

# A Technique for Diagnosing Abnormalities in Intermittent Sound Emission Mechanisms Based on Dynamic Programming Matching

TERUJI SEKOZAWA

Department of Information Systems Creation,

Kanagawa University

3-27-1, Rokkakubashi, Kanagawa-ku, Yokohama 221-8686

JAPAN

sekozawa@kanagawa-u.ac.jp <http://www.is.kanagawa-u.ac.jp/>

*Abstract:* - This paper proposes an acoustic diagnosis technique for detecting abnormalities in and deterioration of machines that emit intermittent sounds during operation. The effectiveness of this technique is demonstrated experimentally. Acoustic diagnosis is generally applied to continuous sounds by analyzing the power spectrum patterns of regular, periodic sounds emitted by rotating components. However, machines such as automatic teller machines (ATMs) emit intermittent, episodic sounds during operation, making it impossible to employ the same diagnosis techniques as those used for conventional, continuous sounds. The proposed technique enables intermittent acoustic abnormalities to be diagnosed. It achieves this by constructing two vector series that are polygonal chain approximations of the temporal changes in the pressure levels of the most characteristic frequencies of the acoustic emissions during normal operation (the “standard vector series”) and during inspection (the “measured vector series”). The technique employs dynamic programming (DP) matching to collate and compare the two vector series at standard intervals. The technique consists of the following six steps: (1) acquisition of the temporal changes in the pressure level, as acoustic data; (2) extraction of the diagnosis regions; (3) selection of relevant features using a polynomial expansion filter; (4) polygonal chain approximation of the acoustic waveforms by vector series; (5) collation of the resulting measured vector and standard vector series by DP matching; (6) diagnosis of abnormality by vector dissimilarity. This paper provides detailed descriptions of steps 3 to 6. Steps 3 and 5 are particularly notable: in step 3, the acoustic data are approximated as vectors in a polygonal chain using a Hermite polynomial and the relevant features are extracted; in step 5, the DP collation absorbs operational asynchronicities, thereby eliminating what has been the greatest impediment to intermittent sound diagnosis. The effectiveness of this method for localizing and diagnosing abnormalities is demonstrated experimentally by applying it to acoustic data from the paper-slip transport in an actual machine.

*Key Words:* - Acoustic diagnosis, Intermittent sound, Automatic teller machines, Polynomial expansion filter, Polygonal chain approximation, Dynamic programming matching, Vector dissimilarity

## 1 Introduction

Acoustic emission (AE) and vibrational techniques are conventional methods for inspecting mechanical systems and diagnosing deterioration.<sup>1)-7)</sup> Typical examples include acoustic diagnosis of insulated transformers<sup>2),5)</sup> and underwater concrete columns<sup>3)</sup>, using AE sensors that require contact with the inspected object. This requirement, however, makes it difficult to employ them to diagnose small abnormal or deteriorated regions out of the many regions present in precision equipment. In contrast, noncontact methods can readily acquire multipoint

data. Thus, we investigated the possibility of applying them to acquire and utilize the series of sounds emitted by such equipment.

The sounds that precision equipment emit during operation are modified by wear and deterioration in their components over long periods and by changes in the ambient temperature and humidity. Skilled maintenance personnel are able to assess the internal state of equipment from its acoustic emissions based on experience. It may thus be possible to detect abnormalities by analyzing acoustic data. Diagnosis utilizing acoustics is used to detect abnormalities and

failures in vibrating bodies,<sup>2),8),9)</sup> rotational mechanisms (such as bearings, gears, and pumps),<sup>10)</sup> and engine exhaust systems.<sup>11)</sup> The acoustic target in such cases is generally continuous sound and the diagnosis generally utilizes frequency analysis<sup>12)</sup> and power spectral patterns of the periodic sounds emitted by rotating or vibrating bodies. Diagnosis is performed by comparing and pattern matching with spectral patterns from normal operation and by observing changes over time in the appearance of prominent frequency components in spectral patterns. However, these methods are inherently unsuitable for diagnosing precision machines that emit intermittent, episodic sounds, such as automatic teller machines (ATMs), which are described in this report. ATMs perform a wide variety of functions, including depositing, paying, transferring, displaying current balances, and saving. The sounds emitted by their mechanisms are intermittent and episodic. Power spectrum analysis is unsuitable for such mechanisms for two reasons. The first reason is because the sounds vary over time and analysis of the power spectrum at the sampling time would necessitate recording spectral pattern data at many different times, which is impractical. The second reason is because asynchrony occurs in intermittent sound emissions depending on the state of the mechanisms, making it difficult to establish the timing of abnormal sound emissions from the equipment. Other attempts to apply acoustic diagnosis to ATMs have been reported,<sup>13),14)</sup> but they have been limited to frequency analysis of the ATM stack wheel units. They apply frequency analysis to continuous sounds emitted by rotating mechanisms, and thus belong to the same category as conventional methods. In contrast, the diagnosis technique described in the present report is not restricted to internal rotational mechanisms but is applicable to the entire ATM, including its banknote transporter, stocker, and banknote checker. The sounds emitted from many points within the ATM include not only continuous sounds emitted by wheels and other rotational mechanisms considered in Refs. 13 and 14, but also sounds from transport drives, banknote engagement, roll winding, banknote impact on boxes, and friction involved in the movement of both machinery and banknotes — a complex combination of sounds that is impossible to diagnose solely using frequency analysis.

