Acoustic monitoring of rotating machine by advanced signal processing technology

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Abstract: The acoustic data remotely measured by hand held type microphones are investigated for monitoring and diagnosing the rotational machine integrity in nuclear power plants. The plant operator's patrol monitoring is one of the important activities for condition monitoring. However, remotely measured sound has some difficulties to be considered for precise diagnosis or quantitative judgment of rotating machine anomaly, since the measurement sensitivity is different in each measurement, and also, the sensitivity deteriorates in comparison with an attached type sensor. Hence, in the present study, several advanced signal processing methods are examined and compared in order to find optimum anomaly monitoring technology from the viewpoints of both sensitivity and robustness of performance. The dimension of pre-processed signal feature patterns are reduced into two-dimensional space for the visualization by using the standard principal component analysis (PCA) or the kernel based PCA. Then, the normal state is classified by using probabilistic neural network (PNN) or support vector data description (SVDD). By using the mockup test facility of rotating machine, it is shown that the appropriate combination of the above algorithms gives sensitive and robust anomaly monitoring performance.

Keyword: Acoustic Monitoring, PCA, Kernel-based PCA, PNN, SVDD, Cepstrum

1 - Introduction

Condition based maintenance (CBM) is one of the important activities for both reliable and efficient nuclear power plant operation. Recently, the new maintenance regulation has started in Japan to allow the utilities to decide optimum maintenance and operating periods for the plants. This helps the flexible and efficient plant operation, however, at the same time, the responsibility of utilities increases to assure high plant reliability. From this point of view, the condition monitoring activities will be more and more important.

In the present paper, the acoustic data remotely measured by handy type microphones are investigated for monitoring and diagnosing the rolling bearing type rotational machine integrity in nuclear power plants. The plant operator's patrol monitoring is one of the important activities for the above-mentioned condition monitoring. However, remotely measured sound has some difficulties in its measurements for its precise diagnosis or quantitative judgment of rotating machine anomaly, since the measurement sensitivity is varied in each patrol, and also, is less than the attached type accelerometer.

Hence, the author investigates the various kinds of advanced acoustic signal processing methods to increase their sensitivity of anomaly monitoring. Furthermore, the robustness of the monitoring to the operating condition change is also discussed, since both the sensitivity and robustness are very important in practical applications. In the author's previous paper [1], the signal pre-processing method was proposed, where the acoustic signal is normalized based on the fundamental oscillation period which is extracted by a zero-crossing interval of filtered acoustic signal. Then, the individual periodic pattern is converted into the same length data and used for pattern recognition. In this study, it was noticed that the sensitivity and robustness of the monitoring largely depended on this pre-processing algorithm. So, effectiveness of signal pre-processing, or, in other words, signal feature extraction algorithms was further examined by using the mockup test facility of rolling bearing type rotational machine which can simulate

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various kinds of anomaly [2-4]. Here, the extracted signal feature patterns were classified by using both the standard principal component analysis (PCA) and kernel-based PCA (KPCA) approach, which were able to reduce the dimensions of feature vectors and extract an effective feature space for the visualization. The reason why different kinds of signal processing methods were examined was conducted in order to find both sensitive and robust methods for acoustic monitoring of rotating machines. Since the skilled human ability is superior to the machine learning capability from viewpoints of anomaly detection sensitivity, it is desired to investigate how to catch up the human ability by machine learning technologies. Furthermore, it should be noted that human experts also have the robust classification capability which can discriminate abnormal states from normal ones even though the machine is operated in different conditions. So, both sensitive and robust machine learning capability should be pursued by using the above signal processing methods, or, some heuristic data mining methods.

In the above research [1-3], extracted small dimension's feature vectors were modeled by the probabilistic neural network (PNN) and support vector data description (SVDD) in order to discriminate the normal state from the abnormal ones. Since the PNN or SVDD can classify the known normal state from other unknown abnormal states, so-called 'don't know states', it is very useful for automated condition monitoring. The developed algorithm was applied to the acoustic data measured by mockup test facility. Here, several kinds of known abnormal state data were measured, which consisted of inner and outer race defects, or bearing ball defects, as well as normal operation data in different rotating speed conditions.

