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Diversity and Integration of Rotating Machine Health Monitoring Methods

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Health monitoring for rotating machines is investigated through two kinds of mock-up experimental data analysis. One is an anomaly mock-up test of roll bearing type rotating machine. Here, inner ring defect anomaly is simulated and its operating data are measured by both attached type accelerometer sensor and non-attached type microphone. Three kinds of signal pre-processing methods, frequency spectrum, principal component analysis and cepstrum, are applied to discriminate normal and abnormal states using several different classification algorithms, such as adaboost or random forest. Through analysis of their performance with the help of receiver operating characteristic (ROC) curve, the importance of diversified health monitoring methods is discussed. Another mock-up experiment is an accelerated test of roll bearing wear. Here, acoustic emission counts, accelerometer signal and wear particle number in lubricating oil are measured. Using these observation data, we make clear the relationships between deterioration mechanisms of bearing and behaviour of different observations.

1. Introduction

Condition based maintenance (CBM) is one of important activities for improving both equipment reliability and maintenance costs. The reliability is expected to increase by avoiding unnecessary overhaul or inspections. In a viewpoint of cost, CBM would contribute not only to reduce maintenance cost but also to allocate limited manpower to other important maintenance work. Reliable health monitoring technology is a key issue to make CBM successful.

Based on these general backgrounds, the present paper investigates health monitoring technologies for rotating machines in power plants. To provide reliable health monitoring technologies, it is important to combine various kinds of sensing technologies, signal processing and data classification algorithms. Here, the concept of diversity is important since rotating machines have various kinds of anomaly states. However, we have to take into account that the simple diversity may induce some confusion if diversified monitoring methodologies give different monitoring results. So, it is also important how we can integrate the diversified monitoring results to obtain a reasonable result. Of course, we cannot expect a unique solution for this integration process, but, it is worthwhile to investigate the diversity and integration process by using concrete examples of health monitoring.

In the present paper, we will discuss the effectiveness of various kinds of health monitoring methodologies, as well as the importance of integration process of diversified monitoring results, by utilizing two kinds of mock-up experiments of rotating machine anomaly. One is an anomaly mock-up test of roll bearing type rotating machine. Here, normal operating data are compared with inner ring defect data. The other mock-up experiment is an accelerated test of roll bearing wear by adding excessive load on the bearing.

In these experiments, various kinds of sensing data were measured, such as accelerometer sensor data, a non-attached type microphone data, acoustic emission data, or, wear particle number in lubricating oil. These data are utilized to investigate what kinds of signal processing and classification algorithms are effective to discriminate normal and abnormal states, or, to predict anomaly progress in the acceleration

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test. Furthermore, we will discuss anomaly discrimination performance with the help of receiver operating characteristic (ROC) curve.

Through these two kinds of experimental data analysis, we will show the importance of the diversification of sensing methods and data processing algorithms, and also the importance of the methodology to integrate the diversified information to obtain accurate, precise and robust diagnosis results.

2. Health monitoring methods

2.1 Signal pre-processing

Signal pre-processing for feature extraction is the most important part to assure performance of health monitoring. For rotating machine monitoring, the frequency transformation of measured vibration or sound time series data is widely used. This is referred as auto-power spectral density (APSD) in this paper. Here, we should note the difference of linear-scale and log-scale of APSD when we apply APSD to health monitoring. If we want to pay attention to the ratio of oscillation magnitude change, we should use log-scale APSD. In addition to APSD, principal component analysis (PCA) is also useful to extract more abstracted information from APSD (Tamaoki et.al, 2003, Kanemoto, 2009, 2010). Also, in speech or speaker recognition research (Furui, 1992), Cepstrum analysis is often used. Cepstrum is defined as Fourier transformation of log-APSD.

Considering these previous research, in the present paper, we try to compare the following three features: (1) log-APSD, (2) log-APSD+PCA, (3) Cepstrum. We can expect these diversified signal pre-processing methods will provide different monitoring results and contribute to increase the reliability of health monitoring.

