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Modification of acceleration signal to improve classification performance of valve defects in a linear compressor

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Abstract. In general, it may be advantageous to measure the pressure pulsation near a valve to detect a valve defect in a linear compressor. However, the acceleration signals are more advantageous for rapid classification in a mass-production line. This paper deals with the performance improvement of fault classification using only the compressor-shell acceleration signal based on the relation between the refrigerant pressure pulsation and the shell acceleration of the compressor. A transfer function was estimated experimentally to take into account the signal noise ratio between the pressure pulsation of the refrigerant in the suction pipe and the shell acceleration. The shell acceleration signal of the compressor was modified using this transfer function to improve the defect classification performance. The defect classification of the modified signal was evaluated in the acceleration signal in the frequency domain using Fisher's discriminant ratio (FDR). The defect classification method was validated by experimental data. By using the method presented, the classification of valve defects can be performed rapidly and efficiently during mass production.

Keywords: defect classification; linear compressor; valve defect; transfer function; frequency analysis; scale factor; total least square; FDR

1. Introduction

Linear compact refrigerant compressors are used in refrigerators and are closely related to the brand value for consumers. If defective products are put on the market, there is a big loss to the brand value of the company. Accordingly, compressor manufacturers are interested in improving the efficiency and reliability of the compressor while reducing the defect rate. In order to meet these needs, various studies have been conducted on the defect classification using various methods.

AlThobiami and Ball (2014) proposed a method for detecting defects in a compressor valve using wavelets from the pressure and acceleration signals of the compressor. Jung and Koh (2014) and Zhu *et al.* (2010) conducted a study to analyze the fault diagnosis of the reciprocating motion device using wavelet transform. Pichler *et al.* (2016) proposed a technique for classifying compressor valve defects using a two-dimensional autocorrelation of the radiated noise of the compressor while controlling the load applied to it. A method has also been proposed for diagnosing the defects of a valve with data measured by different operating conditions of the compressor by Mathioudakis and Stamatis (1992), Kim and Kim (2005) and Tassou and Grace (2005). Aretakis and Mathioudakis (1998) and Cui *et al.* (2009) proposed a technique to improve the fault diagnosis performance by processing data measured from a compressor.

One of the most effective ways to diagnose a compressor valve defect is to observe the direct behavior of the compressor valve directly. However, the compressor valve behavior and pressure signals around the valve are not easy to measure directly. Therefore, Wang *et al.* (2015) and Elhaj *et al.* (2008) simulated the behavior of a compressor valve with a computer and proposed a fault diagnosis based on the signals derived from it. Techniques for failure diagnosis of a compressor have been developed to apply artificial intelligence or big data. Yang *et al.* (2005), Zhou *et al.* (2006), Shen *et al.* (2014) and Tran *et al.* (2017) proposed fault diagnosis techniques in which a computer learns and classifies various signals of a compressor by using an artificial neural network. Qi *et al.* (2016) and Fan *et al.* (2015) proposed a pattern analysis method for big data that analyzes the vast amount of data of various signals from a compressor and finds the pattern of a fault signal.

These studies mainly focus on only the failure of the valve in the compressor. In the case of small compressors for home appliances, most of the defects are caused by defects of the valve, poor assembly, or leakage of the refrigerant due to production defects. In this case, an intuitive method of measuring the amount of refrigerant flowing through the compressor's refrigerant piping would be more effective than the techniques proposed by other studies.

Generally, the pressure pulsation of the refrigerant in the piping of a compressor is directly affected by the opening and closing movements of the refrigerant suction valve. Therefore, a refrigerant leakage measurement method could be used to detect defects. A defect classification method using pressure data of the refrigerant would be easy to use

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because it is intuitive. However, it needs extra process to insert a pressure transducer into a compressor to obtain the refrigerant pulsation signal, so this method might not be suitable for defect classification in a mass production line.

However, an accelerometer can be easily attached to the surface of the compressor shell. Therefore, the acceleration signal can be acquired very easily compared with the refrigerant pressure signal. The acceleration measured in a compressor is influenced by the excitation force from the opening and closing movement of the compressor valve. There is also a specific relationship between the pressure pulsation of the refrigerant and the shell acceleration. Therefore, if the relationship between the pressure pulsation and the shell acceleration is determined beforehand for a compressor prototype, it will be possible to improve the fault classification performance by measuring only the shell acceleration during mass production.