In the present paper, the author will review the above results and discuss how the classification capability increases by introducing the new signal processing methods. Furthermore, robust classification capability to the operating condition change will also be discussed.

2 - Signal processing methods

2.1 - Pre-processing for feature extraction

For anomaly detection using acoustic signals, three kinds of steps will be proposed in the present paper: (1) acoustic signal pre-processing for feature extraction, (2) visualization in the two-dimensional space by extracting typical signal features, and, (3) evaluation of discrimination function for anomaly monitoring. In step (1), various kinds of methods have been examined by referring the speech or speaker recognition research technologies [5]. In this research area, various combinations of signal pre-processing and classification algorithms have been pursued to improve their speech recognition performance. So, these algorithms will be expected to increase the acoustic anomaly monitoring performance. Among them, the following three feature patterns are adopted and compared with each other.

2.1.1 - Log-scale auto-power spectral density (log-APSD)

This is a simple frequency spectrum of raw acoustic data. Here, the log-scale pattern of 0-22 kHz frequency range divided by 512 points is used as the feature vector. The frequency axis is treated by the linear scale. Each pattern is evaluated by 0.2 second length acoustic data. Also, in order to compensate the measurement sensitivity variation, each signal is normalized by its RMS (Root Mean Square) value.

2.1.2 - Mel-scale auto-power spectral density (Mel-scale-APSD)

Mel-scale is a perceptual scale of frequency pitches which is often used in speech recognition [5]. The frequency scale is converted into the following Mel-scale:

$$m = 1127 \times \log_e (1 + \frac{f}{700}) \tag{1}$$

Here, the 512 frequency resolutions are compressed into 30 dimensions by this transformation. As for the amplitude, the log-scale is used.

2.1.3 - Cepstrum [5]

Cepstrum is defined by the Fourier transformation of log-APSD, and has a time domain scale called by quefrency. If the frequency spectrum *X(w)* can be assumed as the product of sound source *G(w)* and transfer function *H(w)*, Cepstrum can be calculated as follows:

$$c(\tau) = \mathrm{F}^{-1}\log|X(\omega)| = \mathrm{F}^{-1}\log|G(\omega)| + \mathrm{F}^{-1}\log|H(\omega)| \quad (2)$$

The second term placed on the right-hand-side of the equation corresponds to the envelopment of frequency spectrum. So, lower quefrency (τ) parts represent the envelop shape of log-APSD and express vocal tract transfer characteristics. Although the size of Cepstrum vector is the same as log-APSD, the author uses the first 60 components as a feature vector in the present study.

2.2 - Dimension reduction for visualization

The above-mentioned feature vectors could be directly used for state classification. However these feature vectors have a large dimension, and also, extensive information about machine states, it might be effective to find essential and low-dimension features from them. If two effective features are extracted, each state can be visualized in the two-dimensional space. This visualization is very important for the anomaly monitoring, since it makes easy and instinctive understanding of the equipment states. For this purpose, PCA and KPCA are utilized. Also, a heuristic feature selection method will be presented.

2.2.1 - PCA based classification

Given M sets of p-dimensional centered observations (pre-processed feature vectors), $x(m)$ $(m=1,M)$, PCA diagnoses its covariance matrix,

$$\overline{C} = \frac{1}{M}\sum_{m=1}^{M} x(m)\cdot x(m)^T . \quad (3)$$

To do this, the following eigenvalue equation has to be solved:

$$\lambda V = \overline{C} V . \quad (4)$$

Then, m-th observation, $x(m)$, is projected onto the k-th eigenvector, $V(k)$, as follows:

$$z_k(m) = V^{(k)T}\cdot x(m) \quad (5)$$

Here, $z_k(m)$ is the k-th score value in PCA. In the present state classification method, appropriately selected two score values, $z_k(m)$, $(k=1,2,\ m=1,M)$, are used to discriminate the machine state.