2.2 Classification

Another important part of health monitoring is the classification algorithm which discriminates normal and abnormal states of the target system. To evaluate what kinds of classification algorithms is better for rotating machine monitoring, we need the test data set of normal and abnormal machine conditions. So, the present research will utilize a mock up test facility of rotating machine which can simulate some types of anomaly operation. Among various kinds of classification algorithms, the most basic one would be traditional Fisher's linear discrimination analysis (LDA) (Bishop, 2006). However, the recent progress of pattern recognition or machine leaning research, many kinds of algorithms have been proposed. Among them, we focus on a typical boosting algorithm, adaboost which constructs a strong classifier by linear combination of simple weak classifiers (Bishop, 2006). In addition, we also focus on one of a decision tree classifier, random forest (RF), which is an ensemble classifier that consists of many decision trees and outputs the class by voting of individual decision trees (Breiman, 2001). Outline of algorithm is shown below:

Step-1 Create some number of bootstrap samples from the original learning data set. A number of random sampled attributes is recommended to be square root of original attribute number.

Step-2 Create best split decision tree using each bootstrap sample data. Here, each tree is fully grown and not pruned.

Step-3 Construct the final classifier by voting of each decision tree result.

In this RF algorithm, classification and regression tree (CART) algorithm is used for individual decision tree of a bootstrap sample. So, each decision tree is chosen so as to maximize Gini's diversity index (Witten and Frank, 2005).

The above adaboost or RF is useful for not only classification but also knowledge discovery, since we can know what attributes of feature parameters are important in these algorithms.

In the present research, we will examine the monitoring performance for combination of three feature extraction methods shown in the previous section and four classification methods, LDA, adaboost, RF and CART.

2.3 Performance evaluation using receiver operating characteristic (ROC)

Receiver operating characteristic (ROC) curve is a graphical plot which illustrates the performance of a binary classifier as its discrimination threshold is varied. It is created by plotting the fraction of true positives out of the positives (normal) data (TP) vs. the fraction of false positives out of the negatives (abnormal) data (FP), at various threshold settings. Here, we have another definitions of true negative (TN) and false negative (FN). According to the definitions, TN+TP=1 and FN+FP=1 hold. TP could be regarded as the index of sensitivity, and FP could be regarded as the index of robustness. In other word, if TP is high, we can regard that the discrimination method is sensitive, and, if FP is low, we can regard that the discrimination method is robust. Usually, the ROC curve is plotted by changing the discrimination threshold. But, we utilize this to compare the above mentioned various feature extraction and classification method combinations. Then, we will try to find both sensitive and robust health monitoring algorithm for rotating machine based on the ROC curve. This procedure could be said as the integration phase of diversified monitoring methods.

3. Anomaly discrimination mock-up test

3.1 Mock-up test facility

Figure 1(left) shows the mock-up test facility for rotating machine anomaly simulation. Here, the motor is located the left-side, and, connected to the shaft of rotator via the coupling. In two ball bearings, the right-side bearing can be replaced to defected one in order to simulate anomaly operation. In this research, the inner ring defect bearing is used for anomaly operation.

In the experiment, we measured two kinds of sensor data, an attached type acceleration sensor and a non-attached sound sensor (microphone) under the normal and abnormal conditions. The acceleration sensor was attached near the right-side bearing. The microphone measured the sound data at 10cm away from the right-side bearing. A merit of microphone usage in condition monitoring is its easiness of measurement. But, we have to take into account its poor sensitivity. So, both sensors' data were measured in this experiment and compared each other to quantitatively evaluate the sensitivity for anomaly detection. The vibration and sound signals were measured during 50 seconds length. The sampling frequency of vibration and sound signals were 25.6kHz and 44.1kHz, respectively. The 50 second length data were divided into 250 case's data of each 0.2 second length and used for the following analysis.

Figure 1(middle and right) is the comparison of log-APSD between normal and abnormal conditions. Here, 250 cases of vibration and sound data are shown. In this figure, we can see that overlap is seen between the normal and abnormal data. The overlap of vibration data is smaller than the sound data. Hence, the vibration data are easier to distinguish the abnormal data from normal ones than the sound data.

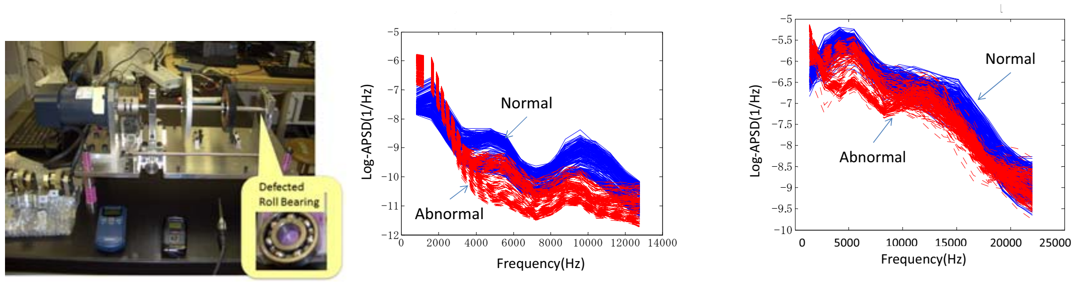


Figure 1: Mock-up test facility of rotating machine and data logging system (left) and comparison of log-APSD between normal and inner ring defect anomaly (middle: acceleration sensor, right: microphone)