However, unlike the refrigerant pulsation signal, the signal due to the compressor structure characteristics and the pressure pulsation affect the acceleration signal at the same time. Therefore, it is not easy to distinguish a defect using only the shell acceleration signal. In the process of estimating this relationship, the noise ratio of the refrigerant pressure pulsation and surface acceleration plays a very important role. In this paper, the relationship between the refrigerant pressure pulsation and the shell acceleration of a linear compressor is expressed as a transfer function while considering the respective noise ratios. An improved method is proposed for classifying faults using only the acceleration signal in a linear compressor shell.

2. Theory

2.1 Estimation of Transfer Function between Pressure Pulsation and Shell Acceleration

Pressure pulsation of refrigerant is generated in a pipe due to the movement of the compressor valve, which vibrates the pipe and the compressor shell along various transmission paths. Let H(f) be a transfer function between the refrigerant pressure pulsation and the acceleration of the compressor shell. The true value of the refrigerant pressure pulse is u(t). The noise m(t) is also included, and the value of p(t) is measured with a pressure transducer. Similarly, the measured signal a(t) of the accelerometer also includes a noise signal n(t) in the true signal v(t). This relationship is shown in Eq. (1) and Fig. 1 (Shin and Hammond 2008).

$$\begin{aligned} p(t) &= u(t) + m(t) \\ a(t) &= v(t) + n(t) \end{aligned} \tag{1}$$

The input-output signal is assumed to be the pressure pulsation and the shell acceleration. Fig. 2 shows the error to be considered when estimating the transfer function between the Fourier transform P(f) of the pressure pulsation p(t) and the Fourier transform A(f) of the shell acceleration a(t). The commonly used transfer functions $H_1(f)$ and $H_2(f)$ are defined in Eq. (2)

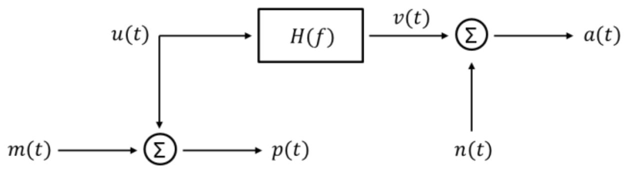


Fig. 1 Schematic of single input-output system with extraneous noise

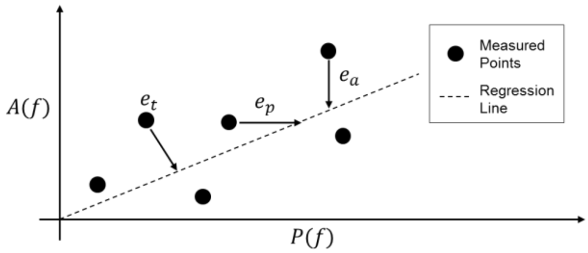


Fig. 2 Several forms of errors in linear regression

$$H_1(f) = \frac{S_{pa}(f)}{S_{pp}(f)}, \qquad H_2(f) = \frac{S_{aa}(f)}{S_{ap}(f)} \tag{2}$$

where $S_{pa}(f)$ represents the cross-spectral density function between the pressure pulsation p(t) and the shell acceleration a(t). $S_{pp}(f)$ and $S_{aa}(f)$ represent the power spectral density (PSD) function. Assuming that noise is present in only the accelerometer, the estimate of the transfer function that minimizes the mean squared value of the errors e_a in Fig. 2 can be expressed as $H_1(f)$. Similarly, by assuming there is noise in only the pressure transducer, the optimal transfer function that minimizes the mean squared value of the error e_p in Fig. 2 can be expressed as $H_2(f)$. When there is noise in both the pressure transducer and the accelerometer, the true value $H_{true}(f)$ of the transfer function is between $H_1(f)$ and $H_2(f)$. This can be expressed as follows

$$H_1(f) \le H_{true}(f) \le H_2(f) \tag{3}$$

The total least square (TLS) method is used for estimating $H_{true}(f)$ by minimizing the mean squared value of the error e_t in Fig. 2 according to the ratio of the noise in input and output signals. The transfer function estimation method by TLS is defined as (White *et al*. 2006)

$$H_S(f) = \frac{S_{aa}(f) - k(f)S_{pp}(f) + \sqrt{\left\{S_{pp}(f)k(f) - S_{aa}(f)\right\}^2 + 4\left|S_{pa}(f)\right|^2 k(f)}}{2S_{ap}(f)} \tag{4}$$

where the scale factor k(f) represents $S_{nn}(f)/S_{mm}(f)$; that is, the ratio of the auto-spectral density function of the noise of the pressure transducer to the noise of the accelerometer. When $k(f)\to 0$, $H_s(f)$ converges to $H_1(f)$, and $H_s(f)$ converges to $H_2(f)$ when $k(f)\to\infty$. In order to estimate $H_s(f)$ while considering both the noise of the pressure transducer and the accelerometer, it is first necessary to estimate the scale factor k(f).

