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Application of compressive sensing and variance considered machine to condition monitoring

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Abstract. A significant data problem is encountered with condition monitoring because the sensors need to measure vibration data at a continuous and sometimes high sampling rate. In this study, compressive sensing approaches for condition monitoring are proposed to demonstrate their efficiency in handling a large amount of data and to improve the damage detection capability of the current condition monitoring process. Compressive sensing is a novel sensing/sampling paradigm that takes much fewer data than traditional data sampling methods. This sensing paradigm is applied to condition monitoring with an improved machine learning algorithm in this study. For the experiments, a built-in rotating system was used, and all data were compressively sampled to obtain compressed data. The optimal signal features were then selected without the signal reconstruction process. For damage classification, we used the Variance Considered Machine, utilizing only the compressed data. The experimental results show that the proposed compressive sensing method could effectively improve the data processing speed and the accuracy of condition monitoring of rotating systems.

Keywords: compressive sensing; condition monitoring; receiver operating characteristic; variance considered machine

1. Introduction

Condition monitoring is the process of detecting damage in rotating machinery. It usually measures vibration signals to assess the parameters of machine condition, which allows users to reduce maintenance costs and prevent catastrophic failures. Current practice of condition monitoring identifies feature changes in the time, frequency, and time-frequency domain and applies statistical models to diagnose structural anomaly. In addition, machine learning algorithms, including neural networks and support vector machines are increasingly used in condition monitoring to overcome the uncertainty and non-linearity problems of measured signal parameters. Literatures in this area are vast and well-summarized in Carden and Fanning (2004), Peng and Chu (2004), Samuel and Pines (2005), Jardine *et al*. (2006) and Tchakoua *et al*. (2014).

In order to accurately diagnose rotating systems, a number of sensors are usually deployed, measuring the vibration signals at a high sampling frequency. A significant data handling problem is encountered in such cases (Hakim and Abdul Razak 2014, Jung and Koh 2014). We are trying to address this issues by introducing compressive sensing into the condition monitoring practice.

Donoho (2006) proposed a compressive sensing technique as a new data sampling method. Compressive sensing involves the measuring and recovering of a signal the length of which is significantly shorter than that of the original signal. Because this method measures only a small number of data from the data acquisition stage, signal processing efficiency can be improved. Compressive sensing was applied in various fields such as image processing and structural health monitoring. Mascarenas *et al.* (2013) developed compressive sensing data acquisition devices using a microcontroller and applied the compressive measurements to structural damage detection. Höglund *et al.* (2014) performed damage detection of bridges by recovering the compressive sensing data, while Bao *et al.* (2010) compared the performance of the compressive sensing technique and other data compression techniques. Jayawardhana *et al.* (2017) compared the performance wavelet compression and compressive sensing techniques, and damage detection was executed using reconstructed data. Park *et al.* (2014) conducted modal analysis using compressed data without reconstructing the original measurements.

In the present study, compressive sensing, which has been applied in many other fields, is applied to condition monitoring. Various damage sensitive features were extracted from the measured data by compressive sensing, and damage detection and classification were carried out using several statistical parameters and a machine learning algorithm, referred to as variance considered machine.

2. Theory of compressive sensing

Currently, the signal measurements are based on the Nyquist sampling theory, which specifies that the sampling rates need to be at least two times the signal bandwidths to preserve all the information in the signals. For condition

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monitoring applications, data are generally collected using a distributed sensor network with a high sampling frequency, which creates a number of problems, including a lack of storage space and an increase in the signal processing effort.

Compressive sampling was introduced by Donoho (2006), proposing that compressive sensing can recover signals without the need to measure the signals above a certain level in the Nyquist sampling frequency under a certain condition.

The theory of compressive sensing states that sampling rates depend on the sparsity of signals. Natural signals are normally not sparse by themselves. However, they are typically sparse when expressed in the Ψ basis, if one choose the discrete Fourier transform (DFT) as the sparsity basis.

$$s=\Psi^{-1}x \tag{1}$$

where $x \in \mathbf{R}^n$ is the signal in the temporal domain and and **s** is the sparse coefficient sequence of x in the Ψ basis. As shown in Fig. 1, typical time domain signals are represented as a sparse signal in the frequency domain, which contains only a few dominant frequency component. Therefore, Ψ^{-1} is the inverse discrete Fourier transform.