3.2 Test results

Each 250 cases' experimental data of normal and abnormal states are divided into training and test data set of 125 cases each. After learning the classification model using the training data set, TP and FP are evaluated using remaining 125 cases test data set of normal and abnormal states. This evaluation was made for vibration and sound data using three feature extraction methods and four classification methods mentioned in the previous section. The results are summarized in Table 1. It is seen that the TP and FP results depend on the combination of features and classification methods. The ROC curves of normal and abnormal classification are shown in Fig. 2 for the vibration and sound data. This figure shows that vibration data measured by accelerometer are superior to sound data since the ROC points are located in the upper left region. As for individual methods, the combination of log-APSD/RF and Cepstrum/LDA has perfect classification performance for both vibration and sound data. Since this result is obtained just from the inner ring defect anomaly data and also the length of experimental data was not enough long, the present conclusion is not universal one. However, this table shows importance of the choice of feature extraction and classification methods. Also, the fact that RF is superior to CART suggests a bootstrap method is useful to obtain reliable results when the training data are limited.

In another point of view, Fig. 3(left) shows an example of the mean decrease Gini's index obtained by RF analysis using log-APSD features. Higher scores mean high contribution for classification. In this case, the best two attributes were APSD2 and APSD4 which correspond to the amplitude of second and fourth frequency points. Figure 3(right) shows comparison of normal and abnormal states using amplitudes of these two attributes. We can see these two attributes can effectively discriminate normal and abnormal states. This result also suggests RF is useful to find new knowledge to classify machine states, that is, knowledge discovery.

Table 1: Summary of TP and FP evaluation

data	feature extraction	classification	Attribute Number	TP (%)	FP (%)
sound	log-APSD	LDA	16	100	0
sound	log-APSD	adaboost	16	72	0
sound	log-APSD	CART	16	72	0
sound	log-APSD	RF	16	100	0
sound	PCA	LDA	6	75.2	8.8
sound	PCA	adaboost	6	76.8	19.2
sound	PCA	CART	6	72	0
sound	PCA	RF	6	80.8	24.8
sound	Cepstrum	LDA	16	100	0
sound	Cepstrum	adaboost	16	100	49.6
sound	Cepstrum	CART	16	100	4
sound	Cepstrum	RF	16	100	0
vibration	log-APSD	LDA	16	100	2.4
vibration	log-APSD	adaboost	16	80.8	0
vibration	log-APSD	CART	16	100	2.4
vibration	log-APSD	RF	16	100	0
vibration	PCA	LDA	6	100	0
vibration	PCA	adaboost	6	87.2	0
vibration	PCA	CART	6	100	2.4
vibration	PCA	RF	6	100	7.2
vibration	Cepstrum	LDA	16	100	0
vibration	Cepstrum	adaboost	16	100	8
vibration	Cepstrum	CART	16	100	0
vibration	Cepstrum	RF	16	100	4

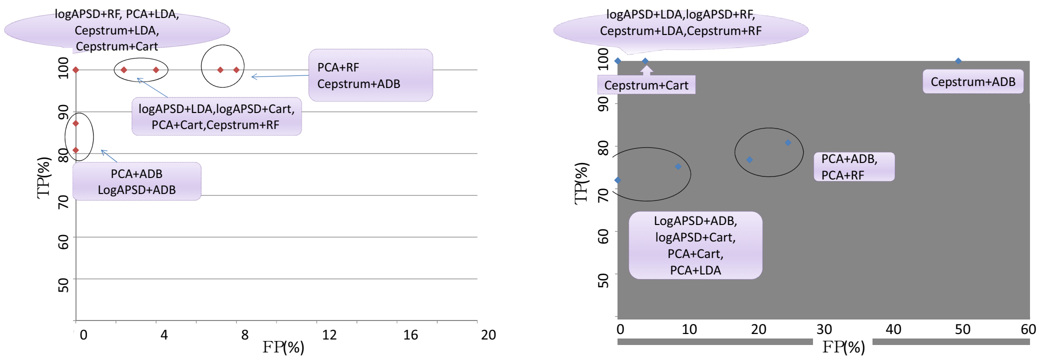


Figure 2: ROC curve of normal and abnormal state classification (left: vibration, right: sound)