The present report proposes a technique for acoustic detection and diagnosis of abnormalities in machines that emit nonperiodic, intermittent sounds. Using vector series, this technique performs polygonal chain

approximations of temporal changes in the acoustic pressure at the frequencies that exhibit the most conspicuous changes in emitted sounds during normal operation and inspection. Abnormality diagnosis is performed by collating and comparing the two vector series. By collating with the waveform obtained by polygonal chain approximation during normal operation, the operation interval is obtained in the target region of the diagnosis. This enables acoustic diagnosis of machines that have indefinite operating times in the component regions. The collation is performed by dynamic programming (DP) matching, which facilitates temporal compression. Furthermore, polygonal chain approximation of the data waveform by a vector series enables the acoustic data to be stored in compressed form, thereby reducing the data-storage volume and enabling high-speed calculation.

In this report, Section 2 describes the abnormality diagnosis method including the diagnostic process, acoustic data feature extraction, and feature collation. It also discusses various aspects of abnormality diagnosis. Section 3 provides an example of its application in the diagnosis of abnormalities in regions within actual paper-slip transporters of ATMs and it evaluates its effectiveness for this purpose.

## 2 Method of abnormality diagnosis

### 2.1 Diagnostic process

Machines consist of various types of operating regions. The acoustic emissions from each region tend to vary over time. Accordingly, these changes can be observed in the waveforms of acquired acoustic data. Diagnosis of abnormalities in these constituent regions is performed by analyzing these waveform changes. Figure 1 illustrates the diagnostic method of the proposed technique.

#### (1) Data acquisition

At the time of inspection, the series of sounds emitted from various operating regions that operate in a given sequence is acquired as electrical signals using a microphone. The acoustic pressures in the frequency range most characteristic of the condition of each region are sampled and the acoustic pressure levels are converted into acoustic data. In this way, temporal changes in the acoustic pressures are obtained.

#### (2) Extraction of diagnosis points

Diagnosis of particular operating regions requires obtaining acoustic data for each portion of that region during its operation. However, the timing of operation

in each portion fluctuates with its operating environment. For this reason, acoustic data extraction from the region in the vicinity of its time of operation is performed in a predetermined time range. Smoothing of the acoustic data is also performed to eliminate noise.

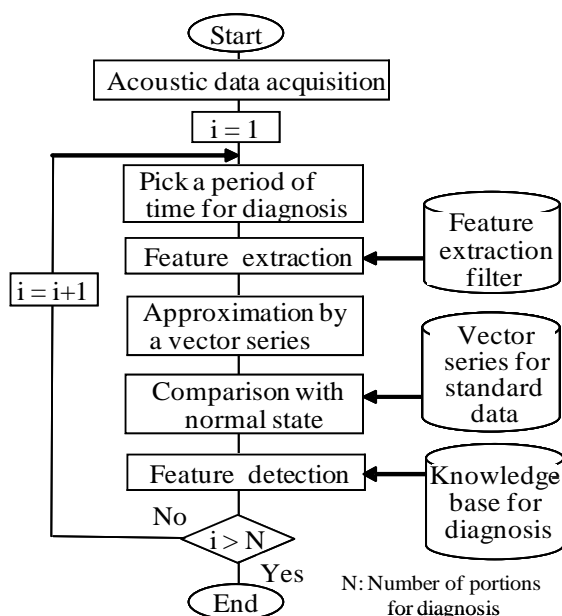


Fig. 1 Overview of abnormality diagnosis technique

### (3) Feature extraction

To enable polygonal chain approximation of the acoustic data by a vector series, the peak and trough times of the acoustic data waveform are obtained by polynomial expansion of the acoustic data for each time point, in which the second-order coefficient of expansion represents the peak and trough times. Approximate values (restoration values) are computed from the polynomial expansion of the data at these times. These times and the calculated restoration values occurring at these times are hereafter referred to as the *feature points*.

### (4) Construction of measured vector series

Successive feature points are connected, forming vectors in which each vector embodies the difference between two feature points in time and acoustic pressure. The vector series formed by linking these vectors enables polygonal chain approximation of the acoustic data waveform, and is hereafter referred to as the *measured vector series*.

### (5) Feature collation

The measured vector series is next collated by DP matching with a vector series (hereafter, called the

*standard vector series*) previously obtained during normal equipment operation by the same procedure as that used for the measured vector series, which was stored for this purpose. Those spans of the measured vector series that most closely resemble those of the standard vector series are taken as representing waveforms of the operating regions in the equipment.

### (6) Abnormality diagnosis

If an abnormality exists in the region being diagnosed, the corresponding vector in the measurement vector series will, as a result of collation, have very different lengths and slopes from that of the standard vector series. The difference in vector conformation (also known as the dissimilarity) is calculated using an equation that relates the differences in length and slope. If any part of the vector series exceeds a standard value, which is established as an error limit to allow for ordinary fluctuations that occur during normal operation, it is judged to be abnormal.

The above processing is performed for each region, with the abnormality diagnosis progressing through extracting the acoustic data corresponding to each of the regions in the order of their operation.

This section has provided an overview of the abnormality diagnostic process. Section 2.2 onwards provides a more detailed description of Steps (3) to (6) of the process in their application to a single region.

## 2.2 Feature extraction

A polynomial expansion filter is used in the polynomial expansion of the acoustic data in the vicinity of each sampling time, to determine the coefficient of each order in the polynomial. The acoustic data are time-series data and are generally referred to by that term in Section 2.2.1.

### 2.2.1 Polynomial expansion

As the raw time sequence data would require a huge amount of processing, the waveform of the data series is approximated by a vector series, which eliminates excess data on the waveform. The feature points of the data series are extracted by polynomial expansion.