The process of compressive sensing can be represented by Eq (2)

$$y = \Phi x \tag{2}$$

where x refers to the original signal with the length of N, Φ is the matrix of the compressed measurement with the size of MxN, and y is the compressively sampled signal of length M. In this case, the compression ratio is M/N.

The matrix Φ shall satisfy the restricted isometry property (RIP) condition, which is represented by Eq. (3),

$$(1-\delta_{2K})\,\|x\|_2 \le \|\Phi x\|_2 \le (1+\delta_{2K})\,\|x\|_2 \tag{3}$$

Where δ_{2K} represents the RIP condition parameter. If the value of δ_{2K} approaches to zero, the left and the right side of Eq(3) becomes approximately the same and the matrix Φ is said to satisfy the requirement for compressive sensing.

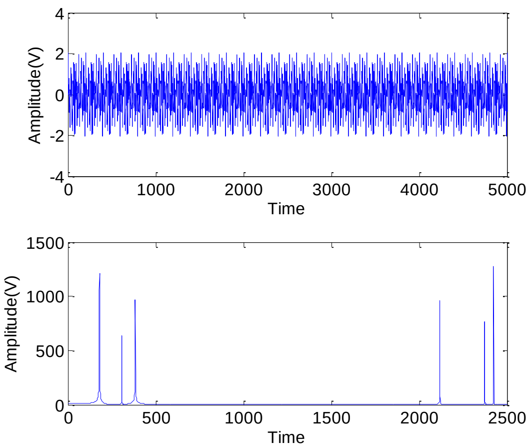


Fig. 1 Signal in the time and frequency domain

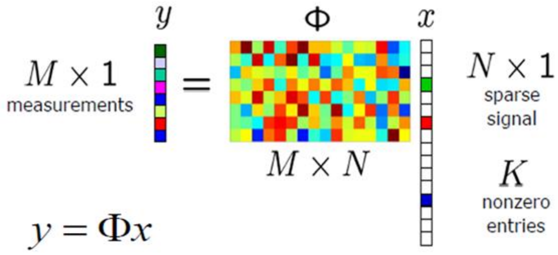


Fig. 2 Mathematical model of compressive sensing

In summary, an RIP condition refers that matrix Φ projects signal x with uniform energy, and the signal projected with constant energy can be reliably compressed and recovered (Tropp and Gilbert 2007). For a compressive measurement matrix that satisfies the above condition, Gaussian or binary matrices with independent and identical distributions are mainly used.

The compressively sampled signal can be recovered to the original signal by applying the inverse process of Eq(2). This process usually imposes an underdetermined problems, which could be solved by the application of the L1 minimization algorithm or Greed algorithm (Tropp 2004, Tropp and Gilbert 2007, Needell and Tropp 2009). Fig. 2 shows the compressive sensing process.

A problem of incomplete recovery can occur while recovering the original signal from the compressed signal. The characteristics of the original signal and the compressive ratio should be carefully examined for such cases. A more comprehensive overview of compressive sensing could be found in Donoho (2006) and Jayawardhana *et al.* (2017).

In this study, damage sensitive features were extracted from the signals measured by compressive sensing without incorporating the reconstruction process.

3. Experimental setup and procedure

For experiments, the RK4 equipment of Bently Nevada was employed, as shown in Fig. 3. At both ends of the structure, a journal bearing supports the shaft on which two 0.8 kg disks are mounted. This system allows several typical structural damage to be readily and repeatedly introduced for condition monitoring tests.

Three accelerometers (PCB 357A08) were attached at both ends and at the center of the system to measure the vibration signals at the sampling frequency of 5 kHz with a dynamic signal analyzer (NI-4431). First, the measurements are taken for 1,080 second under the normal condition. After then, two simulated damage conditions were imposed; misalignment and bearing damage. For the bearing damage, a normal bearing was replaced with a damaged bearing, and for misalignments, a mass (0.01 kg) was attached to the disk mounted to the rotating body. At each condition, the responses are again measured for 1,080 second. The measured signals are then segmented into a 1 second interval, constructing 1,080 independent data sets for each condition.

