Condition monitoring using compressive measurement with variance considered machine algorithm

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ABSTRACT

In this study, compressive sensing approaches for condition monitoring are proposed to demonstrate their efficiency in handling a large amount of data and the improved damage detection capability. A built-in rotating system was used for demonstration. Data were then compressively sampled to obtain compressed measurement. For damage detection, Variance considered machine (VCM) algorithm was employed to classify failure modes of rotating systems. The experimental results showed that the proposed method could effectively improve the data processing speed and the accuracy of condition monitoring of rotating systems.

1. INTRODUCTION

Condition monitoring is a technique that measures the vibration signal of the machinery and detects damage in the rotating body [1]. Extensive research efforts have focused on damage detection and classification [2]. In order to diagnose the target system accurately, many sensors with a high-sampling frequency are deployed, which requires to process a huge amount of data. . Donoho [3] proposed a compressive sensing technique to overcome such difficulties. With compressive sensing, the length of the measurements is significantly shorter than that of the original signal.

In this study, compressive sensing is applied to condition monitoring. Various damage sensitive features were extracted from the compressive measurement and damage detection and discrimination were conducted by using a statistical and machine learning algorithm.

2. COMPRESSIVE SENSING

In 2006, Donoho[3] proposed compressive sensing that could recover signals without measuring the signals a certain level in the Nyquist sampling frequency under a certain condition i.e , Sparsity.

This sparse signal can be recovered into the original signal by the compressive sensing employing Eq(1)

$$y = \Phi x \qquad (1)$$

Where y refers to the signal measured though compressive sensing and x refers to the original signal. Here, Φ is matrix of the compressed measurement, which is applied to the amount of data held by x to yield a small amount of compressed data y. Matrix Φ shall satisfy the restricted isometry property(RIP) condition that matrix Φ projects signal x with uniform energy, and the signal projected with constant energy can be reliably compressed and recovered. For a compressive measurement matrix that saticsfies the above condition, the random Gaussian matrix with independent and identical distributions are mainly used.

In this study, signal features were extracted from the compressive measurement without the reconstruction process.

3. STATISTICAL CONDITION MONITORING TECHNIQUE

3.1. Selection of signal features appropriate for condition monitoring

Twenty signal features are used to quantitatively represent the status of a rotating system. The selected signal features are widely used signal features in condition monitoring, and are the same as those used in the studies by Youn et al. [4]. As listed in Table 1, twenty health signal features were extracted, where N refers to the number of measured data samples and x(n) refers to a data value in each sample.

Table 1. Signal features in time domain

Features	Formula	Features	Formula
P1	$\frac{\sum_{n=1}^{N} x(n)}{N}$	P11	$\frac{\sum_{n=1}^{N} x(n)^4}{N(P2^4)}$
P2	$\sqrt{\frac{\sum_{n=1}^{N}(x(n)-P1)^2}{N-1}}$	P12	$\max(x)+\frac{max(x)-min(x)}{2(N-1)}$
P3	$\max\lvert x(n)\rvert$	P13	$\min(x)+\frac{max(x)-min(x)}{2(N-1)}$
P4	$\sqrt{\frac{\sum_{n=1}^{N}(x(n))^2}{N}}$	P14	$\frac{P4}{P1}$
P5	$(\frac{\sum_{n=1}^{N}\sqrt{\lvert x(n)\rvert}}{N})^2$	P15	$\frac{P4}{max(x(n))}$
P6	$\frac{\sum_{n=1}^{N}(x(n)-P1)^3}{(N-1)P2^3}$	P16	$-\sum_{i=1}^{N} P(x_i)lnP(x_i)$
P7	$\frac{\sum_{n=1}^{N}(x(n)-P1)^4}{(N-1)P2^4}$	P17	$\frac{P4}{\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert}$
P8	$\frac{P4^2}{\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert}$	P18	$\frac{P5}{\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert}$
P9	$\frac{P5^2}{\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert}$	P19	$\frac{\sum_{n=1}^{N}(x(n)-P1)^2}{N-1}$
P10	$\frac{\sum_{n=1}^{N} x(n)^3}{N(P2^3)}$	P20	$\frac{\sum_{n=1}^{N}\lvert x(n)\rvert}{N}$