The waveform of small data intervals can be approximated by the quadratic function  $f(x) = ux^2 + vx + w$ , where the coefficient of the quadratic term  $u$  represents the degree of curvature of the second-order peak and the constant term  $w$  represents the peak's maximum value. Using the approximation of the small data series intervals by the second-order polynomial, it is possible to obtain the

features of that interval of the data waveform from the coefficient of the quadratic term and the constant term.

The expansion method utilizes the Hermite polynomial  $H_m(x)$ ,<sup>14) 15)</sup> which is defined as

$$H_m(x) = (-1)^m \{E(x)\}^{-1} \frac{d^m E(x)}{dx^m} \quad (1)$$

$$\sum_{x=-a}^a \{H_m(x)H_n(x)\}E(x) = 0 \quad (m \neq n) \quad (2)$$

where  $E(x)$  is the Gaussian error function

$$E(x) = \exp\left(-\frac{x^2}{2\sigma^2}\right) \quad (3)$$

and the constant  $a$  indicates the defined interval. Moreover,  $x$  is the variable in the time direction in units of the sampling time interval. If the normalization constant  $A_m$  is defined as

$$A_m = \sum_{x=-a}^a \{H_m(x)\}^2 E(x) \quad (4)$$

Then

$$\psi_m(x) = \frac{1}{\sqrt{A_m}} H_m(x) \{E(x)\}^{1/2} \quad (5)$$

constitutes an orthonormal function that may be regarded as a weighting of  $H_m(x)$  by  $E(x)$ . The time-series data  $f(t)$  centered on time  $t$  is approximated. As in Eq. (5), time-series data  $f(t)$  is weighted by  $E(x)$  to obtain  $h(t)$ , which is expanded as:

$$h(t+x) = f(t+x) \{E(x)\}^{1/2} \quad (6)$$

When Eq. (6) is expanded using the orthonormal function in Eq. (5), time-series data  $f(t)$  can be expanded as:

$$\begin{aligned} h(t+x) &= \sum_{x=-a}^{\infty} a_m(t) \psi_m(x) \\ &= \sum_{x=-a}^{\infty} a_m(t) \frac{1}{\sqrt{A_m}} H_m(x) \{E(x)\}^{1/2} \end{aligned} \quad (7)$$

with  $a_m(t) (m = 0, 1, \dots, \infty)$  as the expansion coefficient obtained from:

$$a_m(t) = \sum_{x=-a}^a h(t+x) \psi_m(x). \quad (8)$$

From Eqs. (6) and (7), in the vicinity of time  $t$ , expansion of the time-series data  $f(t)$  can thus be performed by:

$$h(t+x) = \sum_{x=-a}^a a_m(t) \frac{H_m(x)}{\sqrt{A_m}}. \quad (9)$$

Thus, as shown in Eq. (1),  $H_m(x)$  is a polynomial of degree  $m$  and the time-series data  $f(t)$  in the vicinity of time  $t$  is expanded using this polynomial. Substituting Eqs. (5) and (4) into Eq. (8) yields

$$a_m(t) = \sum_{x=-a}^a f(t+x) \frac{H_m(x)}{\sqrt{A_m}} E(x) \quad (10)$$

We can thus obtain the polynomial coefficient  $a_m(t)$ , which is obtained from the function  $W_m(x)$  as

$$W_m(x) = \frac{H_m(x)}{\sqrt{A_m}} E(x) \quad (11)$$

by multiplying and summing the time-series data  $f(t)$ .  $W_m(x)$  is hereafter called the *feature extraction filter*. Figure 2 shows the feature extraction filters used in obtaining the zero-, first-, and second-order polynomial expansion coefficients.

Using the results of the polynomial expansion with the feature extraction filter  $W_m(x)$ , we can obtain the restoration value  $f_e(t)$  for the time-series data at time  $t$  by inserting  $x = 0$  into Eq. (9).

$$\begin{aligned} f_e(t) &= \sum_{x=-a}^{\infty} a_m(t) \frac{H_m(0)}{\sqrt{A_m}} \\ &= \sum_{x=-a}^{\infty} a_m(t) W_m(0) \end{aligned} \quad (12)$$

The feature extraction filter width  $[a, -a]$  is selected on the basis of the curvature at the point that is determined as the feature point. In calculations using Eq. (12), a second-degree polynomial is assumed to be

sufficient for approximating a small data interval and the maximum degree of the polynomial is defined by setting  $m = 2$ .

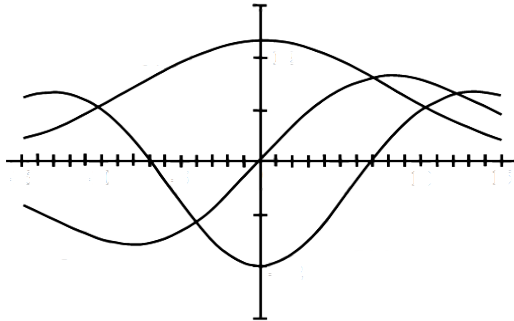


Fig. 2 Feature extraction filter( $\sigma=8$ ) for determining the polynomial expansion coefficient from measured data

**2.2.2 Feature extraction method**

In Eq. (7), the second-order expansion coefficient  $a_2(t)$  represents the time-series curvature in the vicinity of time  $t$ . If  $a_2(t) > 0$  the curve is convex above and if  $a_2(t) < 0$  it is convex below; the larger the value of  $|a_2(t)|$  is, the greater its curvature is.

