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Continuous Fatigue Level Estimation for Classification of Fatigued Bill Based on Acoustic Signal Feature by Supervised SOM

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Abstract: Fatigued bills have harmful influence on daily operation of Automated Teller Machine (ATM). To make the fatigued bills classification more efficient, development of an automatic fatigued bill classification method with continuous fatigue level is desired. We propose a new method to estimate bending rigidity of bill from acoustic signal feature of banking machines. The estimated bending rigidities are used as continuous fatigue level for classification of fatigued bill. By using the supervised SOM, we estimate the bending rigidity from only the acoustic energy pattern effectively. The experimental result with real bill samples shows the effectiveness of the proposed method.

Keywords: Fatigued bill classification, Supervised SOM, Acoustic signal processing.

I. INTRODUCTION

If fatigued bills are fed to an Automated Teller Machine (ATM), the ATM may be disabled by a paper jam. To avoid such harmful influence on daily operation of ATMs, such fatigued bills must be picked up, and should be replaced with new ones in banks. Nowadays, classification of fatigued bills is operated manually at every bank. To make the operation more efficient, development of an automatic fatigued bill classification method is desired. The method is required to be additional function of banking machines.

In case of implementation, two important facilities are required. The first facility is the high speed classification. For this purpose, the physical features of bill should be measured in short time. The second facility is flexibility of fatigue classification judgment. Every bank has different judgment standard of fatigued bill. So the classification method should have capability to modify the judgment according to fatigue levels of bills.

For the first facility, we have developed an effective fatigued bill classification method based on acoustic signal features of bill which is measured during passing bill in the banking machine (Teranishi[1-5]). Calculating the acoustic features from the signal, classification is done in short time.

Our past proposed methods have achieved to classify bills into two or three discrete fatigue levels. To add the second facility, that is, flexibility of fatigue classification judgment, our methods need to introduce the continuous fatigue level of bill.

From the viewpoint of the paper physics, the continuous fatigue level of bill is represented as the stiffness of bill paper. In the field of research of paper physics, stiffness of paper is measured based on the bending rigidity (Okomori[6], Nakajima[7]). Therefore, in this paper, we use the bending rigidity as continuous fatigue level of bills.

But measurement of the bending rigidity of bills requires specialized measuring devices with long measurement time, therefore is not comfort for the banking machine.

If the bending rigidity is estimated from acoustic signal features, bills are classified in continuous fatigue level by only using acoustic feature. To estimate the bending rigidity from the acoustic signal feature, the aids of some soft computing techniques are necessary.

We adopt the Supervised Self Organizing Map (Supervised SOM) (Kohonen[8]).

By using the supervised SOM, we can construct a relation between the acoustic signal features and the bending rigidity of bills. Then we can estimate the bending rigidity from only the acoustic features.

In this paper, we propose a new method to estimate bending rigidity of bill from acoustic signal feature of banking machines. The estimated bending rigidities are used as continuous fatigue level for classification of fatigued bill.

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We execute experiment to estimate bending rigidity by using some real bill samples. Experimental result shows the effectiveness of the proposed method.

II. Acoustic Signal Feature of Bill

The outline of measuring system for the friction acoustic signal of bill is shown in Fig. 1. The friction acoustic signal of bill is observed in many small desktop type banking machines. Such machines have v-shaped bill transportation path inside. At the turning point of path, typical acoustic signal is emitted by friction bill and the metal cover. We can measure the friction acoustic signal by this system.

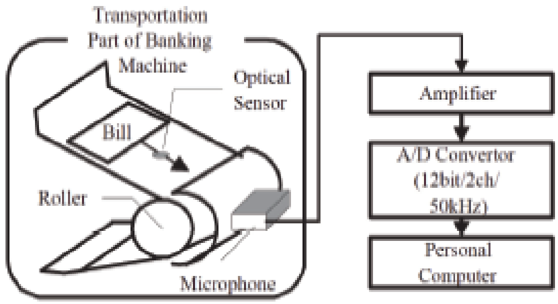

Fig.1. Measurement of friction acoustic signal of a bill.

1. Acoustic Energy Pattern of Bill

The acoustic energy pattern (Teranishi[1]) is a time series of energies of an acoustic signal of a bill. An acoustic energy is calculated by the following processes. First, entire time region of a friction acoustic signal is divided into 81 potions. We call the potions as frames. Each frame f_i has 10ms time length. Every frame f_i is located with overlapped to the next frame f_{i+1}. The length of overlap is 2.5ms. Then an acoustic energy e_i for a frame f_i is obtained by the following equation (Teranishi[1])

$$e_i = 20\log_{10} \frac{1}{M} \sum_{n \in f_i} x(n)^2 \qquad (1)$$

where M denotes the length of a frame.

