Research on Diagnosing the Gearbox Faults Based on Near Field Acoustic Holography

W K Jiang\(^1\) J J Hou\(^1\) J T Xing\(^2\)

\(^1\) State Key Laboratory of Mechanical System and Vibration, Shanghai Jiaotong University, Shanghai 200240, China
\(^2\) Ship Science, School of Engineering Sciences, University of Southampton, UK.

E-mail: wkjiang@sjtu.edu.cn

Abstract. The gearbox fault diagnosis was developed for some decades. The current diagnosis techniques were mostly based on analyzing the shell vibration signals especially close to the bearing seat of gearbox. In order to utilize the spatial distribution information of fault signal, the near field acoustic holography (NAH) is employed for the condition monitoring and fault diagnosis of the gearbox in this presentation. The distribution images of sound pressure on the surface of gearbox are reconstructed by NAH, and the feature extraction and pattern recognition can be made by image processing techniques. A gearbox is studied in a semi-anechoic chamber to verify the fault diagnosis technique based on NAH. The pitting and partial broken tooth faults of gears are artificially made on one gear as the fault statuses, and the differences of acoustic images among normal and fault working states under the idling condition are analyzed. It can be found that the acoustic images of gearbox in the three different situations change regularly, and the main sound sources can be recognized from the acoustic images which also contain rich diagnosis information. After feature extraction of the acoustic images, the pattern reorganization technique is employed for diagnosis. The results indicate that this diagnosis procedure based on acoustic images is available and feasible for the gearbox fault diagnosis.

1. Introduction
Gearboxes are key parts of machinery, and their failure can lead to downtime loss even some disastrous catastrophes. Many fault diagnosis techniques based on periodic non-destructive inspection were developing very quickly. Three main types of methodologies such as vibration analysis, debris monitoring [1-4] and acoustic signal analysis [5-6] were used for gearbox fault diagnosis.

The vibration-based diagnosis was the most popular technique, in which many analysis techniques such as the time synchronous average, spectrum, cepstrum, time-frequency, amplitude and phase modulation techniques. The acoustic fault diagnosis of machinery was developed slowly. Some reason may be that acoustic signals were considered as contaminated easily in industrial environment. Owing to the progress in the capability of acoustic instrument as well as sophisticated signal-processing techniques, the acoustic signals could be processed like vibration [5-12] in the last couple of decades. The main advantage of acoustic-based diagnosis (ABD) was measuring in a non-contact way, so that it was more safety in some cases such as high temperature or corroding environment. The selections of measurement positions and distances were studied for improving the traditional ABD techniques based on single microphone measurement [6]. The spatial distribution of
sound signals was not researched enough, although it may contain sensitive information related with the working statuses of machinery. Gearbox is actually a nonlinear system. The vibration and sound energy transfers among its deferent components. The working statuses of gearbox determine the features of vibration and acoustic energy transmission, which can change the distributions of vibration and sound fields on the surface of gearbox. Therefore, the spatial distribution information of the sound pressure can be applied for fault diagnosis and may be more effective than the analysis based on single microphone measurement. The NAH-based fault diagnosis technique, which combined NAH with image processing and pattern recognition for fault diagnosis, was developed recently [13]. The NAH algorithm reconstructed the sound pressures on the source surface. The sound pressure distribution features on the reconstruction acoustic images were extracted for fault diagnosis. In this presentation, the NAH-based procedure is employed to diagnose the faults of gearbox in idling condition, which suggests a new way for gearbox fault diagnosis.

2. Procedure of gearbox fault diagnosis

The diagnosis procedure consists of four steps as follows: sampling of acoustic signals in faulty and faultless gear conditions, imaging acoustic field on the surface of gearbox, feature extraction, training and recognition using support value machine (SVM).

2.1. Sampling of acoustic signals

To sample the pure sound signals radiated from the gearbox, the experiment is carried out in a semi-anechoic chamber, in which the impact of random factors can be removed mostly. The experimental system, as shown in figure 1, consists of a gearbox, a motor, 5 microphones as reference sources and a microphone array. The gearbox and motor are joined together by a flexible coupling on the test-bed. There is no loading device coupling with the output axis 3, so the load is only from internal friction of the gearbox. In the idling condition, the fault signals originated from weak defects can be covered easily and only some severe gear faults can be diagnosed. Although the severe faults may be recognized by the traditional ABD techniques, the spatial distribution information of the sound signals radiated from gearbox is processed to fault diagnosis. Therefore, some severe gear faults are artificially made to verify the feasibility of the NAH-based diagnosis technique.

