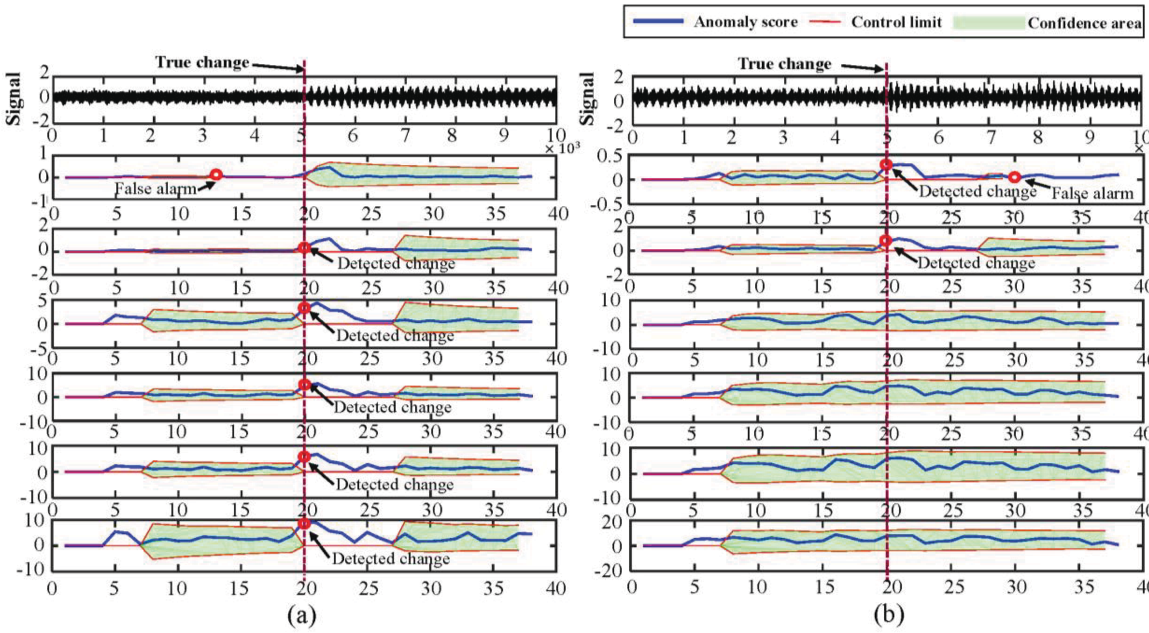

Fig. 3. Two examples of detecting speed changes: (a) A testing data of 350→350+50 (*rpm*), and (b) a testing data of 400→400+50 (*rpm*). In each figure, from top to bottom: original vibration signal, and detection results by the selected features number of 2,3,4,5,6,7.