Finally, every acoustic energy e_i is arranged into a vector x_e with 81 dimensions, $x_e = [\, e_1, e_2, \ldots, e_{81}]^T$. The vector x_e is called the acoustic energy pattern.

Examples of acoustic energy patterns for a not fatigued bill and a fatigued bill are shown in Fig. 2.

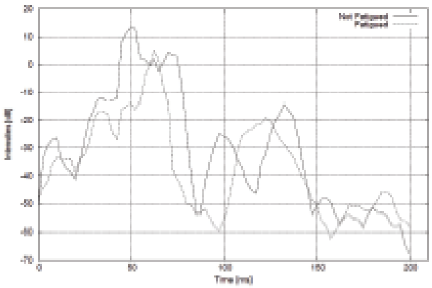

Fig. 2. Examples of acoustic energy patterns of bills.

III. Measurement of the Bending Rigidity

If an end of a bill is fixed and the other end is free, the bill is bended by self-load. In such case, the bill is assumed to be a cantilever. The side view of the bended bill becomes a deflection curve as shown in Fig. 3. The formulation of deflection curve $y(x)$ is defined as the following equation

$$y(x) = \frac{w}{24EI}(x^4 - 4Lx^3 + 3L^4) \qquad (2)$$

where EI denotes bending rigidity of bill, w is self load of bill per unit area, L denotes the horizontal distance between the free end and the fixed end of a bill. From the deflection curve, the bending rigidity is measured.

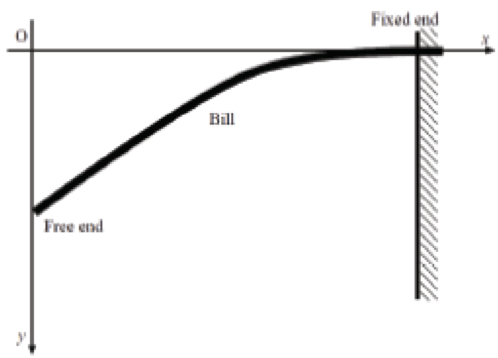

Fig. 3. Deflection curve of a bill.

IV. Estimate Bending Rigidity by Supervised SOM

The acoustic energy pattern is comfortable feature for fatigued bill classification, especially in the case of discrete fatigue level. But the property of acoustic energy pattern in continuous varying of fatigue levels is still unknown. On the other hand, the bending rigidity of bill is useful value to represent continuous fatigue level of bill. But we cannot measure the bending rigidity fast like acoustic signal features. If we can construct a relation between the acoustic signal feature and bending rigidity, we can estimate the bending rigidity of unknown bill from only acoustic energy pattern. By estimating bending rigidity of bill, we can take continuous fatigue level into acoustic energy pattern. For this purpose, we use the supervised SOM as estimator of the bending rigidity. The supervised SOM has the capability to estimate the bending rigidity by supervised learning.

To construct the supervised SOM as the estimator for the bending rigidity of bill, we take two phases. The phase 1 is supervised learning. The phase 2 is estimation of bending rigidity.

1. Supervised Learning of Bending Rigidity

The concept of the supervised learning phase is shown in Fig. 4. In the supervised learning, the feature map of the SOM is learned with concatenated learning data. The learning data consists of two components. One is acoustic energy pattern x_e. The other is magnified bending rigidity $x_r=\mu EI$, where μ is magnification factor. A learning data x is made by concatenating two data vectors as $x=[x_e^T x_r]^T$.

By learning such input data, each unit in the feature map has information about acoustic energy pattern and bending rigidity as a codebook vector m_i. A codebook vector m_i consists of two components as $m_i=[m_e(i)^T\ m_r(i)]^T$, where i denotes the unit number, $m_e(i)$ is a acoustic energy component corresponding to x_e, and $m_r(i)$ is a bending rigidity component corresponding to x_r.

Iteration of self-organizing learning embeds both information in a feature map. To get appropriate estimation of the bending rigidity, the SOM is learned with typical acoustic feature data whose bending rigidities are known. The main object of the supervised SOM is to construct topological relation about the bending rigidity and acoustic energy pattern in the same map. The role of given bending rigidity is a supervising signal for learning.

2. Estimation of Bending Rigidity

In the estimation phase, input data for the SOM consists of only acoustic energy pattern component as shown in Fig. 5.

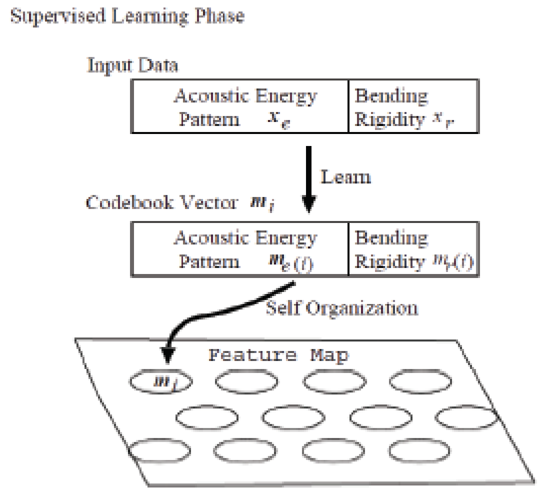

Fig. 4. Learning of bending rigidity.