2.2.2 - KPCA based classification [6, 7]

KPCA is the extension of PCA to non-linear space and is expected to choose more sensitive signal features of abnormal state from observations. First, $x \rightarrow \Phi(x)$ is assumed to be a possible non-linear mapping. In KPCA, it is enough to define just the dot product of $\Phi(x)$ to compute the projected score values in non-linear space. To do this, the covariance matrix in non-linear space is defined, instead of Eq. (3), it is as follows:

$$\overline{C} = \frac{1}{M}\sum_{m=1}^{M}\Phi(x_m)\cdot\Phi(x_m)^T \quad (6)$$

The eigenvalue problem is the same as Eq. (4). Here, it is noted that the dimension of V becomes M in non-linear space. Since all solutions of V lie in the span of $\{\Phi(x_1)\ldots\Phi(x_M)\}$, the following relations are satisfied.

$$\begin{aligned} &\lambda(\Phi(x_m)^T\cdot V) = \Phi(x_m)^T\cdot CV \qquad (m=1,M) \\ &V = \sum_{m=1}^{M}\alpha_m\Phi(x_m) \end{aligned} \quad (7)$$

Here, M-dimensional vector α can be computed by solving the following eigenvalue equation:

$$M\lambda\alpha = K\alpha \quad (8)$$

The kernel matrix K is defined as follows:

$$K(x_i, x_j) = \Phi(x_i)^T\cdot\Phi(x_j) \quad (9)$$

In the present paper, the following Gaussian kernel function is used:

$$K(x_i, x_j) = \Phi(x_i)^T\cdot\Phi(x_j) = \exp\left(-\frac{|x_i - x_j|^2}{2\sigma^2}\right) \quad (10)$$

Here, α in Eq.(8) has to be normalized so as to satisfy the relation, $\lambda_k(\alpha^{(k)T}\cdot\alpha^{(k)})=1$, since the eigenvector, $V^{(k)}$, have to satisfy $(V^{(k)T}\cdot V^{(k)})=1$. After obtaining the eigenvector $V^{(k)}$ in the non-linear space, the score value can be computed by the dot product of $\Phi(x)$ and α as follows:

$$z_k = V^{(k)T}\cdot\Phi(x) = \sum_{m=1}^{M}\alpha_m^{(k)}(\Phi(x_m)^T\cdot\Phi(x)) \quad (11)$$

The machine state is classified using appropriately selected two score values, $z_k(m)$, $(k=1,2,\ m=1,M)$. Although the dimension of eigenvector V in the linear PCA should be less than p, the dimension of observation vector, the dimension of KPCA eigenvector can be extended to the learning data number M. This means the KPCA will have to be more flexible and require sensitive classification capability.

2.2.3 - Heuristic classification

Since humans can learn speech recognition ability without any theories, there is a possibility of finding heuristically the good features of vectors for the normal and abnormal state classification. In order to find such good features, the positive factors should be defined at first. So, it is assumed that a good classification index is to maximize the following criterion:

$$C(F_i, F_j) = D_{NA}(F_i, F_j) - D_{NN}(F_i, F_j) - D_{AA}(F_i, F_j) \quad (12)$$

Here, F_i and F_j are the *i*-th and *j*-th elements extracted from the multi-dimensional feature vector. $D_{NA}(F_i, F_j)$ is the Maharanobis distance between normal and abnormal state data defined by:

$$D_{NA}(F_i,F_j) = (\mu_A^{(i,j)} - \mu_N^{(i,j)})^T (\Sigma_A^{(i,j)} + \Sigma_N^{(i,j)})^{-1} (\mu_A^{(i,j)} - \mu_N^{(i,j)}) \quad (13)$$

Here, the symbols 'N' and 'A' mean normal and abnormal states respectively. Also, the notations μ and Σ express the average and variance of *i*-th and *j*-th elements for normal and abnormal states respectively. To maximize the above criterion means that the abnormal state is allocated away from the normal state and each normal or abnormal state is allocated near in the two dimensional feature spaces.