After the measurement, compressed signals were acquired using the compressive operation matrix to simulate the compressive sensing technique. This procedure was taken because the authors do not have a hardware to directly measure compressively sampled data. A binary matrix was used as the compressive measurement matrix Φ for this study. The hardware implementation of compressive sensing in the structural dynamics field was first attempted by Mascarenas *et al*. (2013), in which the authors uses a microcontroller to measure the compressive data, while the other areas, such as camera image processing, utilizes hardware that directly measures the compressive data.

After the compressive sampled data are obtained, the original signals are reconstructed to analyze the data. Figure 4 shows the comparison between the original and the reconstructed signals from the compressed data with the compression ratios of 2, 4, and 10, respectively. In the case where the compression ratio was set to 2, the overall signals are very similar to the original signal as the signal could be reconstructed with only a slight distortion. In cases where the compression ratios were set to 4 and 10, the signal could also be reconstructed with high accuracy, although the degree of distortion is increased.

The correlation coefficients between the original and reconstructed signals are used to assess the performance of the reconstruction. The coefficient was 0.98 when the compressed signal of compression ratio of 2 is reconstructed. As the compression ratio increased, the signal reconstruction performance is decreased to 0.90 (compression ratio: 4), and 0.86 (compression ratio: 10). Even with the high compression ratio, it still shows the high performance in reconstruction.

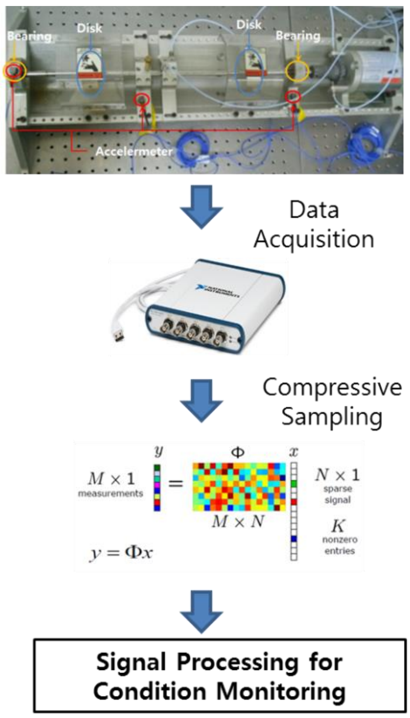


Fig. 3 RK4 rotating system used for experiment

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	$\max\|x(n)\|$	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	$(\frac{\sum_{n=1}^{N}\sqrt{\|x(n)\|}}{N})^2$	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	$\frac{P4}{\frac{1}{N}\sum_{n=1}^{N}\|x(n)\|}$
P8	$\frac{P4^2}{\frac{1}{N}\sum_{n=1}^{N}\|x(n)\|}$	P18	$\frac{P5}{\frac{1}{N}\sum_{n=1}^{N}\|x(n)\|}$
P9	$\frac{P5^2}{\frac{1}{N}\sum_{n=1}^{N}\|x(n)\|}$	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	$\frac{\sum_{n=1}^{N}\|x(n)\|}{N}$

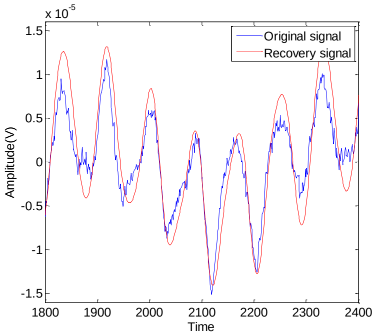
It should be noted that the reconstruction performance of compressive sensing is not better than other signal compression techniques, such as wavelet transform. The wavelet transform usually perfectly reconstruct the original signal even with a very high compression ratio (Bao *et al.* 2010). The difference between compressive sensing and other widely used signal compression technique, however, is that the compressive sensing measures and compresses the signals at the data acquisition stage. Other techniques, such as wavelet transform, need to take the full measurements and the compression should be made as an additional step. This characteristic certainly provides certain advantages in signal measurement and processing, including the requirements of much smaller data storage, energy, and computation.