2.2 Modification of acceleration signal

The instantaneous power spectrum $S_{aa,i}(f)$, i = 1~L of the measured acceleration a(t) at the compressor shell is defined as

$$\begin{aligned} S_{aa,i}(f) &= A_i^*(f)A_i(f) \\ &= V_i^*(f)V_i(f) + N_i^*(f)N_i(f) + 2\,\mathrm{Re}[V_i^*(f)N_i(f)] \end{aligned} \tag{5}$$

where $A_i(f)$ is the Fourier transform of the measured signal a(t) of acceleration, and $V_i(f)$ and $N_i(f)$ are the Fourier transforms of the true acceleration signal $v_i(t)$ and the accelerometer noise $n_i(t)$, respectively. L denotes the number of averaging, and * denotes the conjugate of a complex number.

Assuming that the true acceleration signal $v_i(t)$ and the accelerometer noise $n_i(t)$ are uncorrelated to each other, the expected value of the power spectral density function $S_{aa}(f)$ of the acceleration signal is expressed as follows

$$S_{aa}(f) = E\left[S_{aa,i}(f)\right] = S_{vv}(f) + S_{nn}(f) \tag{6}$$

where $E[\bullet]$ represents the ensemble average. The variance $\sigma^2_p(f)$ of the PSD of the input noise is expressed as

$$\begin{aligned} \sigma_a^2(f) &= \frac{1}{L}\sum_{i=1}^{L}\left[S_{aa,i}(f) - S_{aa}(f)\right]^2 \\ &= \frac{1}{L}\sum_{i=1}^{L}\left[V_i^*(f)V_i(f) + N_i^*(f)N_i(f) + 2\,\mathrm{Re}\left[V_i^*(f)V_i(f) - S_{aa}(f)\right]\right]^2 \\ &= \frac{1}{L}\sum_{i=1}^{L} 4\left|V_i(f)\right|^2\left|N_i(f)\right|^2\cos^2(\theta_{n_i}(f) - \theta_{v_i}(f)) \end{aligned} \tag{7}$$

where $|V_i(f)|$ and $\theta_{v_i}(f)$ represent the amplitude and phase of the true acceleration signal v(t). $|N_i(f)|$ and $\theta_{n_i}(f)$ represent the amplitude and phase of the accelerometer noise $n_i(t)$. Assuming that the accelerometer noise is white noise, the probability density function of the phase $\theta_{n_i}(f)$ can be defined as

$$\begin{aligned} \Pr\left[\theta_{n_i}(f)\right] &= \frac{1}{2\pi}, \quad 0 \le \theta_{n_i}(f) \le 2\pi \\ &= 0, \quad otherwise \end{aligned} \tag{8}$$

Therefore, the ensemble average of the phase difference of the acceleration signal can be expressed as

$$\begin{aligned} \mathrm{E}\left[\cos^2\left(\theta_{m_i}(f) - \theta_{u_i}(f)\right)\right] &= \frac{1}{2\pi}\int_0^{2\pi}\cos^2\left(\theta_{n_i}(f) - \theta_{v_i}(f)\right)d(\theta_{n_i}(f) - \theta_{v_i}(f)) \\ &= \frac{1}{2} \end{aligned} \tag{9}$$

Eq. (7) can be rewritten as

$$\begin{aligned} \sigma_a^2(f) &= 2S_{vv}(f)S_{nn}(f) \\ &= 2\left(S_{aa}(f) - S_{nn}(f)\right)S_{nn}(f) \end{aligned} \tag{10}$$

Solving Eq. (10), the PSD $S_{nn}(f)$ of the accelerometer noise can be estimated as

$$S_{nn}(f) = \frac{S_{aa}(f) - \sqrt{S_{aa}^2(f) - 2\sigma_a^2(f)}}{2} \tag{11}$$

In the same way, the PSD of the pressure transducer noise can be estimated as

$$S_{mm}(f) = \frac{S_{pp}(f) - \sqrt{S_{pp}^2(f) - 2\sigma_p^2(f)}}{2} \tag{12}$$

where $\sigma^2_p(f)$ represents the variance of the PSD $S_{pp}(f)$ of the true pressure signal. From Eqs. (11) and (12), the scale factor k(f) of Eq. (4) can be obtained as

$$k(f) = \frac{S_{nn}(f)}{S_{mm}(f)} \tag{13}$$

The transfer function $H_s(f)$ considering the scale factor of the noise of the pressure transducer and the accelerometer can be obtained from Eq. (4). The PSD of the improved acceleration signal, $S_{aa,modified}(f)$ can be obtained as

$$S_{aa.\mathrm{modified}}(f) = \frac{S_{aa}(f)}{\left|H_s(f)\right|^2} \tag{14}$$

where $S_{aa}(f)$ represents the PSD of the acceleration signal measured at the compressor shell, and the transfer function $H_s(f)$ is given in Eq. (4).