![Figure 1. The experimental setup](image1)

![Figure 2. The sketch map of gearbox JZQ 250](image2)

| Label | f1  | f12 | f2  | f34 | f3  |
|-------|-----|-----|-----|-----|-----|
| Frequency(Hz) | 25  | 875 | 13.7| 246 | 3.0 |

Table 1. The working frequencies of the gearbox

The gearbox is a two-order reduction industrial gearbox JZQ250, as shown in figure 2. It consists of two meshing pairs, in which reduction ratio is 8.23. When the electrical motor runs at its rated speed 1500 rpm, the working frequencies of three axes and two meshing pairs are shown in table 1.
The severe pitting and partial broken tooth defects are artificially made as shown in figure 3 and 4, in which both the two faults are made on gear Z3. To compare the sound signals under different working statuses, the cover of the gearbox and the gaskets are pre-processed, by which the gearbox can be disassembled and reassembled easily, and the impact of the installation errors can be reduced as much as possible. The axes and gears are firmly amounted on the hull, and the faults are directly tooled on the gears by hand drill. In this way that the offset influence of the axes and bearings can be neglected, and the gear meshing conditions under different working statuses can keep the same. After making the gear faults, the cover of the gearbox is assembled carefully, during which the mounting bolts is installed sequentially. For each mounting bolt, the tightening torque keeps the same by using torque wrench. During the measuring, the mounting bolts are tightened by torque wrench for every 3-5 samples. After three working statuses (normal, pitting and partial broken tooth) are simulated in this way, the array measurement is applied to sample signals. A linear array consisted of 17 microphones are used [14] as depicted in figure 1, in which other 5 microphones are used as references. The distances of two adjacent elements on the linear array are 50 mm. 30 samples are collected in each kind of condition. The sound signals are measured at 23 scanning steps, and each step distance is 50 mm, so that the hologram is an 1100mm×800mm plane paralleling to the top front of the gearbox at a distance 50 mm. The sampling frequency is 4096 Hz, and data length is 12 second. The data is sampled and recorded by using Müller BBM PAK 32.

2.2. Imaging the acoustic field by NAH

NAH is one of hot technique of visualising sound fields, since it can re-construct sound field on any observing surface based on sound pressure measured on a two-dimensional holographic surface. The two-dimensional fast Fourier transform (2D-FFT) is employed in the Helmholtz’s equation, and the fast transform between spatial domain and wave number domain is achieved. Therefore, the sound field variables on the source plane, such as sound pressure, particle velocity, sound intensity and etc., can be reconstructed by the sound pressure on the holographic measurement plane.

Here, the spatial distribution of sound pressure outside the gearbox is applied to fault diagnosis, so the FFT-based NAH is employed. The holographic measurement plane $S_h$ is at $z = z_h$, the reconstruction plane $S_c$ is at $z = z_c$, and the source plane $S_s$ is at $z = z_s$. The sound pressure of reconstruction plane $S_c$ is assumed as $\Phi(x, y, z_c, f)$, the sound pressure at $S_h$ is $\Phi(x, y, z_h, f)$ and the Green’s function under the Dirichlet conditions is $G_D(x, y, z_h - z_c, f)$, so the generalized reconstruction equation is written as[15] :

$$\Phi(x, y, z_c, f) = F^{-1}[\tilde{\Phi}(k_x, k_y, z_k, f)\tilde{G}_D (k_x, k_y, z_k - z_c, f)]$$

$$\tilde{\Phi}(k_x, k_y, z_k, f) = F[[k_x, k_y, z_k, f]]$$

$$\tilde{\Phi}(k_x, k_y, z_c, f) = F[[k_x, k_y, z_c, f]]$$

$$\tilde{G}_D (k_x, k_y, z_h - z_c, f) = F[G_D(x, y, z_h - z_c, f)]$$

where $F$ representes 2D-FFT and $F^{-1}$ denotes the inverse 2D-FFT. $k_x$ and $k_y$ are the spatial wave numbers.
of $x$ and $y$ directions respectively. The symbol $-1$ in $\tilde{G}_D^{-1}$ represents the inverse function of $\tilde{G}_D$. The two-dimensional spatial Fourier transform of $\tilde{G}_D$ which satisfies the homogeneous Dirichlet boundary conditions can be found explicitly:

$$\tilde{G}_D(k_x, k_y, z_h - z_c, f) = \begin{cases} \exp\left[ j(z_h - z_c)\sqrt{k^2 - k_x^2 - k_y^2}\right], & k_x^2 + k_y^2 \leq k^2 \\ \exp\left[ -(z_h - z_c)\sqrt{k_x^2 + k_y^2 - k^2}\right], & k_x^2 + k_y^2 > k^2 \end{cases}$$ (2)

When $k_x^2 + k_y^2 \leq k^2$, the expression of $\tilde{G}_D$ represents the surface waves in the $z_c$ plane simply coupled to ordinary propagating plane waves in the three-dimensional region $z_h > z_c$. When $k_x^2 + k_y^2 > k^2$, surface waves with $k_x^2 + k_y^2 > k^2$ must be matched with evanescent waves which have imaginary $z_h$ components in their wave vector, and which exponentially decayed in the $z_h$ direction as $\exp[-(z_h - z_c)\sqrt{k_x^2 + k_y^2 - k^2}]$.