Fig. 5 shows the signals measured by the original Nyquist sampling frequency and those by compressive sensing under the normal condition. The compressive ration was set to 4, reducing the original data to one fourth the size.

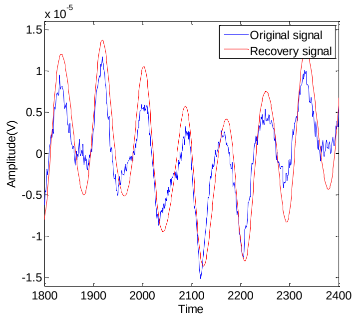
4. Compressive sensing to condition monitoring

To apply the compressively sampled data for damage detection and classification, 20 signal features that can quantitatively represent the status of a rotating system was used. The selected signal features are widely used in condition monitoring, used in the study by Loutas et al. (2009). In table 1, N refers to the number of measured data samples and x(n) refers to a data value in each sample.

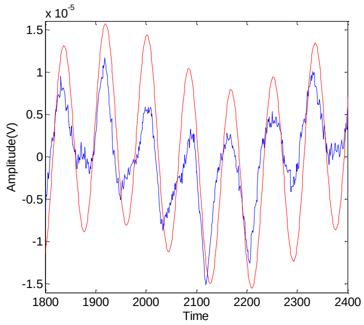
As first, the changes in the original signals and the changes in the compressed signals with the introduced damage were analyzed to identify whether the characteristics of the original signal (20 features in Table 1) are preserved in the compressed signal.



(a) Compression ratio of 2 (time domain)

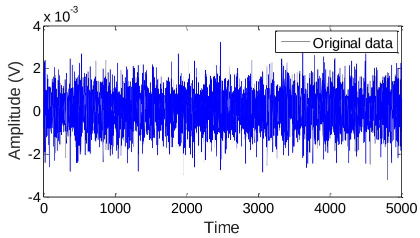


(b) Compression ratio of 4 (time domain)

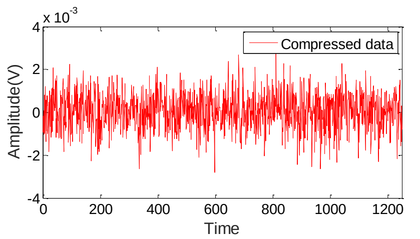


(c) Compression ratio of 10 (time domain)

Fig. 4 Comparison of the original and reconstructed signals with different compression ratios

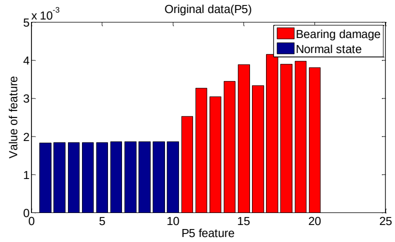


(a) Original data

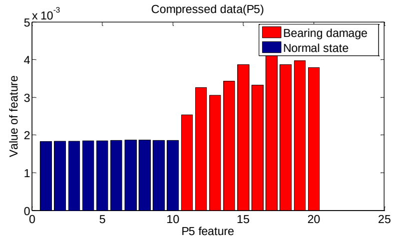


(b) Compressed data with compressive ratio of 4

Fig. 5 Original and compressive time domain data



(a) Original data



(b) Compressed data with compressive ratio of 4

Fig. 6 P5 feature changes with bearing damage

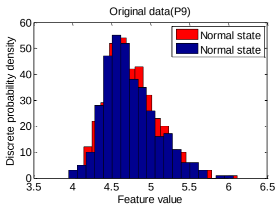
Fig. 6 shows the comparison result of the P5 feature changes with the bearing damage. As can be seen, the difference in the signal feature values between the normal and bearing damage in the original data was approximately 1.91 times, whereas the difference between the normal and bearing damage measured by compressive sensing (with compressive ratio of 4) was approximately 1.97 times, indicating a similar difference in the feature values between the original and the compressed data for the normal and bearing damage conditions.