2.3 Defect classification performance index

Fisher's discrimination ratio (FDR) was used as a performance index of defect classification in a compressor valve. FDR is a useful indicator that can be used for classification by simply using the mean and variance. The generalized FDR can be expressed as (Attoui *et al*. 2017)

$$FDR_{M.class} = \sum_{i}^{M}\sum_{j \ne i}^{M}\frac{(\mu_i - \mu_j)^2}{\sigma_i^2 + \sigma_j^2}, \qquad M > 2 \tag{15}$$

where σ is the variance, μ is the mean, and M is the number of clusters. Smaller variance in the cluster and greater distance between the clusters result in higher FDR. This means that larger FDR results in better classification of the cluster.

The cluster in the classification technique consists of a group of representative statistical values of the signals to be discriminated. The frequency center (FC), root-mean-square-frequency (RMSF), and root-variance-frequency (RVF) are widely used as representative statistical values in the frequency domain and have been used as a feature to evaluate fault classification performance (Lei *et al*. 2008). The equations are expressed as

$$FC = \frac{\int f_i \times s(f_i)df}{\int s(f_i)df} \tag{16}$$

$$RMSF = \sqrt{\frac{\int f_i^2 \times s(f_i)df}{\int s(f_i)df}} \tag{17}$$

$$RVF = \sqrt{\frac{\int (f_i - FC)^2 \times s(f_i)df}{\int s(f_i)df}} \qquad (18)$$

3. Experiment

3.1 Experimental overview

To evaluate the defect classification performance, experiments were carried out to obtain the refrigerant pressure pulsation and shell acceleration signals of compact compressors for a commercial refrigerator. The pressure pulsation data of the refrigerant inside the pipe was measured by inserting a pressure transducer through a hole in the suction pipe outside the compressor. Acceleration data at the compressor shell were measured from an accelerometer attached to the compressor's upper shell. Fig. 3 shows the compressor used in the experiment.

Two types of compressors with a defective valve and one normal compressor were used for the defect classification, as shown in Fig. 4.

The defects are due to leakage in the suction valve and the discharge valve, respectively. The leakage defect of the suction valve is caused by misalignment of the valve port and the center of the valve body during assembly. The leakage defect of the discharge valve is caused by the deviation of the tolerance or the occurrence of a crack in the manufacturing process of the discharge plate.

The characteristics of the circulation cycle of the refrigerant in the compact compressor of the refrigerator vary depending on the operating procedure and the settings of the refrigerator, even with the same compressor. To prevent such a situation, the simple refrigerant supply device shown in Fig. 5 was applied in the experiment. By maintaining constant conditions for setting the refrigerant circulation cycle of the refrigerator by the refrigerant supply device, it was possible to test several refrigerant compressors under the same conditions. The operating frequency of the compressor is 60 Hz.

Experimental data were obtained using an LMS Test.Lab measuring device. The pressure transducer was a 211B3 model from KISTLER, and the accelerometer was an A397 model from Bruel & Kjaer. The pressure pulsation of the refrigerant in the suction pipe and the acceleration data of the compressor shell were acquired for 60 seconds at intervals of 4.88×10^{-5} seconds. The acquired data were RMS-normalized to account for cases where the refrigerant leakage was the same and the types of defects were different.

Figs. 6 and 7 show some of the pressure pulsation signals and acceleration signal data obtained by experiments. Figs. 6(a) and 6(b) show that a strong component appears at 60 Hz in all pressure signals. The high frequency component is also more prominent in the pressure signal of the defective discharge valve than the other two signals.