By obtaining the second-order expansion coefficient  $a_2(t)$  for time-series data  $f(t)$ , we can therefore find the “center of balance” of intervals having either a positive or a negative value. The center of balance lies near the point of greatest curvature in the interval and is therefore taken as the feature point time  $t_j$ . The method for calculating  $t_j$  is illustrated in Fig. 3 for the interval  $(t_s, t_e)$  having a positive value. As shown, the areas under the curve to the left and right of point  $t_j$  are equal and the center of balance  $t_j$  lies in the region of maximum height in the waveform peak, which is the point of greatest curvature, and thus close to the feature point. The center of balance is thus taken as the feature point and  $t_j$  is obtained from the equation:

$$t_j = \frac{\sum_{t=t_s}^{t=t_e} (t \cdot a_2(t))}{\sum_{t=t_s}^{t=t_e} a_2(t)} \quad (j = 0, 1, \dots, J) \quad (13)$$

where  $t_s$  is the starting point of a given interval,

$t_e$  is its end point, and  $J$  is the number of feature points in the time-series data. From the point  $t_j$  on the time axis and the restoration point  $f_e(t_j)$  obtained from Eq. (12). It is possible to obtain the feature point  $(t_j, f_e(t_j))$ .

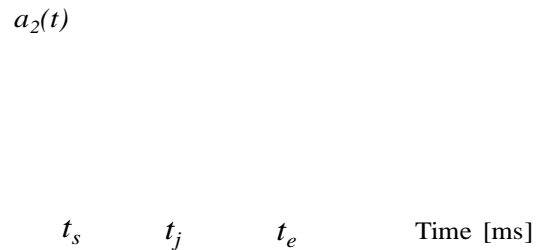


Fig. 3 Location of the center of balance ( $t_j$ ) is nearest the point of maximum curvature in a positive-value (or negative value) interval  $(t_s, t_e)$ ; hatched and dotted portions are of equal area

**2.3 Measured vector series construction**

The time-series data restoration point  $t_j$  is obtained from Eq. (12) and the corresponding feature point  $(t_j, f_e(t_j))$  is calculated. The successive feature points are then connected to express the time-series data  $f(t)$  as a vector series:

$$a_j = (t_{j+1} - t_j, f_e(t_{j+1}) - f_e(t_j)) \quad (j = 1, 2, \dots, j - 1). \quad (14)$$

Figure 4 illustrates the course of the polygonal chain approximation of the acoustic data by the vector series. In this example, (a) shows the raw acoustic data, (b) is the smoothed acoustic data obtained by the average movement of each point together with the three points on either side of it, (c) is the second-degree polynomial expansion coefficients  $a_2(t)$  calculated with a feature extraction filter having  $\sigma = 8$ , and (d) is the waveform obtained by the vector series approximation.

**2.4 Feature collation**

As noted above, DP matching is used to collate and extract the vector series of the range of movement in the region to be diagnosed from the measured vector series. In the collation results, it is necessary to avoid

the correspondence states shown in Fig. 5.

In Fig. 5(a), the third vector from the left in the lower vector series is in redundant correspondence with the second and third vectors in the upper series.

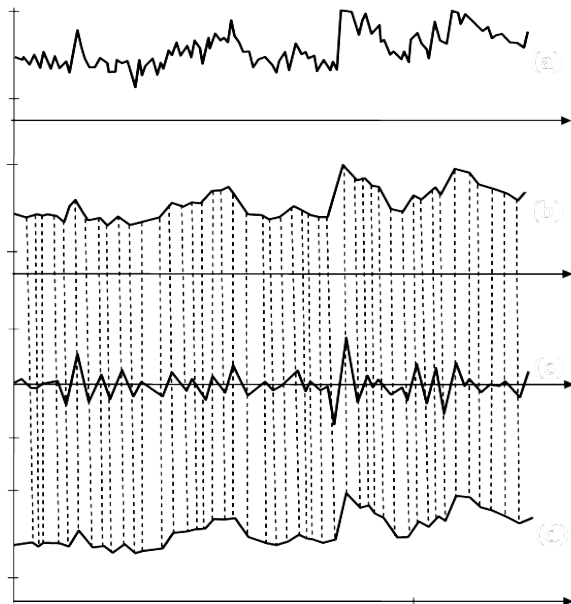


Fig. 4 Acoustic data approximation process:

- (a) acoustic data;
- (b) mean movement in acoustic data;
- (c) second-order coefficient  $a_2(t)$  of polynomial expansion ( $\sigma=8$ );
- (d) waveform approximated by a vector series.

In Fig. 5(b), the third vector in the lower series does not correspond to any vector in the upper series. To avoid these states at any given node  $(i, j)$  and to obtain the route that minimizes the evaluation function value for the two vector series, the route is selected from three directions, as illustrated in Fig. 6.

The evaluation function is applied to route selection at each node  $(i, j)$ . In the DP matching, during determination of the correspondence for set  $t$  in the two vector series, the optimum correspondence of the previous set  $t-1$  for minimizing the difference between the two vector series (hereafter referred to as the “error”) has already been determined.

When determining the correspondence for set  $t$ , at node  $(i, j)$ , the evaluation function is expressed by:

$$\sum_{c=1}^t g_c = \sum_{c=1}^{t-1} g_c + g_t, \tag{15}$$

where  $g_t$  is the correspondence error in set  $t$  and  $\sum_{c=1}^{t-1} g_c$  is the sum of the correspondence errors in sets 1 to  $t-1$ .