To find the optimum feature indices in Eq. (12), some optimization algorithms, such as particle swarm optimization (PSO) could be used. However, in the present study, the whole possible combinations were searched to maximize the criterion, since the computational load was not critical in a two dimensional parameter space.

2.2 - State discrimination for anomaly monitoring

2.2.1 - State discrimination by PNN [8]

PNN is defined as a model of a certain state class using mixed Gaussian distribution of class members, X_{ij}, as follows:

$$f_j(X) = \frac{1}{(2\pi\sigma^2)^{p/2}} \cdot \frac{1}{n_j} \cdot \sum_{i=1}^{n_j} \exp\left[-\frac{(X - X_{ij})^T (X - X_{ij})}{2\sigma^2} \right] \quad (14)$$

Here, X_{ij} means the *i*-th member of score vector which belongs to the *j*-th class. The n_j is the number of *j*-th class members and σ is the smoothing parameter. The classification can be made by using this probability and a certain threshold level ε as following:

$$\begin{aligned} f_j(X) &\geq \varepsilon \Rightarrow X \in G_j \\ f_j(X) &< \varepsilon \Rightarrow X \notin G_j \end{aligned} \quad (15)$$

If learning data of K classes exist, it can be discriminated whether a target observation belongs to one of known K classes or an unknown class. The case where the observation doesn't belong to any known classes is important for practical applications. This is called as 'don't know class'.

For continuous anomaly monitoring, the following monitoring index, *MI*, which is the log-likelihood of PNN can also be used:

$$MI(X(t)) = \log(f_{normal}(X(t))) \quad (16)$$

Here, $X(t)$ is a target feature vector and $f_{normal}(X)$ is a PNN model of the normal state.

2.2.2 - State discrimination by SVDD [9]

SVDD (Support Vector Data Description) is often used for the one-class classification problem. In the anomaly monitoring system development, just the normal data are observed and the abnormal data are not usually observed. Hence, the deviation from the normal state has to be detected from the information of the normal data. SVDD is one of the effective methods to obtain the normal class discrimination function which can envelop the normal state data in the non-linear kernel space.

Assume the globe whose radius is R and center position a, then, the minimum size of the globe which covers most of the normal data, x_i $(i=1,N)$, is obtained so as to minimize the following criterion:

$$\begin{aligned} &\min_{R,a,\xi} \quad R^2 + C\sum_{i=1}^{N} \xi_i \\ &s.t. \quad (x_i - a)^T (x_i - a) \leq R^2 + \xi_i, \xi_i \geq 0, (i = 1,..N) \end{aligned} \quad (17)$$

Here, the slack variable ξ_i is introduced to allow exceptional data that could be outside of the globe. The coefficient C is the trade-off parameter to control the degree of allowance. In order to solve Eq. (17), the dual problem is introduced as following:

$$\begin{aligned} &\min_{\alpha} \sum_{i,j} \alpha_i \alpha_j (x_i \cdot x_j) - \sum_i \alpha_i (x_i \cdot x_i) \\ &s.t. \quad 0 \leq \alpha_i \leq C, \sum_i \alpha_i = 1, \end{aligned} \quad (18)$$

Then, the solutions α_i $(i=1,N)$ can be solved by the standard quadratic problem algorithm. Among N solutions, the sample vector x_i which corresponds to $0<\alpha_i<C$ is located on the boundary of the globe and called as the support vector. Also, one which corresponds to $\alpha_i=0$ is located inside the globe and belongs to the normal class. One which corresponds to $\alpha_i=C$ is located outside the globe. Since the above quadratic problem is defined by inner products of the sample vectors, the problem can be directly converted

into the kernel space as by the following:

$$\begin{aligned} &\min_{\alpha} \sum_{i,j} \alpha_i \alpha_j K(x_i \cdot x_j) - \sum_i \alpha_i K(x_i \cdot x_i) \\ &s.t. \quad 0 \le \alpha_i \le C, \sum_i \alpha_i = 1, \end{aligned} \tag{19}$$

Here, the kernel function is defined by Eq. (10), for example. Based on the obtained coefficients, the discrimination function is calculated as follows:

$$f(x) = R^2 - \sum_{i,j} \alpha_i \alpha_j K(x_i \cdot x_j) + \sum_i \alpha_i K(x_i \cdot x) - K(x \cdot x) \tag{20}$$

The plus value of Eq. (20) means the sample x belongs to the normal class.