In NAH the reconstruction frequencies should be determined in the first instance. Based on the traditional spectrum analysis of rotating machinery, the meshing frequency $f_23$ and its side frequencies with the interval $f_2$ are chosen as the feature frequencies, such as 246Hz, 218Hz, 232Hz, 260Hz and 274Hz. The NAH-based diagnosis technique applies the acoustic image features instead of the amplitudes features to fault diagnosis. Some of the acoustic images at the frequencies are shown in figure 5-9, in which regular changes under the three situations can be found. It can be understood from figures 5, 8 and 9 that the positions of main sound sources change regularly depend on the working conditions, while the changing of sound pressure distributions depend on the fault degrees. However, the main positions of sound sources nearly do not change in figures 6 and 7, in which only the sound pressure distribution changes can be observed directly. Although the acoustic images at the side frequencies contain some fault information in this study, there are some potential problems for the side frequencies being feature frequencies. Side frequencies may emerge in normal working conditions in practice, which may be caused by installation errors or minor errors of the gear. In the traditional spectrum analysis based on single vibration sensor, the differences of amplitude features at side frequencies can be hardly recognized even in fault conditions. The change of the amplitude feature at meshing frequency can not be employed to identify the different faults alone, because it may be influenced by most gear faults. The fundamental reason that the amplitude features at only one feature frequency can not be employed to diagnose different faults is that the acoustic signals sampled only at one location contain less fault information. In this study, the NAH-based diagnosis technique would attempt to apply the sound field changing information only at the meshing frequency to fault diagnosis.

![Acoustic Images](image-url)

(a) Normal  (b) Pitting  (c) Partial broken tooth

**Figure 5.** The acoustic image at meshing frequency 246Hz
2.3. Feature extraction

The faults may result in various changes of vibration on gearbox surface as well as the distribution of acoustic pressure. These changes can be depicted by textural features, in which the textural features
generated by various spatial gray-level co-occurrence matrices based (SGLCM-based) feature descriptors are employed. SGLCM is based on the estimation of the second-order joint conditional probability density functions $P(i, j, d, \theta)$[16], in which $d$ denotes the inter-sample spacing and $\theta$ expresses the direction angle. The $(x, y)$-th element of one two-dimensional gray image is expressed as $f(x, y)$. Each $P(i, j, d, \theta)$ denotes the transition probability from gray level $i$ to $j$ as following:

$$p(i, j, d, \theta) = \# \{[(x, y), (x + dx, y + dy)] \mid f(x, y) = i, f(x + dx, y + dy) = j\}$$  \hspace{1cm} (3)

where the inter-sample spacing $d$ indicates that $(x, y)$ and $(x+dx, y+dy)$ are $d$-pixels apart, $\#$ denotes the number of the type pixel pair in gray image is counted. In this presentation, the inter-sample spacing $d$ is set as 1 and the angles $\theta$ are quantized to 45° intervals, such as 0°, 45°, 90° and 135°. Therefore, the SGLCM $M(d, \theta)$ is defined as a matrix, of which the $(i, j)$-th element is $P(i, j, d, \theta)$ as follows:

$$M(d, \theta) = [P(i, j; d, \theta)]$$  \hspace{1cm} (4)

Based on the $M(d, \theta)$ matrices, the fault can be diagnosed based on 12 measures as follows: 1) Angular Second Moment, 2) Contrast, 3) Correlation, 4) Entropy, 5) Sum of Squares: Variance, 6) Inverse Difference Moment, 7) Sum Average, 8) Sum Variance, 9) Sum Entropy, 10) Difference Average, 11) Difference Variance, 12) Difference Entropy[17].

Before calculating the SGLCM-based texture features, it is necessary to determine the size of gray-scale. To only utilize the texture variations for fault diagnosis, the sound pressure ranges of each sample data are normalized for dividing the gray levels in this paper. Five kinds of gray-scale: 8, 16, 32, 64, 128 are selected, in which the feature vectors in four directions of 0°, 45°, 90° and 135° are calculated respectively. Five feature frequencies are employed, and the acoustic field is imaged in each feature frequency. Five acoustic images for one sample data can be obtained in this way. The texture features extracted from these five acoustic images are combined into a feature vector with the same gray scale and direction, and each feature vector has $12 \times 5$ feature parameters.