(a) (b)

Fig. 5 Unallowable correspondence between two vector series, where the dotted lines mean the correspondence between vectors.

- (a) A vector marked arrow is duplicated by two vectors.
- (b) A vector marked arrow has no corresponding vector.

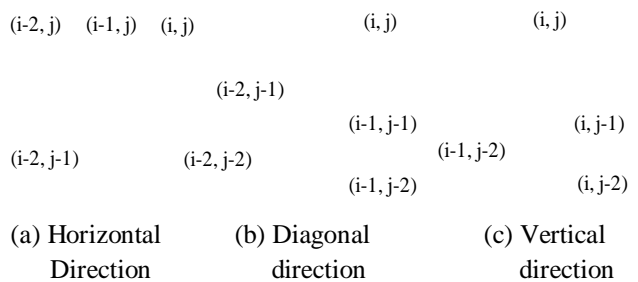


Fig. 6 Route candidates to the node  $(i, j)$

Error  $g_t$  also represents the square of the error between the two vectors. In the correspondence between the two vectors  $\alpha$  and  $\beta$ , this “squared error” can be expressed as:

$$g_t = |\alpha - \beta|^2 = |\alpha|^2 - 2(\alpha \cdot \beta) + |\beta|^2. \tag{16}$$

This involves the correspondence of one vector to just one vector and is the case for route (b) in Fig. 6, and would thus lead to its selection. If either route (a) or route (c) were selected, the number of vectors  $r (r \geq 1)$  involved in the correspondence to one vector would be larger. In the correspondence of vectors  $\beta_1 \dots \beta_r$  to  $\alpha$ , the squared error may be expressed as:

$$g_t = \left| \boldsymbol{\alpha} - \sum_{p=1}^r \boldsymbol{\beta}_p \right|^2 = |\boldsymbol{\alpha}|^2 - 2 \sum_{p=1}^r (\boldsymbol{\alpha} \cdot \boldsymbol{\beta}_p) + \left( \sum_{p=1}^r |\boldsymbol{\beta}_p| \right)^2 \quad (17)$$

It should be noted that  $\boldsymbol{\beta}_1 \dots \boldsymbol{\beta}_r$  vector sum in this equation is not  $|\boldsymbol{\beta}_1 \dots \boldsymbol{\beta}_r|$  but rather  $|\boldsymbol{\beta}_1| + \dots + |\boldsymbol{\beta}_r|$ .

The former would apply in the case of correspondence to  $\boldsymbol{\alpha}$  by a vector extending from the initial point of  $\boldsymbol{\beta}_1$  to the terminal point of  $\boldsymbol{\beta}_r$ . The latter applies for correspondence to  $\boldsymbol{\alpha}$  by the vector series  $\boldsymbol{\beta}_p (p = 1, 2, \dots, r)$ , and the difference between the vector series peak and trough conformations is thus included in the error.

### 2.5 Abnormality diagnosis

The dissimilarity is calculated for each vector as the correspondence determined by the collation. The dissimilarity is compared with the standard value (the “error limit”), which is established on the basis of the error variation in similar equipment units during normal operation as determined from the frequency distribution of the variations among those units.

When abnormality symptoms begin to appear, changes are generated in the acoustic data waveform. Within the vector series, large changes occur in the slope of the component vectors. Changes in vector length (i.e., shortening or lengthening relative to the time axis) can be attributed in large part to normal fluctuations in acoustic emissions depending on variations in the state of the equipment and other such factors. Accordingly, the change in slope is more strongly represented in quantification of the difference between two corresponding vectors in length and slope as the dissimilarity. For this reason, it is calculated as the product of the squared error and  $1 - \cos \theta$  ( $\theta$ : angle between the two vectors). However, a further consideration of vector length is necessary due to the use of DP matching, in which the vector correspondence is not necessarily one to one. Therefore, when correspondence occurs between one vector and  $r (r > 1)$  vectors, a one-to-one correspondence is constructed by dividing one vector into  $r$  parts in accordance with the component time ratios of the other, and the dissimilarities of the

vectors in the one-to-one correspondence are then summed. Thus, in the event of correspondence to  $\boldsymbol{\alpha}$  by  $\boldsymbol{\beta}_1 \dots \boldsymbol{\beta}_r$ ,  $\boldsymbol{\alpha}$  is divided into  $\boldsymbol{\alpha}_1 \dots \boldsymbol{\alpha}_r$  in accordance with the component time ratios of  $\boldsymbol{\beta}_1 \dots \boldsymbol{\beta}_r$ , and the dissimilarity between  $\boldsymbol{\alpha}$  and  $\boldsymbol{\beta}_1 \dots \boldsymbol{\beta}_r$  is then obtained as

$$E = \sum_{p=1}^r \{ (\boldsymbol{\alpha}_q \cdot \boldsymbol{\beta}_q)^2 (1 - \cos \theta_q) \} \quad \cos \theta_q = (\boldsymbol{\alpha}_q \cdot \boldsymbol{\beta}_q) / (|\boldsymbol{\alpha}_q| |\boldsymbol{\beta}_q|) \quad (18)$$

The enhancement of the increase in dissimilarity with increasing angle between the vectors that results from using the product of the squared error and  $1 - \cos \theta$  is illustrated by the vector series shown in Figs. 7 and 8. In Fig. 7, the dissimilarity is calculated from the squared error alone, whereas in Fig. 8 it is calculated from the product of the squared error and  $1 - \cos \theta$ . In Fig. 7, large dissimilarities are rather pervasive and the waveform changes are not clearly presented. In Fig. 8, all the dissimilarities are smaller, but those representing differences in the inter-vector angle are much more prominent than those representing differences in vector length, thus more clearly and accurately representing the waveform changes and enabling more reliable detection of the waveform change regions.