3 - Test results

3.1 - Test facility and measurement

In order to verify the above mentioned algorithms, the acoustic data were measured using the rolling bearing type test facility shown in Fig. 1. This machine can be operated under several conditions of simulated defects, such as inner and outer race defects (Large, Middle, Small) or ball defects by changing bearing elements, in addition to normal condition's operation [4]. An example of defects is shown in Fig.1. The measurement was made using handy type microphone with digital sampling of 44.1kHz and 10 sec length. The data were measured under different rotating speeds, 3000, 2000, 1500, 1000 and 500 rpm.

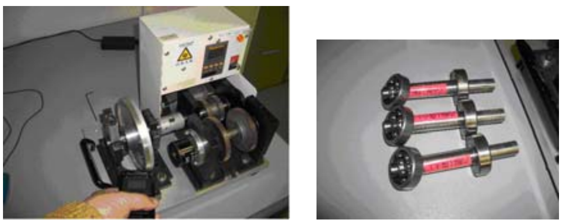


Fig.1 Mockup facility of rolling bearing and simulated failures (Outer and Inner race defects)

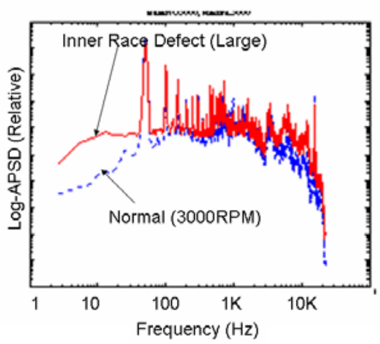


Fig.2 log-APSD of acoustic sound for Normal and Inner race defect (Large) condition

The examples of auto-power spectral density (APSD) of measured anomaly data are shown in Fig. 2. Here, the abnormal data of inner race large defect are compared with the normal data under the 3000 rpm rotating speed. It is seen that the typical resonance frequencies are observed at the 50Hz fundamental mode and its higher oscillation modes. Also, it is noted that differences between the normal and anomaly state are not so large. When vibration data are measured using the attached type accelerometer, these differences become clear. However, in the case of the remotely measured acoustic data shown here, the differences become very small. This means that signal processing techniques are important for amplifying the small signal features to distinguish anomaly states.

3.2 - Evaluation of classification performance of PCA, KPCA and a heuristic method

The purpose of the present classification is to discriminate the abnormal state based on the normal feature vector database. In order to evaluate the classification performance, the normal state database labeled by NN3000 and NN2000 and the abnormal state data labeled by InL3000 and InL2000 are used. Here, numeric labels mean the machine rotating speed in the rpm unit. Hence, the 3000 and 2000 rpm conditions have 50Hz and 33Hz fundamental oscillation modes respectively. The label InL means the inner race large defect abnormal state. The reason why two different operating speed data are included is to evaluate the robustness of classification performance to the operating condition change. The appearance of normal state feature vector patterns is different from not only abnormal patterns, but also different operating speed normal patterns. The skilled human engineers can discriminate the abnormal state even though the target machine is operated in different speeds. This situation is similar to the human ability of speaker recognition [10]. It can be easily recognized who speaks, even if they speak different words. Hence, the author tried to discriminate the abnormal states from normal ones, while the target machine was operated in different speeds.

The feature vectors of the above-mentioned four kinds of state data are evaluated by the afore-mentioned three algorithms for every 0.2 second length sound waveform with 44.1kHz sampling, which include 8820 points digital data. Since the measured data length was 10 seconds, each state has 50 samples of feature vectors.