All other signal features showed the same characteristics as the feature values changed at a constant rate regardless of the type of damage introduced. For instance, the P2 feature showed about the 2.1 times changes with the bearing damage in both original and compressed data, while P3 feature did not show any noticeable changes in both data with the introduced misalignment damage.

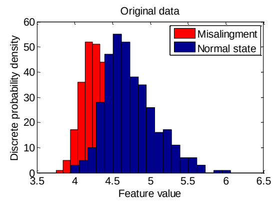
The results showed that the characteristics of the original signal are preserved in the compressed data. For this reason, the data measured by compressive sensing are directly used for condition monitoring without a reconstruction process in this study.

Fig. 7 shows histograms of P9 features under the normal and damaged conditions of the original and the compressed data (with compression ratio of 4).

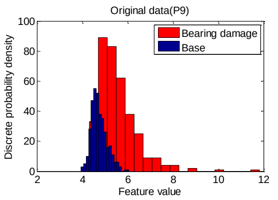
When the normal conditions measured at the different time were compared, no difference in the distribution was observed between both data groups. When the misalignment damage condition was imposed, both the original and the compressed data showed a slight deviation from the normal condition. With the bearing damage, the P9 feature show the clear separation between the normal and damaged condition from both the original and compressed data. The area under the receiver operating characteristic curve (AUC) value of the original data was 0.91, and that measured by compressive sensing was 0.86. AUC ranges from 0.5 to 1, in which AUC of 1 represents a perfect separation between two data groups, and 0.5 represents no separation between two data groups.



(a) Normal-normal conditions



(b) Normal-misalignment conditions

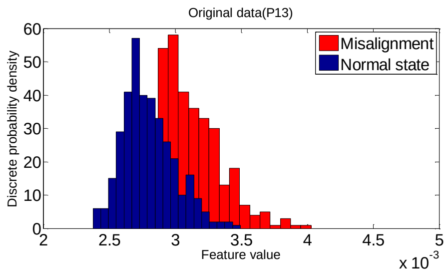


(c) Normal-bearing damage conditions

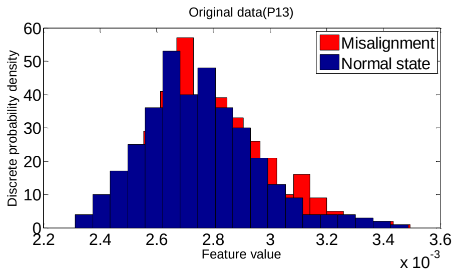
Fig. 7 Comparison of P9 feature changes from the original and compressed data

These results once again confirmed that the same damage detection performance could be achieved using only the compressed data without the reconstruction process. All the signal features from compressive sensing showed the comparable performance with the original data, demonstrating that the feature based condition monitoring can be performed using only the compressed data.

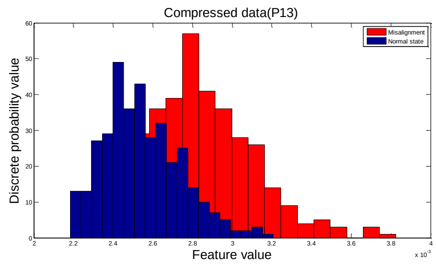
The data measured at a higher sampling frequency show a better sensitivity to a minor defect in a structure because the sensitivity is directly related to the wavelength of the excitation. Fig. 8(a) shows the P13 feature changes from the data measured at the sampling frequency of 25 kHz. The misalignment damage (a 0.006 kg mass attached to the disk) was introduced to the system. As can be seen, there is a clear separation between the normal and the damaged condition. The Fig. 8(b) shows the results of uniformly down-sampled the original data with the factor of 5, which reduced the size of the data to one fifth of the original data and effectively reduced the sampling frequency to 5 kHz. With the low-frequency sampled data, it was difficult to distinguish the damage as the figure illustrated. However, as can be seen in Fig. 8(c), the difference in the distribution of the signal features could be clearly identified for the compressed data with the same data length, as shown in Fig. 8(c). When the data measured at high sampling frequency are compressed, the dynamic characteristics of the data are preserved and the data would have a much higher sensitivity to defects in a system compared to the same length of the data measured at a lower sampling frequency, as illustrated in this example.