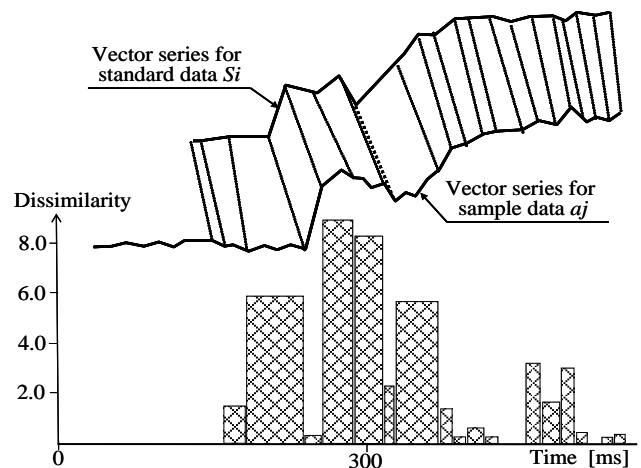


Fig. 7 Dissimilarity between standard vector series and vector series for diagnosis using the squared error

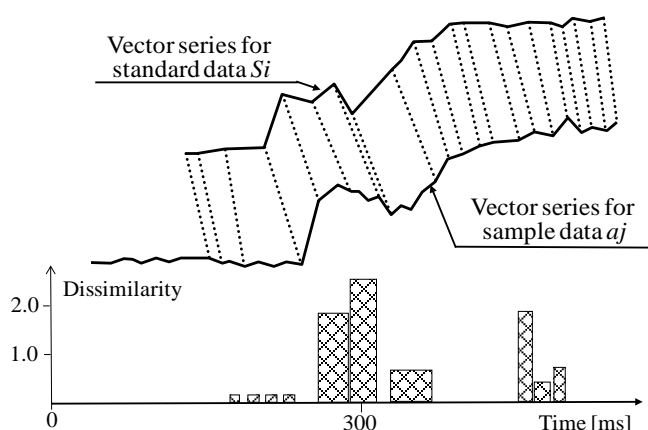


Fig. 8 Dissimilarity between standard vector series and vector series for diagnosis, by product of squared error and  $(1-\cos\theta)$

### 3 Experimental results and evaluation

The proposed method described in the previous section was applied experimentally to diagnose the paper-slip transport portion (hereafter called the “transporter”) of an actual machine.

The operation of such a transporter during its processing of a slip proceeds in a prescribed sequence, and its acoustic emissions are thus intermittent. During mechanism initialization, operation in the constituent regions of the transporter proceeds in the order determined by an operation verification program. In the evaluation, the acoustic emissions during that time were subjected to a 1/6 octave bandpass filter that passes only 10 kHz, and an envelope was then obtained by squared detection of the resulting output signal. The frequency of 10 kHz was chosen because transporter abnormality is generally most conspicuous at that frequency and 1/6 octave attenuation was used to enable accurate acquisition of the changes in the shape of the waveform. The output signal was sampled at a sampling rate of 1 ms to obtain the time-series data.

In the proposed method, diagnosis of the state of each region within the transporter is performed on the basis of the waveforms of the operating sounds acquired from it in the above-described manner. It is first necessary, however, to establish a standard value as the “error limit”, to allow for normal variations among products in a given product line that result in differences among their acoustic data and thus their waveform peak shapes and widths. For this purpose, we measured the acoustic emissions of 84 transporters of the same model during actual operation and

determined the resulting error frequency distribution. The term “error” here refers to the divergence between the data from a normally operating transporter and the data from the others. Figure 9 shows the resulting data distribution. The value shown by statistical calculations to be equivalent to a 97% degree of certainty was taken as the standard value. A feature extraction filter having  $\sigma = 8$  and a width of 33 ( $a = 16$ ) was used throughout.

Figure 10 shows typical results of the experimental diagnoses by the proposed method for abnormality detection and Fig. 11 shows results for normal operation. The abnormality in Fig. 10 occurred during paper slip insertion when the paper-slip push plate came into contact with a guide. In the upper half of this figure, (a) and (b) show the standard acoustic data and the acoustic data obtained during the mechanism inspection, respectively. The lower half shows the results obtained by the proposed diagnostic method in the vector correspondence between the two vector series and in dissimilarities between corresponding vectors as shown by the bar graph. A symptom of abnormality is indicated by the circled peak shape in Fig. 10(b), which is absent in Fig. 10(a). In the diagnosis, the dissimilarity in peak shape in the circled portion clearly exceeds the error limit, thus demonstrating the detection of an abnormality. Variations in peak shape can also be observed prior to the circled peak shape, but these represent acoustic emissions just before the start of operation in this region and correspond to ordinary acoustic fluctuations during normal operation. Their dissimilarities, as shown in the bar graph, are smaller than the differences in peak shape that appear in the vector series, due to the use of the method described in Section 2.5 for calculating the dissimilarity. Thus, these results demonstrate the ability of this method for strong representation of vector slope. In contrast to Fig. 10, Fig. 11 shows no difference such as that existing between the circled portions in (a) and (b) of Fig. 10 or any conspicuous dissimilarity such as that in the bar graph in Fig. 10. This demonstrates the ability to detect abnormalities by establishing a standard value.