2.4. SVM and results

SVM was an approach in machine condition classification, and it had gained acceptance in machine learning, computer vision and pattern recognition communities for its high accuracy and good generalization capability [18]. SVM was originally designed for binary classification [19]. The multiclass problems are usually encountered in fault diagnosis now. Here, the multi-classification function of Libsvm [20] is employed. It constructed and combined several binary classifiers to solve multiclass problems, and the one-against-one strategy was applied [21]. This strategy constructs $k(k-1)/2$ classifiers where each one is trained on data from two classes. For training data from the $i$th and $j$th classes, the following binary classification problem is solved as follows:

$$\min_{w^y, b^y, \xi^y} \frac{1}{2} (w^y)^T w^y + C \sum_{i} \xi^y_i (w^y)^T \phi(x_i) + b^y \geq 1 - \xi^y_i, \quad \text{if} \quad y_i = i$$

$$\left( (w^y)^T \phi(x_i) + b^y \right) \leq -1 + \xi^y_i, \quad \text{if} \quad y_i = j$$

$$\xi^y_i \geq 0$$  \hspace{1cm} (5)

After all $k(k-1)/2$ classifiers are constructed, the “Max Wins” voting strategy is used as following. If $x$ is judged as in the $i$th class based on the sign $((w^y)^T \phi(x) + b^y)$, the vote for the $i$th class adds by one. Otherwise, the $j$th is increased by one. The $x$ is predicted in the class with the largest vote.

The diagnosis results based on the acoustic images at five feature frequencies are shown in table 2; the diagnosis results based on the acoustic images only at the meshing frequency are shown in table 3.

The best diagnosis result is 100% as shown in table 2 and 98.8% in table 3. Some reason leading to high correct ratio may be the ideal experimental environment and the strict experimental procedure reduce the impact of random factors and installation errors, and the gear faults are severe and obvious. Besides the ideal experimental conditions, the application of statistical diagnosis method can remove
the impact of the random fluctuations in the gearbox. The experimental results demonstrate that the gear faults can be diagnosed effectively through the spatial distribution information of the sound pressure. Although the diagnosis results in table 2 is better than table 3, the feature dimensions of the later are only 1/5 of the former. The computation consummation of these two procedures is quite different, so that the recognition effect and the feature dimensions should be compromised. The good diagnosis results in table 3 also indicate the superiority of the NAH-based diagnosis technique. For single microphone measurement, it is difficult to diagnose several kinds of faults by the features only at one feature frequency, especially when the features have the similar changes in two or more different fault conditions. Gearbox is a nonlinear system, so there may be some measurement positions which are insensitive to the faults. The selection of the measurement position is crucial and is another shortcoming for the single microphone measurement. The NAH-based fault diagnosis technique solves the problem by employing all measurement positions around the gearbox. The experimental results indicate that it is effective and that the new ABD technique can be a new choice for gearbox fault diagnosis.

Table 2. Recognition results based on the meshing frequency and its side frequencies (%)

| Direction | Size of Gray-Scale |
|-----------|-------------------|
|           | 8    | 16    | 32    | 64    | 128   |
| 0°        | 100% | 98.8% | 100%  | 100%  | 96.6% |
| 45°       | 100% | 100%  | 100%  | 100%  | 96.6% |
| 90°       | 98.8%| 100%  | 100%  | 100%  | 100%  |
| 135°      | 100% | 98.8% | 100%  | 100%  | 98.8% |

Table 3. Recognition results only based on the meshing frequency (246Hz) (%)

| Direction | Size of Gray-Scale |
|-----------|-------------------|
|           | 8    | 16    | 32    | 64    | 128   |
| 0°        | 95.5%| 98.8% | 98.8% | 95.5% | 96.6% |
| 45°       | 95.5%| 96.6% | 95.5% | 95.5% | 94.4% |
| 90°       | 95.5%| 93.3% | 92.2% | 92.2% | 97.7% |
| 135°      | 92.2%| 96.6% | 96.6% | 96.6% | 90.0% |

3. Conclusions
A NAH-based diagnosis technique is applied to gearbox fault diagnosis. The new ABD technique consists of array measurement, NAH algorithm, spectrum analysis, image processing and pattern recognition. After obtaining the NAH images in all kinds of fault conditions, the statistical texture features based on SGLCM are extracted for fault diagnosis, which takes full advantage of the sound pressure distribution information of the gearbox. A gearbox is experimentally studied to verify the NAH-based diagnosis method and its superiority. From the acoustic images in three different situations, the distribution variations of the sound pressure and the main sound sources can be recognized. The diagnosis results indicate that this diagnosis procedure based on acoustic images is available and feasible. The NAH-based diagnosis technique may be anticipated as an appealing tool in ABD techniques for gearbox fault diagnosis.

Acknowledgment
This work was supported by the National High Technology Research and Development Program of China (863 Program), No. 2007AA04Z416.

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