Anomaly Detection of Vibration Signals by Using the Number of their Harmonic Components

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Introduction

The early detection of failures is important for the proper operation of machines, especially for bearings usually used in the rotation parts of the machines. There is a need to construct a practical health indicator (HI) to detect degradation. Various HIs have been proposed in literature [1]. Statistical indicators such as root mean square (RMS) and kurtosis are widely used as primary features of HIs. However, these HIs are not fully appropriate, because they often show small fluctuations in the incipient fault stage or large signs of recovery when degradation progresses [1]. Furthermore, additional analysis is usually required for fault location estimation [2].

In this study, we have developed an anomaly detection method that utilizes the number of harmonic components as a HI. The proposed method was validated by applying to the public dataset of bearing vibrations [3], and enabled us to clearly detect changes in health status and simultaneously estimate the fault location.

Developed Algorithm

The developed algorithm (Fig. 1) consists of two main stages; multiple spectral peak tracking stage and harmonic components extraction stage.

In the multiple spectral peak tracking stage, spectral peaks in the frequency domain at each time are detected and peaks that appear consecutively in time are extracted. In the harmonic components extraction stage, the tracked frequency peaks are grouped into harmonic structures for each base frequency, and the number of harmonic components is extracted as a HI. Then, when the number of harmonic components increases significantly, an anomaly is detected, and the fault location is estimated.

Experimental Result

For the experiments in this paper, we used the public bearing run-to-failure dataset [3]. The equipment configuration is shown in Fig. 2.

In the verification, we used the bearing with the outer race failure at the end of the experiment and tracked the top 20 peaks in intensity for each time. Figure 3 shows the results of harmonic components extraction on the first day (initial condition) and on the fifth day (after the failure).

The actual process execution results are shown in Fig. 4. The ball passing frequency outer race (BPFO), the ball passing frequency inner race (BPFI) and the ball spin frequency (BSF) were used as the base frequency of harmonic components. The number of harmonic components of BPFO significantly increased after 88 hours and gradually increased. These results indicate the outer ring degradation has progressed. It is also possible to obtain a clearer change in the number of harmonic components as a HI by performing envelope extraction of the vibration data in advance (Fig. 5).

Figure 6 shows the comparison of the developed algorithm, kurtosis, and RMS. The developed algorithm shows a clearer change at the beginning of the health stage change than kurtosis and RMS, and shows an increasing trend as the degradation progresses.

Conclusion

In this paper, we have developed the anomaly detection method using the number of harmonic components as a HI. It was confirmed that the proposed method can detect changes in health stages more clearly than RMS or kurtosis and can also estimate the fault location. The algorithm can be applied to the prediction of remaining useful life.

References

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[2] D. Wang et al., IEEE Access, vol. 6, pp. 665–676, 2017.
[3] J. Lee, H. Qiu, G. Yu, J. Lin, Rexnord Technical Services, Bearing Data Set, IMS, Univ. of Cincinnati. NASA Ames Prognostics Data Repository, 2007.

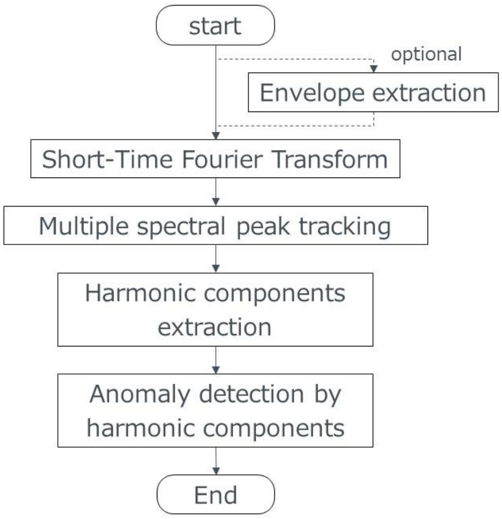

Figure 1. Developed algorithm

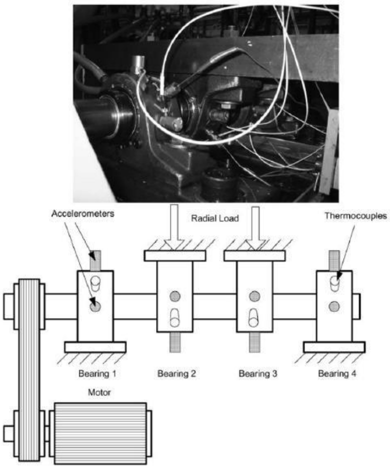

Figure 2. Bearing test rig [3]