(a) Measured data at a sampling frequency of 25 kHz



(b) Down-sampled data at a sampling frequency of 5 kHz



(c) Compression ratio of 5

Fig. 8 Comparison of the original and compressed data at the same size

5. Compressive sensing with variance considered machine

Support vector machine (SVM) has been one of the most widely used machine learning algorithms in condition monitoring. SVM finds the hyperplane that best separates two data groups. SVM predicts the hyperplane with the maximum margin between the two data groups and performs binary classification of the datasets based on the hyperplane.

SVM considers only the maximum margin between the two data groups. Yeom et. al (2009) developed the Variance Considered Machine (VCM) algorithm, which improves the performance of SVM, by considering the variances, averages, and maximum margin between the data groups.

If two data groups (denoted as R_1 and R_2) are classified into two classes (denoted as c_1 and c_2), according to Bayes' theorem, posterior probability $P(c_k|x)$ is calculated by Eq. (4) using the class conditional probability density function $P(x|c_k)$ and prior probability $P(c_k)$. Here, $P(x|c_k)$ is the probability density function of *x* when the class is c_k.

$$P(c_k|x)=\frac{P(x|ck)P(ck)}{P(x)} \tag{4}$$

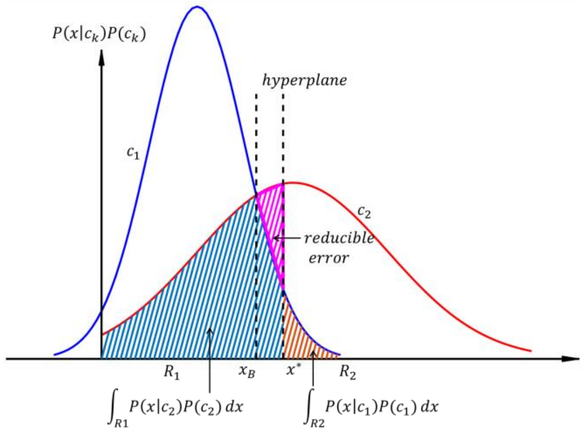


Fig. 9 Variance of error probabilities according to the decision point x^*

The error probability can be calculated using Eq. (5) based on the Bayesian decision theory.

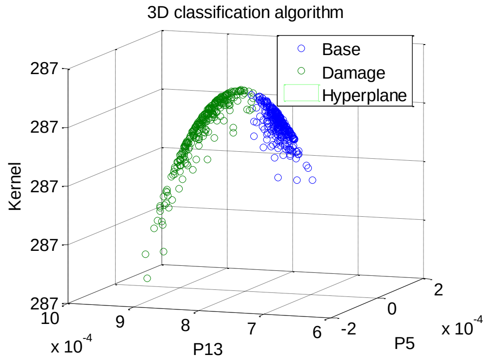
$$P(\text{error})=P(x\in R_2,c_1)+P(x\in R_1,c_2)$$
$$=\int_{R2}P(x|c1)P(c1)\,dx+\int_{R1}P(x|c2)P(c2)\,dx \quad (5)$$

In Fig. 9, the area represented by the diagonal lines is the first integral part of the error probability equation, and the gray area is the second integral part of the equation, when the hyperplane is set at x^* by SVM. Fig. 9 clearly shows that the error probability changes depending on the position of x^*. The error probability becomes minimal by reducing the error by as much as that of the reducible error (triangle) when x^* moves to x_B, which is the Bayesian optimal boundary that minimizes the error probability. As shown, VCM applies the Bayesian decision theory to improve the performance of SVM.