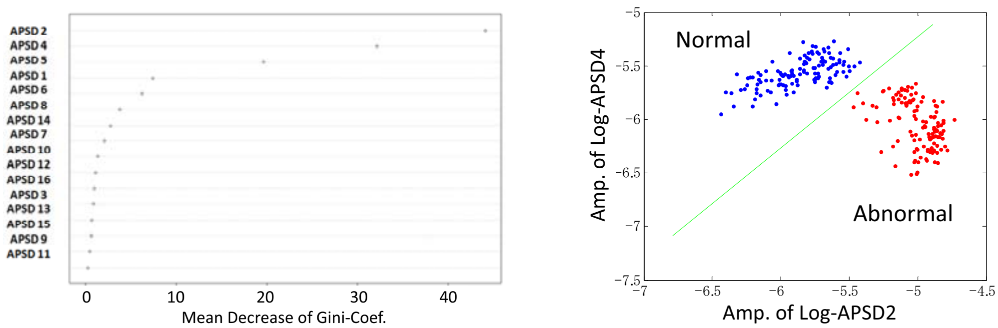


Figure 3: Mean decrease Gini's index by RF (sound data, log-APSD) (left) and comparison of normal and abnormal states using amplitude of log-APSD 2 and 4 (sound data) (right)

4. Bearing wear acceleration test

4.1 Mock-up test facility

In this section, we will discuss rotating machine failure mechanism by deterioration acceleration experiment. This is the most important issue in health monitoring. This experiment was sponsored by Japan Society of Maintenology and executed at TRIBOTEX Company. Figure 4 is photograph of roll bearing deterioration test facility. By adding excessive load on the bearing, the deterioration was accelerated. Here, 450 minutes continuous operating test was done until the bearing broke down. During the experiment, three kinds of data, vibration by accelerometer, number of acoustic emission (AE) per second, and wear particle number in lubricating oil, were measured. Here, vibration data were measured every 5 minutes. The vibration signal was measured with 0.4msec sampling interval. Detailed parameters of the rotating machine and the bearing are shown in this figure.

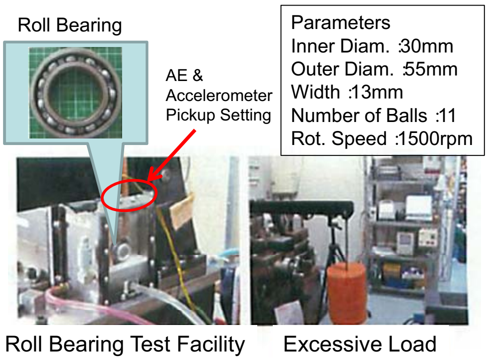
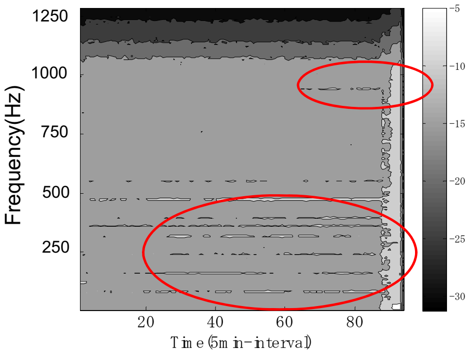


Figure 4: Test facility of roll bearing deterioration experiment by excessive load adding

4.2 Test results and discussions

Figure 5 shows the time-frequency trend of APSD (left) and the trend of AE count, overall amplitude of vibration, and particle number in the lubricating oil (right). Here, it is seen that the AE count starts to increase around 400 minutes after the test start whereas the overall amplitude and particle number start to increase around 440 minutes. Also, in the time-frequency trend of APSD, it is seen amplitude values at several frequency shown by circle increase gradually. Obvious change of overall vibration amplitude and wear particle number around 440 minutes suggests some critical break down occurred in the bearing.

Considering these data, we could presume the following bearing wear mechanism: (1) Small wear begins gradually around 50 minutes after the test start, since wear particle number gradually increase, and APSD shape, especially, higher modes caused by interaction of balls and inner/outer rings increase gradually. (2) Microcracks begin to occur around 400 minutes, since AE number begins to increase obviously. (3) Break down of bearing occurs around 440 minutes, since apparent increase of vibration and particles is observed.