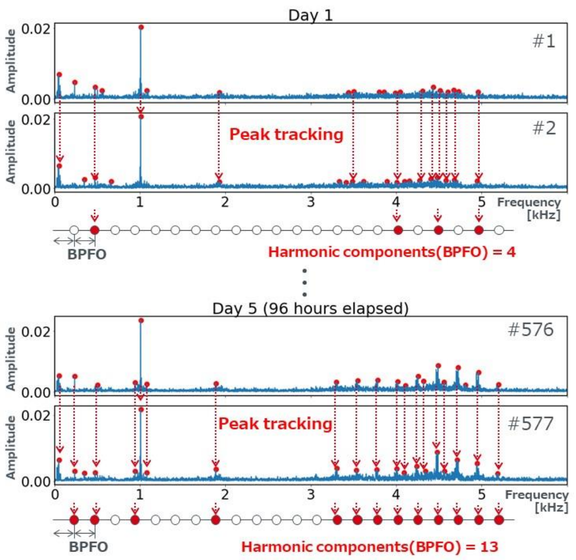

Figure 3. Results of harmonic components extraction on the first day (initial condition: above) and on the fifth day (after the failure: below)

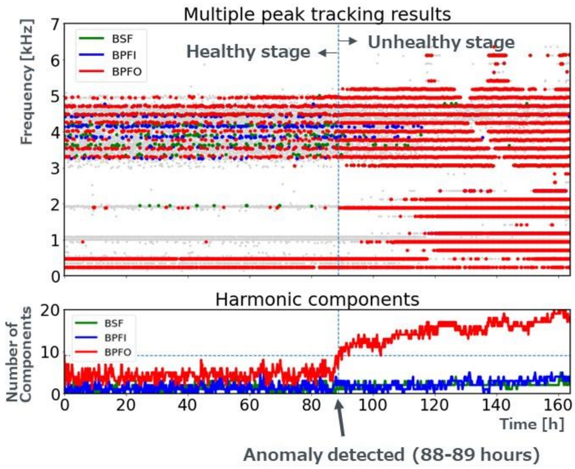

Figure 4. Visualized peak tracking results (above) and anomaly detection results by the number of harmonic components (below).

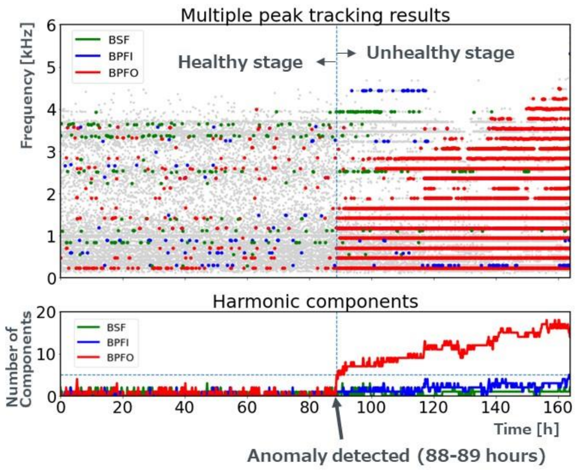

Figure 5. Peak tracking results (above) and anomaly detection results (below) when the envelope extraction process of acceleration data was performed in advance.

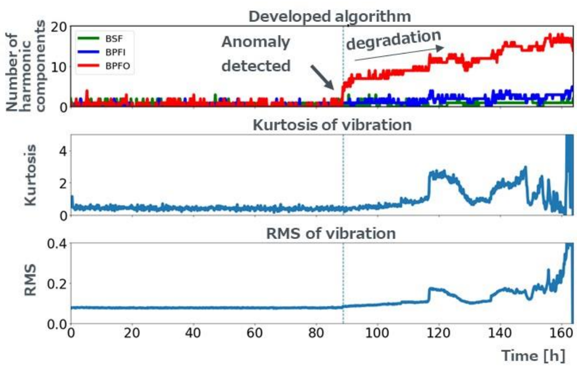

Figure 6. Comparison of the developed algorithm, kurtosis, and RMS. The dotted line indicates the point of change in health stage.