3.2. Variance Considered Machine (VCM)

VCM is a classification algorithm which considers variance, averages, and the maximum margin between the data groups.[5]

According to Bayes' theorem, the posterior probability P(ck|x) is calculated in Eq. (2) using the class conditional probability density function P(x|ck) and the prior probability P(ck).

$$P(ck|x)=\frac{P(x|ck)P(ck)}{P(x)} \quad (2)$$

The error probability can be calculated using Eq. (3).

$$P(error)=P(x \in R2,c1)+P(x \in R1,c2)$$

$$=\int_{R2} P(x|c1)P(c1)\,dx + \int_{R1} P(x|c2)P(c2)\,dx \quad (3)$$

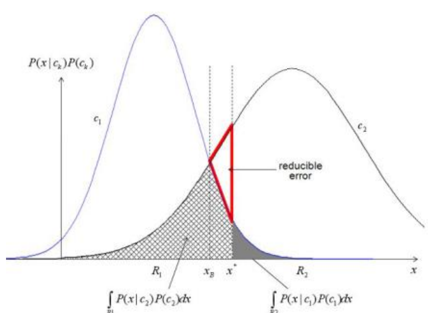


Figure 1. Variance of error probabilities according to the decision point x*

In Fig. 1, the area represented by the diagonal lines is the first part of the error probability equation, and the gray area is the second part of the equation. The error probability changes depending on the position of x*; the error probability becomes minimal by reducing the error by that of the reducible error (red triangle) when x* moves from xA to xB.

This is the Bayesian optimal boundary that minimizes the error probability. VCM has applied the Bayesian decision theory to SVM.

4. EXPERIMENTAL DEVICE AND PRCEDURE

For experiments, the RK4 system was used, as shown in Fig. 2. In the experiment, three conditions were applied: normal, misalignment damage, and bearing damage. For the bearing damage, a normal bearing was replaced with three stage damaged bearings to simulate the damage. Accelerometers were attached at both ends and at the center of the structure to acquire the data, and 5kHz and 25kHz sampling frequencies were used. After the signal measurements, compressed signals were obtained using the compressive operation matrix.

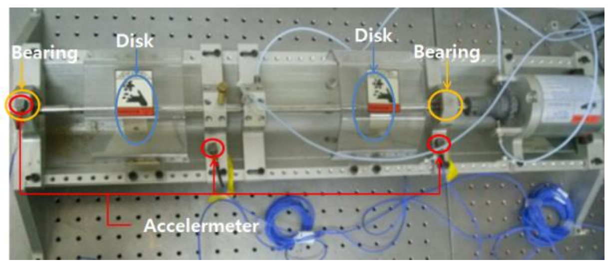
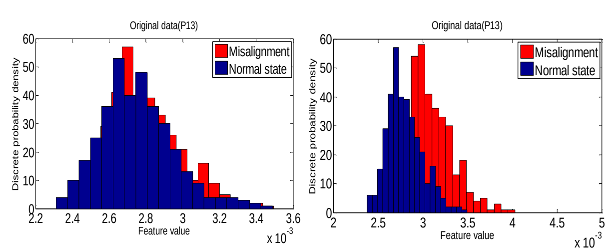


Figure 2. Rotational system

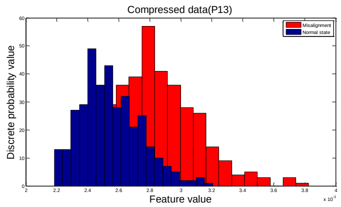
5. EXPERIMENTAL RESULTS

5.1. Comparison of the compressed measurement and original data

The results of the condition monitoring using the compressed measurements are compared to the original data.. For the damage, misalignment damage was used. Fig. 3 shows the comparison result of the P13 signal features. When damage occurrs, high frequency components clearly indicate the presence of damage. However, it was difficult to distinguish the damage by using the data measured at a low sampling frequency (5 kHz). With the higher sampling frequency, the difference in the distribution of the signal features due to the damage could be observed. The difference in the distribution of the signal features also could be verified for the compressed data. It should be noted that the compressive data used in this analysis (c) is 1/5 of the original data length, which is the same as that measured at the sampling frequency of 5 kHz..