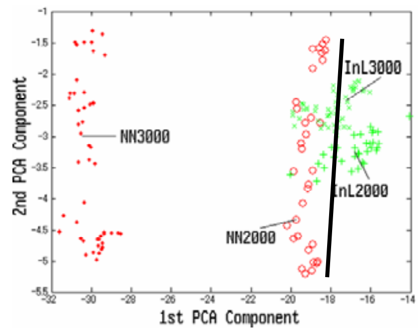
In the present analysis, the dimension of feature vector is 512 in log-APSD, 30 in Melscale-APSD, or, 60 in Cepstrum. These large-dimension data are projected into the two-dimension space by PCA, KPCA, or, the heuristic method, in order to visualize each state feature.

The classification results by log-APSD using PCA and KPCA are shown in Fig. 3. Here, the principal components are evaluated only from the normal state data, NN3000 and NN2000. And the score values of the 1^{st} and 2^{nd} principal components are plotted. It is shown that the discrimination of normal and abnormal state is difficult in the case of PCA, but, is easy in the case of KPCA. Similar conclusions are obtained in Fig. 4, where the results of Mel-scale-APSD are shown.

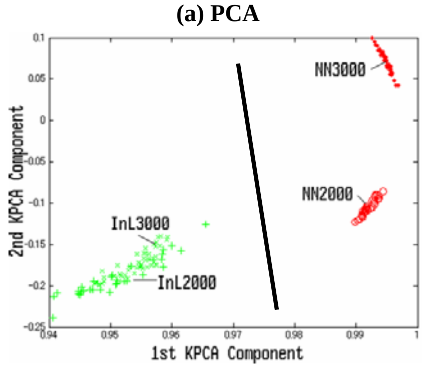
On the other hands, the results of Cepstrum in Fig. 5 are a little bit different from other feature extraction cases. In this case, the plots of 1^{st} and 3^{rd} principal components were shown. Here, both PCA and KPCA are able to discriminate the abnormal states from the normal ones. Furthermore, the differences of operation condition are less noticeable. This suggests that the Cepstrum and KPCA provide the most robust capability, and, almost the same sensitivity to other methods, for the rotating machine acoustic monitoring. From practical viewpoints, this robustness would be very important characteristics.

In Fig. 6, two examples of heuristic classification results are shown, where two frequency's amplitudes of log-APSD are chosen for the plot. In the left figure, the frequencies, 50Hz and 301Hz were chosen to represent the normal and abnormal states. The author assumed that these frequencies represented fundamental and higher modes of rotation which were excited by the inner race defect. However, the classification results are not so good. Hence, the optimum frequencies are searched based on Eq. (12). As a result, it can be found the frequency combination of 301Hz and 1.2kHz can maximize Eq. (12). The results are shown in Fig. 6(b). Here, it is shown that the good discrimination of normal and abnormal states is attained. This result suggests that the high frequency impact sound from inner race defect and rolling balls would be also characteristic features for anomaly monitoring in addition to the higher mode oscillation amplitude.

As a summary, the classification capability is evaluated by the Maharanobis distance defined by Eq. (13), and, shown in Table 1. Here, the larger D_{NA} and smaller D_{NN} or D_{AA} values are preferred for the good classification. The qualitative evaluations are also shown in this table. These results show that the classification performance largely depends on the feature extraction algorithm. Among them, Cepstrum and KPCA provide the good performance for robust and sensitive classification. Furthermore, it is seen that the heuristic method has a good possibility for not only the classification capability but also the knowledge discovery for anomaly condition monitoring.