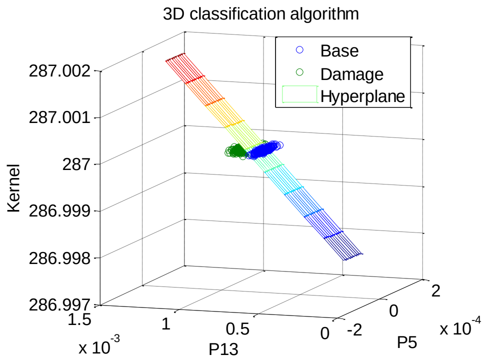
In this study, we extend the three-dimensional (3D) VCM by applying a kernel function to the two dimensional (2D) linear VCM developed by Yeom et al. (2009). The features used in this study are all directly extracted from the compressively sampled data without using the reconstruction process. First, the optimal signal features are selected which show a strong separation capability. The features are selected based on the Z-score method, and in this application, P5 and P13 are ranked the first and the second feature, respectively. Out of 1080 data sets, 700 data are used for training, and the remaining 380 data sets are used for the test.

The flow of VCM is shown in Fig. 10. In Fig. 10(a), the x axis represents the P5 feature, the y axis represents the P13 feature, and each state is projected into a 2D space. The 2D space is then expanded into a 3D space using Gaussian kernel function to increase the classification accuracy shown in Fig. 10(b). Figs. 10(c) and 10(d) shows the position of the hyperplane by SVM and VCM respectively. The hyper plane set by VCM is the Bayesian optimal boundary that minimizes the error probability.

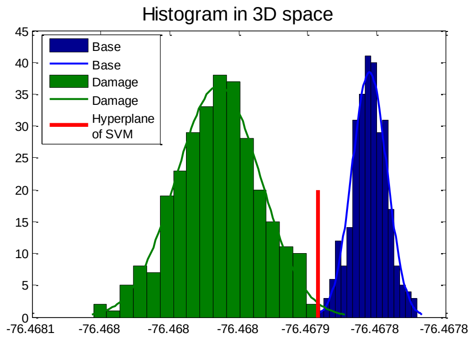
Table 2 lists the results of the classification using SVM and VCM for the normal state, bearing damage, and misalignment groups. When SVM was used, the accuracy rate of the normal group was 96%, that of the bearing group was 100%, and that of the misalignment group was 94%. However, the accuracy rate 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%.



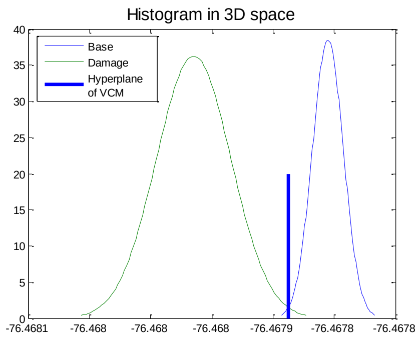
(a) 2D projection of features



(b) 3D projection of features



(c) Hyperplane by SVM



(d) Hyperplane by VCM

Fig. 10 Flow of Variance Considered Machine

Table 2 3D damage classification performance

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

It should be once again noted that this application of VCM was carried out by only using the features generated by compressively sampled data. The results confirm that compressive sensing could be used in condition monitoring with much smaller data sets, which could result in an improved data handling capability.

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6. Conclusions

In this study, compressive sensing was applied to the condition monitoring of rotational systems. Compressive sensing is a novel sensing/sampling paradigm that handles much fewer data than traditional sampling methods, in which data compression and measurement are simultaneously performed. While compressive sensing has been applied to many other engineering field, this study is the first attempt, to the authors' best knowledge, to apply the technique into the condition monitoring practice. For the experiments, a built-in rotating system was used. Through compressive sensing, it is possible to reconstruct the original signal with a high accuracy. The feature extracted from the data by compressive sensing and those extracted from the original data were also compared and the results showed that the damage detection characteristics of the signal features from the original data are preserved in the compressively sampled data. In addition, a new machine learning algorithm, referred to as Variance Considered Machine (VCM), is applied to classify failure modes of rotating systems using the signal features from compressed data. When compared to the performance of Support Vector Machine, the VCM showed the superior capability in classifying damage. The experimental results showed that the proposed compressive sensing could effectively improve the data processing speed and accuracy of the condition monitoring of rotating systems.

Acknowledgments

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