(a) (b)



(c)

Figure 3. Measured data at sampling frequency of 5 kHz (a), 25 kHz (b) and One fifth of the data measured at sampling frequency of 25 kHz (c)

5.2. Fault Diagnosis of Rotating Systems using VCM

Without using the reconstruction process, the features are extracted from the compressive measurements. The extracted features were then used for diagnosis of the rotating system.

The optimal features were selected based on the Z-score method. The VCM process is shown in Fig. 4. In Fig. 4(a), the x axis represents the P13 feature, the y axis represents the P5 feature, and each state is projected into a 2D space.

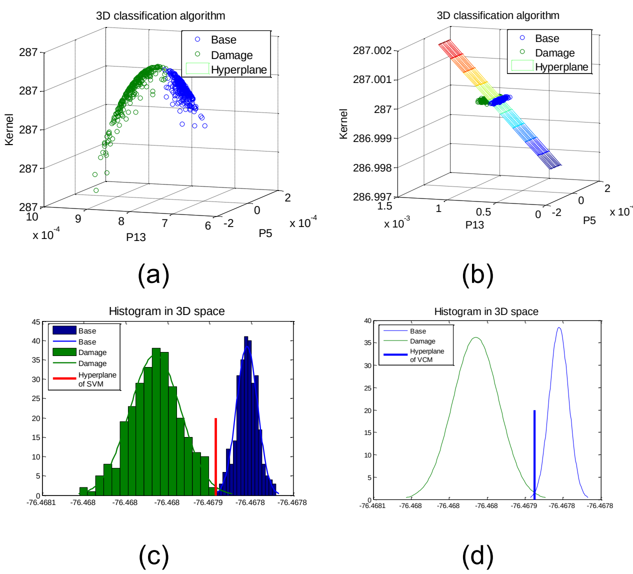


Figure 4. Flow of Variance Considered Machine (VCM)

Fig. 4(b) shows the normal and damage data classified using SVM. We analyzed the histogram of the left and right data group that were separated by the hyperplane generated by SVM. The output is shown in Figs. 4(c) and 4(d). The blue line in Fig. 4(c) indicates the position of the hyperplane in SVM, and the red line in Fig. 4(d) (which is the Bayesian optimal boundary that minimizes the error probability) indicates the position of the hyperplane in the VCM. After changing the position of the hyperplane, machine learning was performed using 700 training data sets and 380 test data sets.

Table 2. Estimation of 3D damage classification performance

	Normal state	Bearing damage	Misalignment
SVM	96%	100%	94%
VCM	98%	100%	98%

Table 2 lists the results of the classification using SVM and VCM for the normal state, bearing damage, and misalignment groups. When SVM was used, the accuracy rate of the normal group was 96%, that of the bearing group was 100%, and that of the misalignment group was 94%. However, the accuracy rate improved with the application of VCM. The accuracy rate of the normal group was 98%, that of the bearing group was 100%, and that of the misalignment group was 98%. Therefore, it was confirmed that the fault detection capability of the VCM is superior to that of SVM.

6. CONCLUSION

In this study, compressive sensing was applied to condition monitoring of a rotational system. For damage classification a new machine learning algorithm, referred to as Variance Considered Machine(VCM), is applied to classify the failure modes of rotating systems. The experimental results showed that the proposed method could effectively improve the data processing speed and accuracy of the condition monitoring of rotating systems.

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