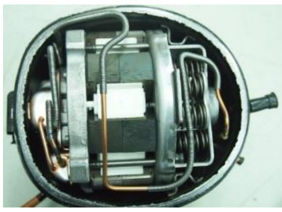


Fig. 3 Refrigerant compressor for experiment

(a) Suction valve poor assembly

(b) Discharge valve poor manufacturing

Fig. 4 Defective type of small refrigerant compressor for refrigerator

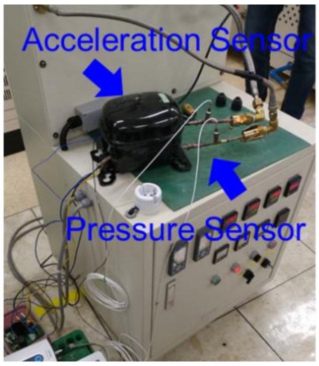
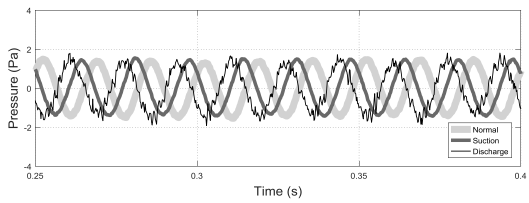
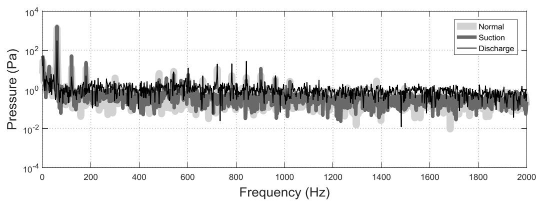


Fig. 5 Refrigerant supply system

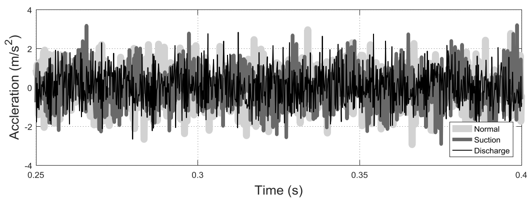


(a) Time domain data

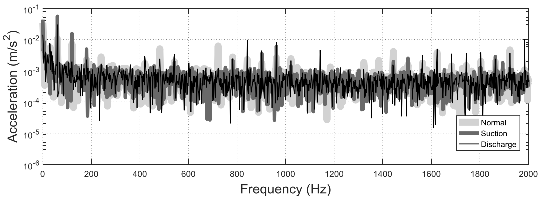


(b) Frequency domain data

Fig. 6 The pressure pulsation signal measured in the experiment



(a) Time domain data



(b) Frequency domain data

Fig. 7 The shell acceleration signal measured in the experiment

Fig. 7(a) shows that a strong high-frequency signal appears in all of the shell acceleration signals. In Fig. 7(b), a relatively strong component appears at 60 Hz, and a strong peak can even be seen at high frequencies of 1000 Hz or higher. The figures show that most of the pressure pulsation signals and shell acceleration signals are generated at an operating frequency of 60 Hz and its harmonics, and the high-frequency component of the shell acceleration signal is stronger than the pressure signal.

3.2 Signal processing

For the normal compressor, the transfer function between the pressure pulsation of the refrigerant and the shell acceleration signal was used. The signal of the normal compressor is suitable as a reference signal since the signal of the defective compressor is likely to change with the magnitude and position of the defects. After estimating the transfer function for the normal compressor, the shell acceleration signals of the defective compressor were converted to modified acceleration signals using the transfer function. A diagram of this process is shown in Fig. 8.

Fig. 9 shows the signal processing results for estimating the transfer function between the pressure pulsation signal and shell acceleration signal for the normal compressor. Figs. 9(a) and 9(b) show the mean and variance of the PSD obtained by Fourier transformation of the acceleration time signal measured in the normal compressor shell shown in Fig. 5 (a). The peak occurs at or harmonic component of 60 Hz which is the operating frequency of the compressor.

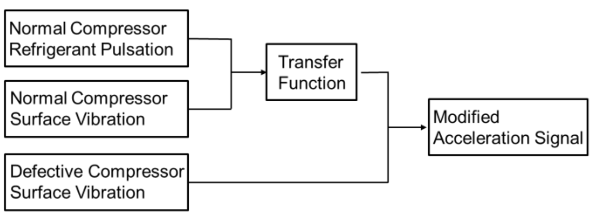
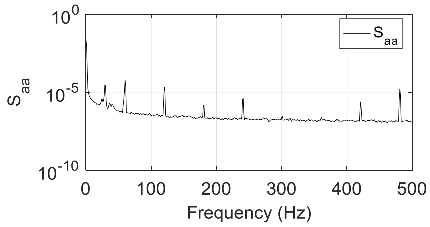
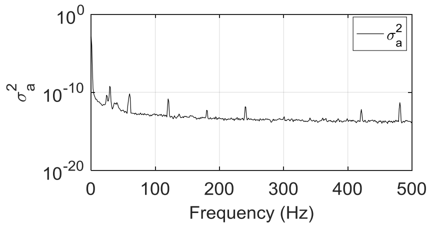