The supervised SOM searches the winner codebook vector m_c which is best-matching of input data x_e by using the following equation

$$\left|\mathbf{x}_e - \mathbf{m}_e(c)\right| = \min_i \left|\mathbf{x}_e - \mathbf{m}_e(i)\right| \qquad (3)$$

where | | denotes the Euclidian norm of a vector. The matching calculation is done with only acoustic energy pattern components of codebook vectors. Finally, the bending rigidity $m_r(c)$ which is the component of winner codebook vector becomes estimated bending rigidity $\hat{x}_r$.

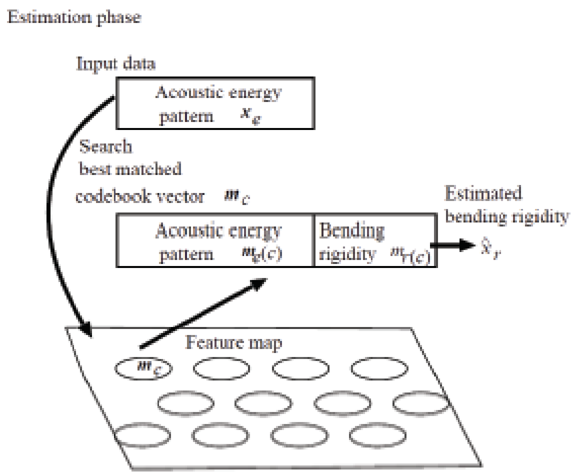

Fig. 5. Estimation of bending rigidity.

V. Experiment with Real Bill Samples

To evaluate the proposed method, we have executed an experiment for bending rigidity estimation. For this experiment, we use 10 real bill samples. Bending rigidities of bills are measured for these samples. Fifty friction acoustic signal data are taken per bill sample. We had total 500 acoustic signal data. Acoustic energy pattern is calculated for every data. The magnification factor of bending rigidity is set to 10^6. The supervised SOM consists of 40×24 units. The feature map is learned by using 30 data per sample, 60 percent of whole data set. We take 10^5 learning steps.

To evaluate the estimation performance, rest 20 data per sample are given to the feature map as unknown input. We obtain estimated bending rigidity for each input. Distributions of estimated bending rigidities versus measured them are shown in Fig. 6.

Distributions of estimated bending rigidities for evaluation data are largely similar to the distributions for learning data. The mean square error of estimation for the evaluation data is 4.069×10^{-3}, and is 4.151×10^{-3} for the learning data. Entire estimation results have certain biases. Estimation is good in medium bending rigidity range. On the other hand, overestimations and underestimations are observed in smallest or biggest bending rigidity.

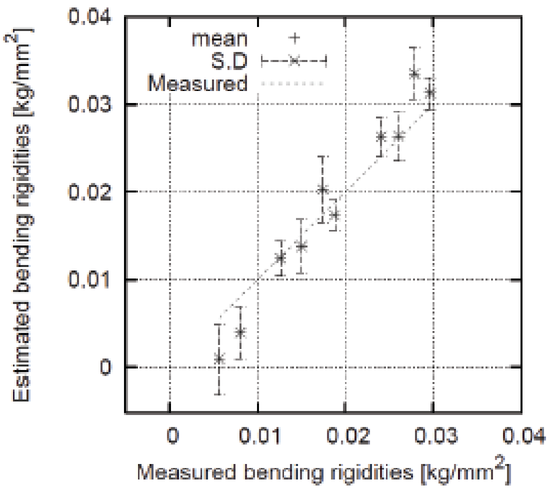

Fig. 6. Estimation result of bending rigidity.

VI. Discussion

Estimation results show effectiveness of the proposed method. Though the supervised SOM did not estimate correct bending rigidity, it can keep original order of bending rigidities. We can use estimated bending rigidity as continuous fatigue level enough. The reason of overestimation and underestimation in smallest and biggest bending rigidities is considered as shortage of data. To reduce overestimation and under estimation, further experiments with additional samples in such range of rigidities is necessary.

VII. Conclusion

In this paper, we proposed an estimation method of bending rigidity of bills for fatigued bills classification. The proposed method estimates the bending rigidity of unknown bill from acoustic energy pattern of bill. It is shown that the supervised SOM works as good estimator of continuous fatigue level. By using estimated bending rigidity, we can now classify bill into continuous fatigue levels.

As a further study, we also intend to verify the advantage of using supervised SOM for estimation of bending rigidity comparing with other soft computing methods, such as the layered neural network.

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