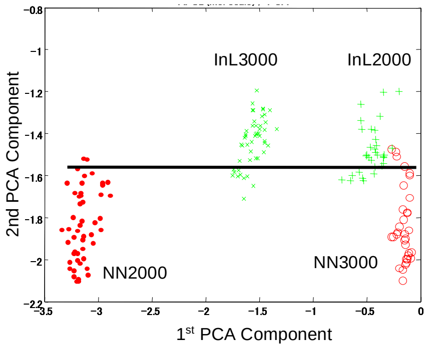


(a) PCA

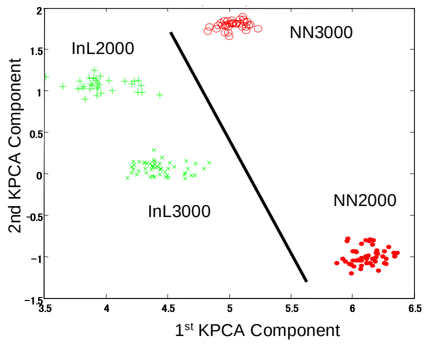


(b) KPCA

Fig.3 State classification by PCA and KPCA based on log-APSD

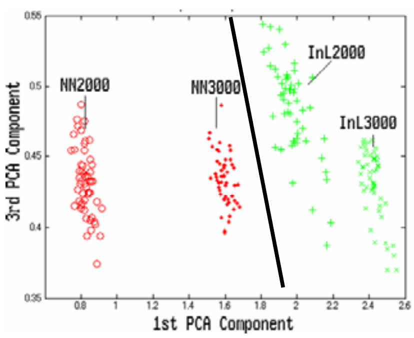


(a) PCA

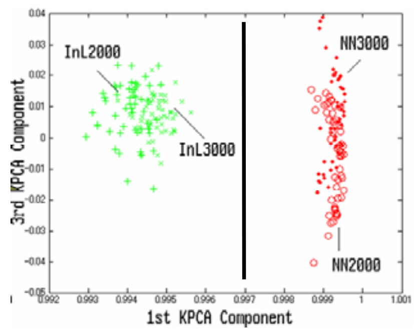


(b) KPCA

Fig.4 State classification by PCA and KPCA based on Mel-scale-APSD

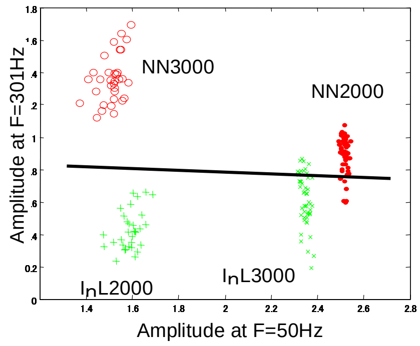


(a) PCA

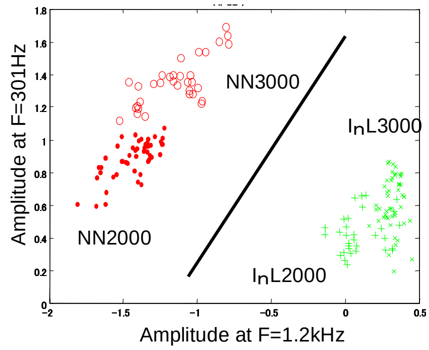


(b) KPCA

Fig.5 State classification by PCA and KPCA based on Cepstrum



(a) PCA



(b) KPCA

Fig.6 State classification by heuristic method of log-APSD

Table 1 Evaluation summary of classification

Feature Extraction	Classification	Components		Maharanobis Distance			Evaluation
		X-axis	Y-axis	DNA	DNN	DAA	
log-APSD	PCA	1	2	2.38	164.37	10.02	×
		1	2	3.21	210.27	1.03	×
	KPCA	1	2	61.61	116.95	0.39	△
		1	3	58.9	4.34	4.28	○
Mel-scale-APSD	PCA	1	2	3.65	694.5	76.14	×
	KPCA	1	2	10.6	439.88	29.07	△
Cepstrum	PCA	1	2	7.27	378.1	21.01	△
		1	3	6.69	261.23	26.08	△
	KPCA	1	2	76.76	9.19	3.61	◎
		1	3	75.83	0.36	1.39	◎
log-APSD	Heuristics	12274 Hz	301Hz	104.88	7.27	2.7	◎
Mel-scale-APSD	Heuristics	13602 Hz	413Hz	109.54	21.13	2.73	◎
Cepstrum	Heuristics	18quefrency	3quefrency	98.65	2.41	5.77	◎

3.3 - Discrimination results by PNN and SVDD

In order to demonstrate the discrimination performance of PNN and SVDD, another experiment results are shown [11]. Here, five different motor speed data were measured at normal and abnormal (inner race defects) conditions. In each condition, 30 sets of acoustic data were measured and analyzed. Among 10 cases of test conditions, the following three condition data sets are chosen as the learning data sets to calculate the normal class discrimination function defined by Eqs. (14) and (20), and then, the discrimination performance is evaluated using the remaining seven data sets including normal and abnormal condition data.