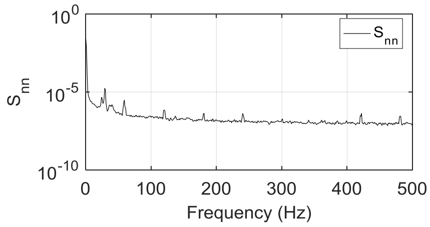
Fig. 8 Schematic of estimating modified acceleration signal



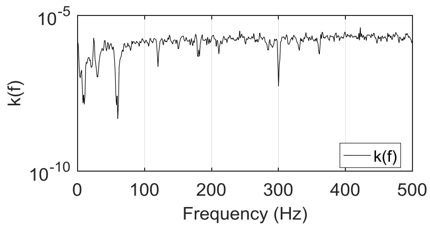
(a) Mean value of auto-spectrum of shell acceleration signals



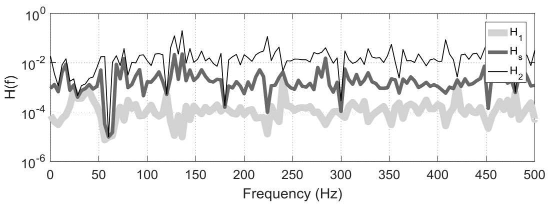
(b) Variance of auto-spectrum of shell acceleration signals



(c) Estimated PSD of noise signal, $S_{nn}(f)$ from Eq. (11)



(d) Estimated scale factor, $k(f)$ from Eq. (13)



(e) Estimation of frequency response function between shell acceleration and pressure pulsation

Fig. 9 Signal processed results of acceleration data

Fig. 9(c) shows the PSD of the accelerometer noise predicted using Eq. (11). The peak occurs at the harmonic component of the operating frequency of the compressor, as in Figs. 9(a) and 9(b). Fig. 9(d) shows the scale factor estimated by Eq. (13) and represents the PSD ratio of the noise inserted into the pressure transducer and the accelerometer. Fig. 9(e) shows the transfer function $H_s(f)$ between the pressure pulsation and shell acceleration estimated by Eq. (4). $H_s(f)$ has a value between $H_1(f)$ and $H_2(f)$ at all frequencies. In addition, the harmonic components of the compressor's operating frequency show that all three transfer functions are close to each other.

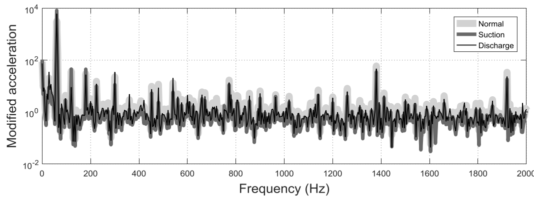
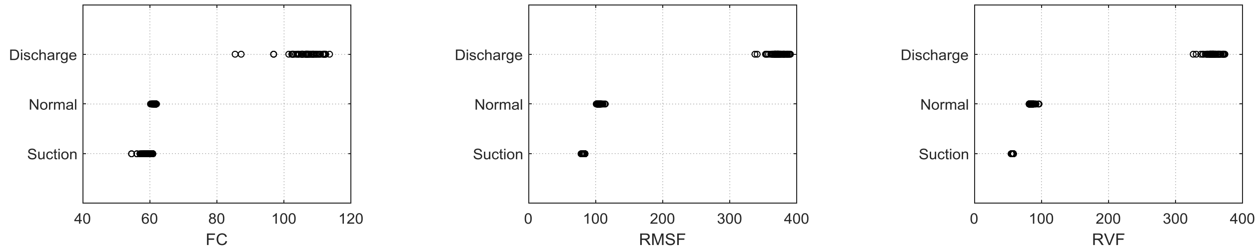
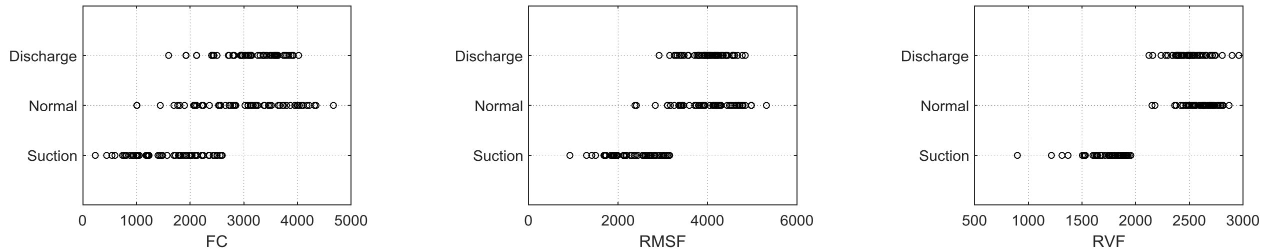