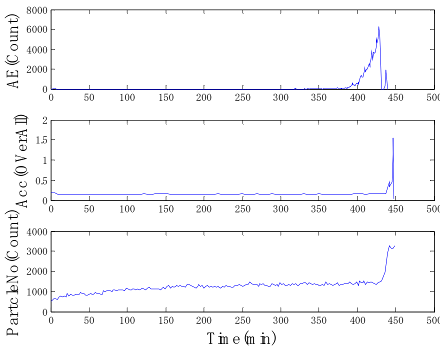


Figure 5: Time-frequency trend of APSD of accelerometer signal during deterioration test (left) and comparison of AE count, overall vibration amplitude and particle count trend (right)

Figure 6 shows typical APSD at different time points compared with the initial APSD. Here, the complicated higher oscillation modes are observed, which are related to the basic rotating frequency, 25Hz, and its integral multiplication. Among them, three typical frequency's amplitude trends at 80Hz (3N), 235Hz (9N) and 470Hz (19N) are shown in Fig. 7. Here, the amplitudes of 3N and 9N largely increase at 90 count whereas the amplitude of 19N diminishes at the same count. This would imply the oscillation mode change due to break down of one of the balls in the bearing. After the experiment, we confirmed break down of the ball. These experimental evidences suggest us the importance of diversified sensing data, here, AE, overall vibration amplitude and frequency spectrum, in order to presume the failure mechanism.

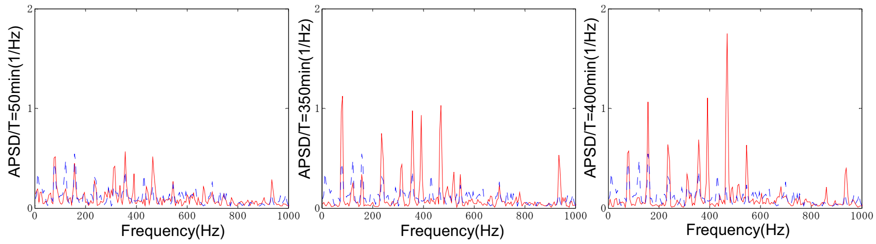


Figure 6: APSD at T=50min(left), 350min(middle), 400min(right) (Blue-dotted: Initial APSD at T=15min)

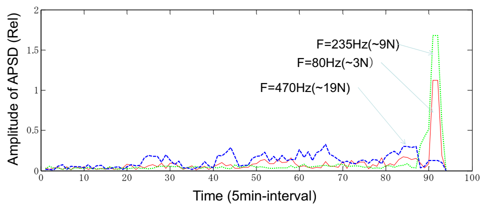


Figure 7: Trend of vibration amplitude on typical frequency

5. Conclusions

Two kinds of mock up test results of rotating machine health monitoring are shown in this paper. Here, various kinds of feature extraction methods, classification methods and sensing methods are mutually compared. In the analysis of simulated anomaly experimental data, it is shown that combination of feature extraction methods and classification methods yields different monitoring performance. We can expect that reliability of health monitoring would increase by integrating these diversified methods through ROC evaluation. In the deterioration acceleration experiment, it is shown the different kinds of sensing data are indispensable to understand the failure progress mechanism.

Through these analyses, it is shown the diversification and integration of sensing methods and data processing algorithms is important for reliable health monitoring.

References

Bishop C.M., 2006, Pattern Recognition and Machine Learning, Springer-Verlag

Breiman L., 2001, Random Forests, Machine Learning, 45 (1), p.5–32

Furui S., 1992, Acoustic and Speech Engineering, Kindai-kagaku-sha, Japan

Kanemoto S., 2009, Sensitivity Enhancement of Acoustic Monitoring Using Kernel PCA and Probabilistic Neural Network, NPIC&HMIT 2009, Knoxville, USA

Kanemoto S., 2010, Acoustic Monitoring of Rotating Machine by Advanced Signal Processing Technology, International Journal of Nuclear Safety and Simulation, 1(1)

Tamaoki T., Enomoto M., Kanemoto S., Higuma K., Nagamori A., 2003, Acoustic Diagnosis Using Principal Component Analysis, CD-ROM Proceedings of Dynamics and Design Conference, Kawasaki, Japan. (in Japanese)

Witten H., Frank E., 2005, Data Mining, Elsevier