(1) Leaning data sets (Normal): NN1435,1209,1004
(2) Test data sets (Normal): NN1301,1107
(3) Test data sets (Abnormal):
InL1435,1301,1209,1107,1004

Figures 7 and 8 are the results of normal class discrimination function by the contour curves and 3D shape plots. Here, the 2nd and 4th PCA components of Cepstrum are chosen as the feature parameters. Also, the test data sets of normal and abnormal class are shown by circle and cross symbols. In the case of SVDD, the shape of contour curve is determined by the support vectors on the boundary of the normal class. On the other hand, the shape of PNN contour curve is determined by all normal class vectors and has the smooth shape.

In order to discriminate the normal class, the threshold is set to the middle value of minimum of the normal class and maximum of the abnormal class as follows:

$$\varepsilon = \{\min f(x_{Normal}) + \max f(x_{Abnormal})\}/2. \quad (21)$$

Then, in the case of SVDD, all of the 150 samples of normal states are classified as the normal class. And furthermore, no abnormal state samples are classified into the normal class. This means the false and miss alarms were zero. On the other hand, in the case of PNN, 2 false alarms and 6 miss alarms were observed. This means SVDD is superior to PNN for detecting small anomaly.

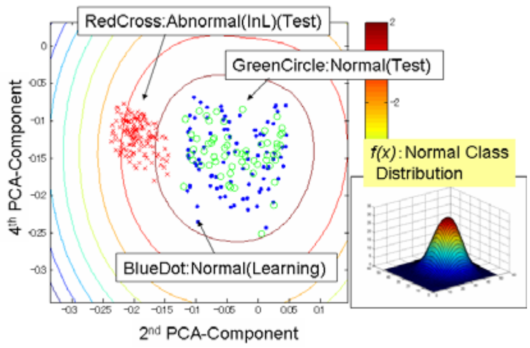


Fig. 7 Classification by PNN using Cepstrum and 2nd and 4th PCA components

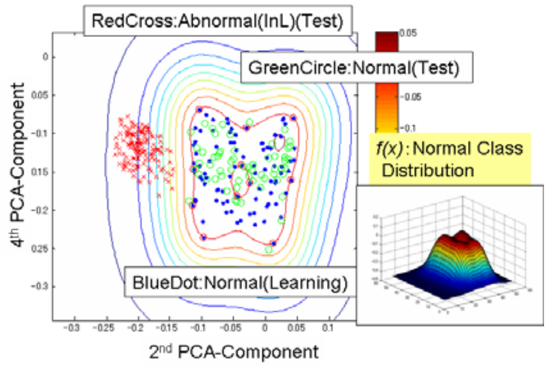


Fig. 8 Classification by SVDD using Cepstrum and 2nd and 4th PCA components

4 - Conclusions

Various kinds of signal processing methods have been discussed for condition monitoring of rotating machines, using remotely measured acoustic signals. Although the remotely measured sound has advantages for condition monitoring, their monitoring accuracy is less than the attached type sensors. To fill the lack of sensitivity, several kinds of advanced statistical signal processing methods were introduced such as PCA, KPCA, PNN and SVDD, in addition to the heuristic knowledge discovery method. Also it was shown the introduction of these signal processing methods contributed to the improvement of both sensitivity and robustness for condition monitoring. In Japan, a new maintenance regulation rule has just been introduced where condition monitoring technologies will be expected to have a more important role, for this reason in the future, perspective new technologies for condition monitoring should be pursued more.

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