Fig. 10 Estimated compressor refrigerant pulsation data



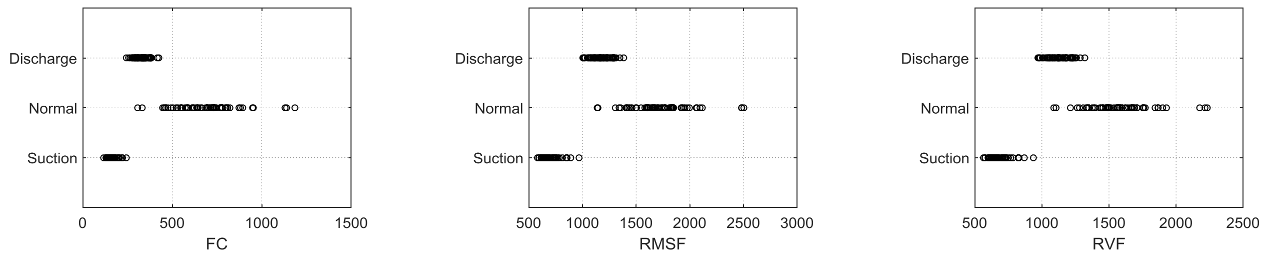
(a) FC (b) RMSF (c) RVF

Fig. 11 Fault classification using only pulsating pressure



(a) FC (b) RMSF (c) RVF

Fig. 12 Fault classification using only shell acceleration



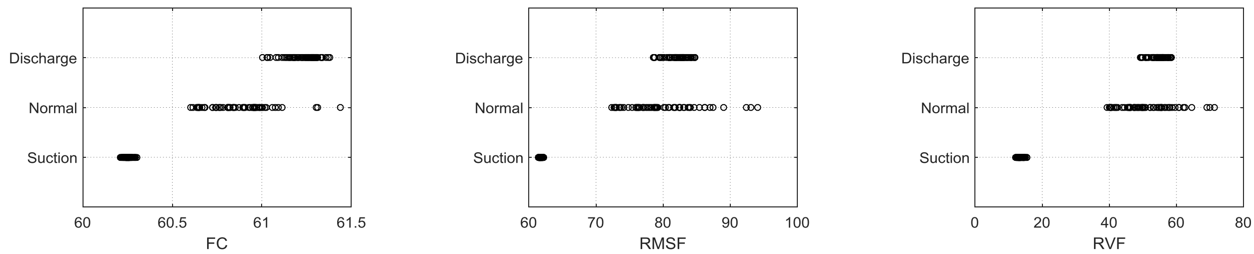
(a) FC (b) RMSF (c) RVF

Fig. 13 Fault classification using modified acceleration signal with $H_1(f)$

The modified acceleration signal estimated from Eq. (14) is shown in Fig. 10. Compared with the PSD of the shell acceleration data in Fig. 2, most of the acceleration peaks at high frequencies have been eliminated, and the harmonic components of the operating frequency in the pressure pulsations are more apparent.

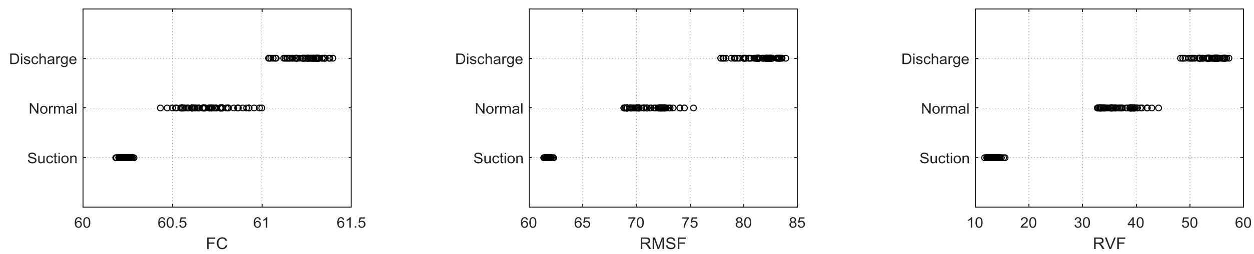
3.3 Results of defect classification performance

The refrigerant pressure pulsation signal and the shell acceleration signal were measured for the normal and defective compressors. The measurement data were acquired for one second. Measurements were performed 60 times to obtain data scatter. Figs. 11 and 12 show the one-dimensional scatter plots of FC, RMSF, and RVF obtained from the refrigerant pressure pulsation signal and shell