The proposed method has been applied to the development of a small, practical acoustic diagnosis system containing a digital signal processor (DSP) for rapid performance. The DSP is a single-chip microprocessor specifically designed to process time-series data and other measured values. The system consists of a microphone for acoustic data acquisition and the main unit, which includes a



diagnostic results display and utilizes memory cards that are particularly convenient for storing the necessary data relating to standard vector series and can thus be selected for acoustic diagnosis of different mechanism models and types.

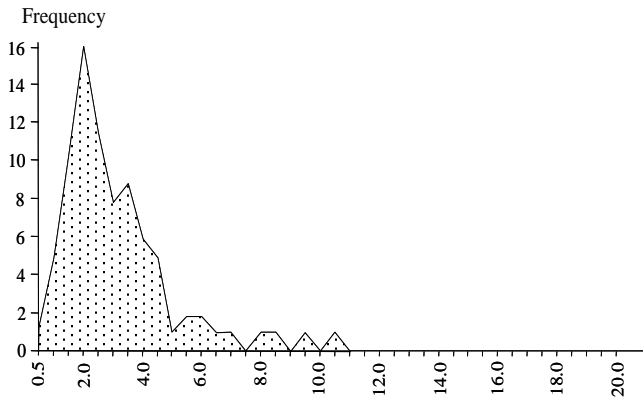
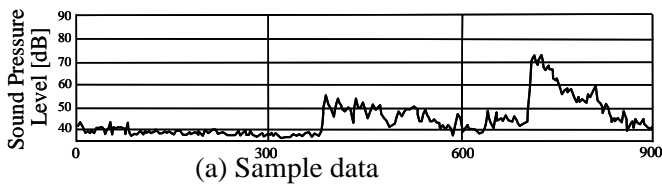


Fig. 9 Error frequency distribution  $t^{Error}$  84-mechanisms in normal cases



(a) Sample data  
(b) Sample data in the case of fault

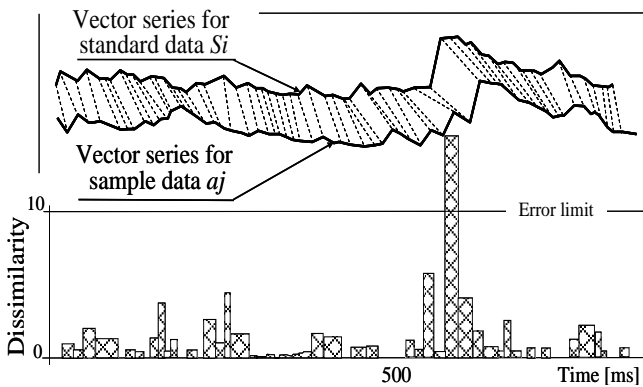
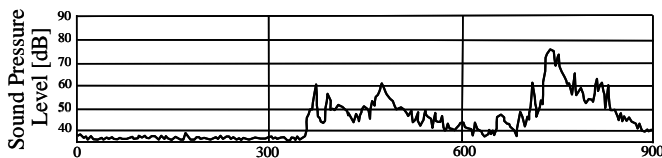
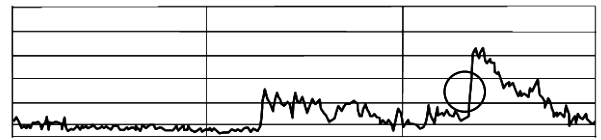
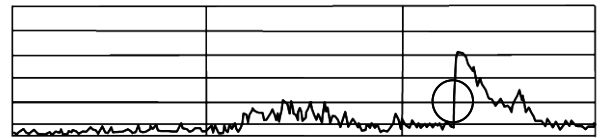


Fig. 10 Diagnosis result in the case of fault



(a) Sample data



(b) Sample data in the case of ordinary

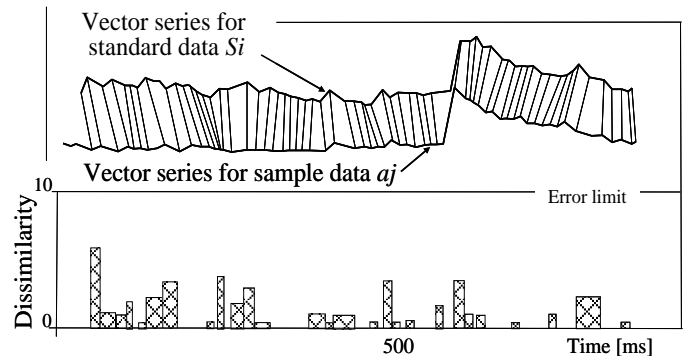


Fig. 11 Diagnosis result in the case of ordinary

### 4 Conclusions

In this report, we have proposed a technique for diagnosing abnormalities in machines by utilizing their intermittent, episodic sound emissions. We have also described the experimental confirmation of its practicality and effectiveness in which the paper-slip transport region of an actual machine was diagnosed.

This technique includes vector approximation of data-series waveforms, thus eliminating the inordinate processing volume that would be required for acoustic data in the form of raw time-series data and extraction of feature points by a polynomial expansion in which the center of balance is obtained by determining the relevant expansion coefficient. The center of balance in an interval of positive or negative value is near its center of curvature, and is thus taken as the time of the feature point, as described in this report.