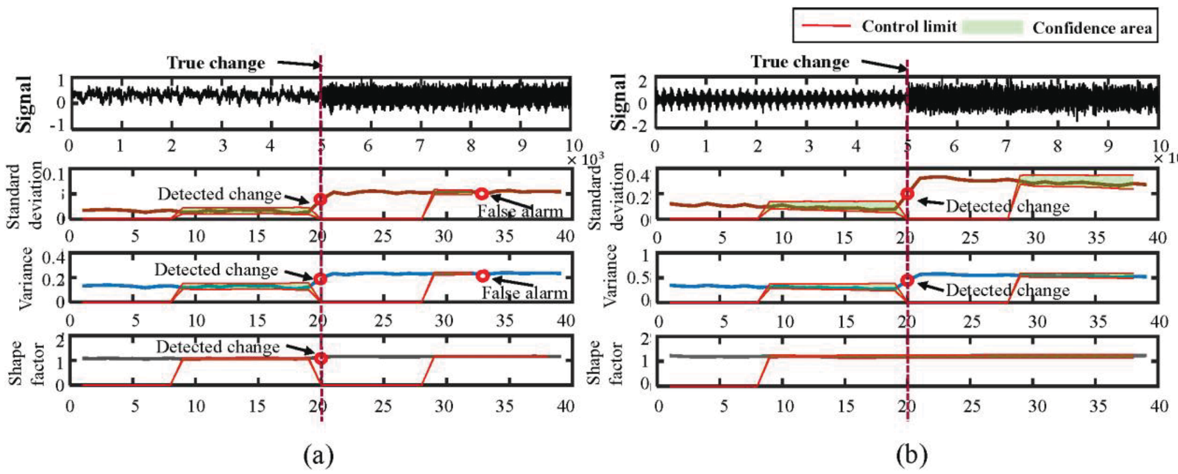

Fig.4. Two examples of detecting speed changes by sole features: (a) A testing data of 300→300+50 (*rpm*), and (b) a testing data of 400→400+150 (*rpm*). In each figure, from top to bottom: original vibration signal, and detected results by *standard deviation*, *variance* and *shape factor*

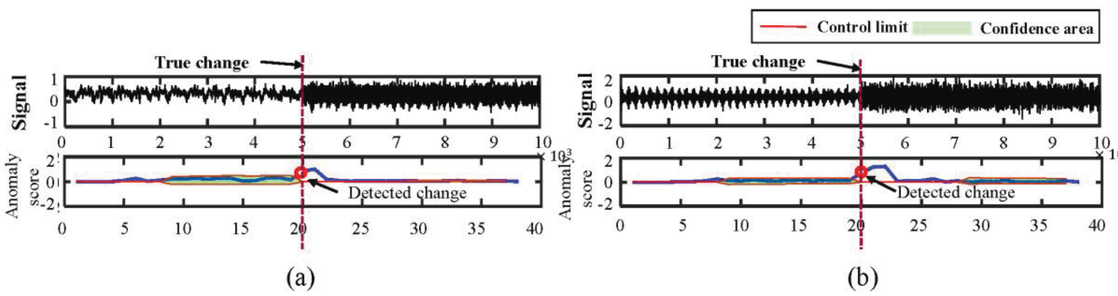

Fig.5. Change detection examples by combination of features of *standard deviation*, *variance* and *shape factor*: (a) A testing data of 300→300+50 (*rpm*), and (b) a testing data of 400→400+150 (*rpm*).

TABLE IV. RESULTS BY DIFFERENT NUMBER OF TOP-RANKING FEATURES

Number of features	***Precision***	***Recall***	***Fscore***
2	62.86%	61.11%	61.97%
3	88.24%	83.33%	85.71%
4	76.47%	36.11%	49.06%
5	88.89%	44.44%	59.26%
6	83.33%	41.67%	55.56%
7	78.95%	41.67%	54.55%

TABLE V. DETECTION RESULT BY COMBINATION OF FEATURES OF *STANDARD DEVIATION*, *VARIANCE* AND *SHAPE FACTOR*

Performance indicators		
Precision	***Recall***	***Fscore***
94.29%	91.67%	92.96%

the first data; in comparison, although the feature of *shape factor* failed to detect the change in the second one, it successor to detect the change in the first data. This observation suggests that, combination of features based on the 'information' would be an alternative of combination only with the rank that has been investigated in the above experiment.

In this experiment, we thus combine two top-ranking features i.e., *standard deviation* and *variance*, and the feature of *shape factor* to construct the graph. Fig.5 shows the detected result where we can see that the changes in both testing data have been successfully detected. A comprehensive detection result is provided in TABLE V.

It is seen that this combination improved the detection performance significantly (compare it to the results in TABLE IV). This result shows the effectiveness of feature combination with information. Here, it is noted that, we do not show the optimal combination by using this strategy since the focus of this study is to provide a universal framework. In our future work, we will consider more statistical features and find the optimal combination in order to further improvement of the proposed method.

IV. CONCLUSIONS

This paper is focused on the problem of speed change detection in condition monitoring applications. We put forward a new feasible method based on time-domain statistical features coupled with structural graph model. Taking merits of the proposed method, an automatic analysis of continuous monitoring of vibration signal can be realized in order to detect the machinery speed change during its continuous operation. Comprehensive experiments have been carried out to investigate the function of proposed method. Significant improvement has been demonstrated, suggesting the great potential of the method in applications. Furthermore, we will consider more features and seek the optimal combination of them in order to improve the accuracy of the method.

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