(a) FC (b) RMSF (c) RVF

Fig. 14 Fault classification using modified acceleration signal with $H_2(f)$



(a) FC (b) RMSF (c) RVF

Fig. 15 Fault classification using modified acceleration signal with $H_s(f)$

Table 1 Fisher discrimination ratio of signals

Signal	FC	RMSF	RVF
Pulsating Pressure	156	1378	1705
Shell Acceleration	5	10	23
Modified Acceleration with $H_1(f)$	27	32	33
Modified Acceleration with $H_2(f)$	133	170	298
Modified Acceleration with $H_s(f)$	143	222	367

acceleration signal. The vertical axis shows the results of the scatter plot measured from compressors with a defective suction valve, normal valve, and defective discharge valve. The scale on the vertical axis has no meaning.

In the classification result using the feature of the refrigerant pressure pulsation signal in Fig. 11, the signal of the defective discharge valve is well distinguished from other signals. However, the feature of the defective suction valve is close to that of the normal valve and is not distinguishable. The results of the classification using the shell acceleration signal of the compressor in Fig. 12 show that all the features are superimposed, and it is difficult to distinguish the defective suction valve signal and the defective discharge valve signal from the normal signal. Therefore, the indicators that directly use the compressor shell acceleration signal have almost no classification capability. Although the pressure pulsation signal has better classification performance than the acceleration signal, it would be difficult to measure the pressure quickly in a mass production line. Therefore, it is more reasonable to improve the classification performance by modifying the shell acceleration signal.

Figs. 13-15 show the results of classification in the frequency domain of the modified acceleration signal obtained by modifying the acceleration signal measured at the compressor shell using each transfer function. Figs. 13 and 14 show scatter plots using transfer functions $H_1(f)$ and $H_2(f)$, and Fig. 15 shows the scatter plot using the proposed transfer function $H_s(f)$. When comparing the defective suction valve with the normal valve, it can be seen that the defect classification performance using the $H_2(f)$ transfer function is better than using the $H_1(f)$ transfer function. However, the defect classification performance using $H_1(f)$ is more distinguishable than when using $H_2(f)$ when the defective discharge valve and the normal valve are considered. When using the modified acceleration signal with $H_s(f)$, the defective suction valve signal, defective discharge valve signal, and normal valve signal are well distinguished. This means that it is more advantageous in defect classification to use a transfer function with scale factor $k(f)$ to consider the noise ratio of each signal.

The FDR index is shown in Table 1. The refrigerant pressure pulsation signal has a relatively high FDR index compared with the other signals. In particular, RVF is significantly higher than the other features. The FDR of the shell acceleration has the lowest value compared to that of the other signals, which confirms that it is difficult to classify defects using the shell acceleration as it is in the FDR index. The values of FDR obtained using the transfer functions are lower than those obtained using the pressure pulsation. However, the FDRs obtained using transfer functions are higher than those obtained with the shell acceleration. In particular, FDR is largest when using $H_s(f)$, which has the best performance.

4. Conclusions

Valve defects in a compact compressor have a direct and significant effect on the pressure pulsation of the refrigerant in the piping. However, measuring the pressure signal in a mass production line is not effective for the classification of valve defects because it requires much effort and time. On the other hand, the compressor shell acceleration signal can be easily measured but is not suitable for use in defect classification because signals including the compressor structural characteristics are measured together. To overcome these difficulties, this paper presented a signal processing procedure to improve the defect classification performance by modifying a compressor shell acceleration signal using a transfer function.

The transfer function $H_s(f)$ considers the noise characteristics of the pressure transducer and the accelerometer. In addition, a procedure for estimating the scale factor k(f) required for the estimation of $H_s(f)$ transfer function was presented. RVF was more advantageous than FC or RMSF as a feature for classifying the defects of a compressor valve. The FDR index value for the RVF feature was 33 for the transfer function $H_1(f)$ and 298 for the transfer function $H_2(f)$, but the FDR value could be increased to 367 by using the proposed transfer function $H_s(f)$. The scatter plot confirmed the improvement of the defect classification performance. The classification performance of compressor valve defects was improved by using the $H_s(f)$ transfer function.

If the transfer function between the pressure pulsation in the piping and the acceleration of the shell is measured for a compressor prototype, only the acceleration signal can be measured in the mass production line to improve the valve defect classification performance. Using this method, it is easy to classify the valve defects of a compressor valve in mass production and improve the reliability of the product. Further improvements will require the accumulation of sufficient data for normal and defective compressors.

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