It is also necessary to locate the region of the mechanism that is the target of diagnosis despite the occurrence of departures from the time of intermittent sound emission that would apply under the operational sequence prescribed for the various regions, due to the particular state then existing in each region. This

problem of operational asynchronicity, which up to now has posed the greatest impediment to practical acoustic diagnosis of intermittent sound, is eliminated by the proposed method by taking the polygonal approximation of the waveforms of acoustic data during normal operation and during inspection and applying DP matching to collate the two waveform approximations, thereby enabling absorption of the asynchronicities.

We have also described the results of experimental diagnosis of a target region within an actual paper-slip transporter, which confirmed that the technique is effective for acoustic diagnosis. Its facilitation of high-speed calculations with a small memory capacity has enabled the development of a compact diagnostic system containing a single-chip DSP.

In further studies, we intend to investigate its application to other units and to other types of mechanisms.

#### References:

- [1] Cheng-Chien Kuo, Teng-Fa Tsuo, A Novel Defect Classification System of Cost-Resin Transformers by Neural Network under Acoustic Emission Signal, *Proceeding of the 6th WSEAS International Conference on Instrument, Measurement, Circuits & Systems*, 2007, pp.93-98
- [2] Gyung-suk Kil, Dae-won Park, Il-kwon Kim, Su-yeon Choi, Analysis of Partial Discharge in Insulation Oil using Acoustic Signal Detection Method, *WSEAS Transactions on Power Systems*, Vol.3, Issue 3, 2008, pp.90-94
- [3] A-lan Jiang, Ying-hua Zhao, Li-wei Zhang, Experimental study of acoustic emission characteristics of underwater concrete structures, *IEEE International Symposium on Piezoelectricity, Acoustic Waves, and Device Applications*, 2008, pp.252-257
- [4] Ince N.F., Chu-Shu Kao, Kaveh, M., Tewfik, A., Labuz J.F., A-lan Jiang, Ying-hua Zhao, Averaged acoustic emission events for accurate damage localization, *IEEE International Conference on Acoustics, Speech and Signal*, 2009, pp.2201-2204
- [5] Dae-won Park, Su-yeon Choi, Gyung-suk Kil, Measurement and Analysis of Acoustic Signal Generated by partial Discharges in Insulation oil, *Proceedings of the 7th WSEAS International Conference on Power System*, 2007, pp.272-275
- [6] Zogovic Vukasin, Vukasojevic Radomir, Stojanovic Radovan, Monitoring of the Processed Surface Quality by an Acoustic Emission Application, *Proceedings of the 5th WSEAS International Conference on Signal and Image Processing*, 2005, pp.50-53
- [7] Runde M., Ottesen G.E., Skyberg B., Ohlen M., Vibration analysis for diagnostic testing of circuit-breakers, *IEEE Transactions on Power Delivery*, Vol.11, Issue 4, 1996, pp.1816-1823
- [8] Xiong Hao, Sun Cai-xin, Artificial Immune Network Classification Algorithm for Fault Diagnosis of Power Transformer, *IEEE Transactions on Power Delivery*, Vol.22, Issue 2, 2007, pp.930-935
- [9] Yuying Shao, Zhushi Rao, Zhijian Jin, Online State Diagnosis of Transformer Windings based on Time-frequency Analysis, *WSEAS Transaction on Circuits and Systems*, Vol.8, Issue 2, 2009, pp.227-236
- [10] Ciocan R., Ida N., Method of early failure detection for elastic diaphragms based on frequency analysis of the acoustic signal, *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, Vol.49, Issue 8, 2002, pp.1025-1028
- [11] J. Show, Adaptive Control for Sound and Vibration attenuation: A Comparative study, *Journal of Sound and Vibration*, Vol.235, No.4, 2000, pp.671-684
- [12] Bayan N., Erfani S., Frequency Analysis of Time-Varying Systems, *IEEE International Conference on Electro/information Technology*, 2006, pp.33-36
- [13] Joo Han Kim, Ha Kyeong Sung, Se Hyun Rhyu, A study on the Vibration Analysis and Test Evaluation for Stack Wheel of Note Handling Units, *IEEE International Electric Machines & Drives Conference*, Vol.2, 2007, pp.1343-1348
- [14] Bershada N.J., Celka P., McLaughlin S., Analysis of stochastic gradient identification of Wiener-Hammerstein systems for nonlinearities with Hermite polynomial expansions, *IEEE Transactions on Signal Processing*, Vol.49, Issue 5, 2001, pp.1060-1072
- [15] Rao M.M., Sarkar T.K., Adve R.S., Anjali T., Callejon J.F., Extrapolation of electromagnetic responses from conducting objects in time and frequency domain, *IEEE Transactions on Microwave Theory and Techniques*, Vol. 47, Issue 10, 1999, pp. 1964-1974
- [16] Ide K., Zhi-Guo Bai, Zi-Jiang Yang, Tsuji, T., Vector approximation method with parameter adaptation and torque control of CSI-fed induction motor, *IEEE Transactions on Industry Applications*, Vol.31, Issue 4, 1995, pp.830-840

- [17] Joo Han Kim, Ha Kyeong Sung, Se Hyun Rhyu, A Study on the Natural Frequency Analysis and Test for Note Handling Units, *2nd IEEE Conference on Industrial Electronics and Applications*, 2007, pp.2072-2077
- [18] Howe R., Carmichael N.E., JET Engine Test Strategy-program overview and objectives, *IEEE AUTOTESTCON Proceedings*, 2000, pp.284-289
- [19] Filippo Neri, Agent based modeling under partial and full knowledge learning settings to simulate financial markets, *AI Communications*, IOS Press, 2012, printing