Neuro-Classification of Bill Fatigue Levels Based on Acoustic Wavelet Power Patterns

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Abstract: - In this paper, we propose a new method to classify bills (paper currencies) into different fatigue levels due to the extent of their damage. While a bill passing through a banking machine, a characteristic acoustic sounds are emitted from the bill. To classify the acoustic signal into three bill fatigue levels, we calculate the acoustic wavelet power pattern. To classify the acoustic wavelet power pattern, a set of competitive neural networks is used. These competitive neural networks are trained with the Learning Vector Quantization (LVQ) algorithm. Also, we propose a new method for classification. The proposed method consists of two classification techniques: one is wavelet level-wise classification, and the other is α -nearest neighbor voting(α -NN voting).
The experimental results show that the proposed method can obtain better classification performance than the conventional classification method.

Key-Words: - Signal Processing, Neural Network, LVQ, Pattern Classification, Wavelet Analysis

1 Introduction

On the practical use of Automatic Teller Machines (ATM), much fatigued bills cause serious mechanical failure for these machines. To avoid this problem, such bills must be picked up, and be exchanged with new ones at banks. To do the selection automatically by banking machines, the development of automatic classification method of fatigued bills and its implementation to bank machines are desired.

In this paper, we propose a new method that classifies the fatigue levels of bill based on the acoustic signal feature generated by passing a bill through a banking machine. The proposed method introduces the wavelet power pattern of the acoustic signal for classification to extract explicit features of a fatigued bill. Furthermore, the proposed method uses competitive neural networks trained with the LVQ[1] algorithm to obtain a good classification performance effectively. To improve the classification performance, we also propose a new classification method which consists of two new classification techniques. One is wavelet level-wise classification, and the other is α -nearest neighbor voting(α -NN voting). Carrying out these two techniques sequentially makes the classification performance more accurate.

To show the effectiveness of the proposed method, we evaluate the classification performance of the proposed method by a classification experiment. The classification experiment is carried out with practical acoustic signal data taken by some real bill samples. In the experiment, we classify bills into three fatigue levels: no fatigue level (level 0), fatigued but reusable level (level 1), and much fatigued level (level 2). The experiment result shows advantages of the proposed method by comparing the classification performance with that of conventional classification method[2-4].

2 Acquisition of Acoustic Signal from a Banking Machine

The block diagram of the acoustic signal acquisition system is shown in Fig.1. A significant acoustic signal is generated when a bill passes through the transportation part of the banking machine. Therefore, we locate the microphone at the cover of the transportation part of the banking machine. The time series data of an acoustic signal from a bill are measured and digitized with the microphone and the Analog-Digital converter, and then stored into a personal computer. An acquisition sequence is triggered by an output of the optical sensor, which detects the passing of a bill.

Examples of acoustic signals for different fatigue levels of bills are shown in Fig.2.

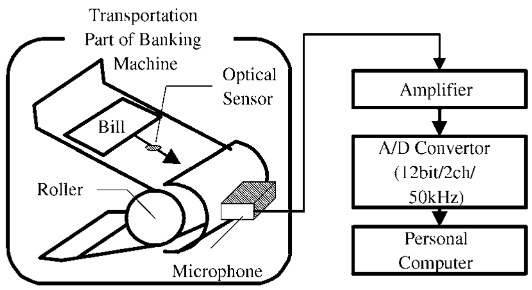

Fig. 1. Sketch of the acoustic data acquisition system.

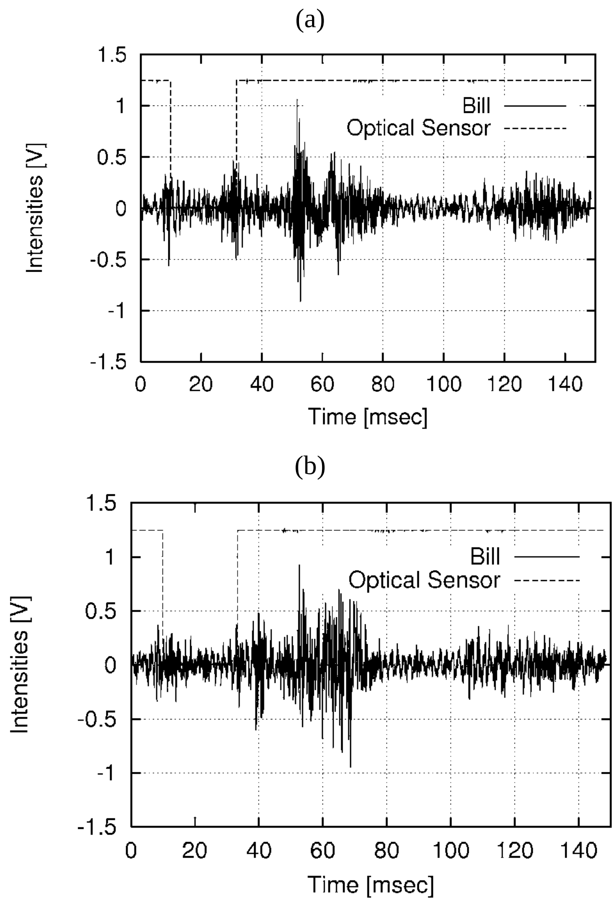

Fig. 2. Examples of acoustic signals of bills : (a) fatigue level 0, (b) fatigue level 2.

From Fig.2, the difference between fatigue levels is not appeared in the time series data of acoustic signals without being slightly changed in amplitude. Therefore, it is difficult to classify the bill into a fatigue level by directly using the acoustic signal. Hence, the proposed method transforms the acoustic signal into the wavelet power pattern as the preprocessing for the neuro-classification. The wavelet power pattern is calculated by using the fast wavelet transformation described in the following section.

3 Calculating the Wavelet Power Patterns

As shown in Fig.2, acoustic signals of bills are considered as non-stationary signals. Therefore, features that represent the fatigue level of a bill are localized in frequency and time domain of the signal. To obtain those features explicitly, we now calculate the wavelet power pattern from an acoustic signal by using fast wavelet transformation[5]. The fast wavelet transformation can obtain short time frequency feature localized in time domain effectively.

First, we illustrate the fast wavelet transformation briefly, and show the procedure of the calculation of the wavelet power pattern from an acoustic signal.

3.1 Fast Wavelet Transformation of Acoustic Signal

We denote the acoustic signal by $x(t)$ where t is the discrete time. By using the fast wavelet transformation, $x(t)$ is represented as the series of “mother wavelets” that has single frequency component and localized in time domain as follows:

$$x(t) = \sum_j \sum_k w_k^{(j)} \varphi_{j,k}(t) \qquad (1)$$

where $\varphi_{j,k}(t)$ denotes a mother wavelet which has own level(i.e., frequency) j and located in discrete time shifted position k, and $w_k^{(j)}$ denotes wavelet coefficients of $\varphi_{j,k}(t)$. By using Eq.(1), we can obtain the intensities of the mother wavelets, that is, wavelet components, which have level j and located in the time k among the source signal $x(t)$ as the magnitude of each $w_k^{(j)}$.

In this paper, we use the Daubechies wavelet ($N = 6$) as the mother wavelet $\varphi_{j,k}(t)$. Then, we can use those wavelet components $w_k^{(j)}$ as the feature pattern for classification of a bill fatigue level. But the size of the feature pattern becomes very large when we use all the wavelet components $w_k^{(j)}$ directly, and causes the difficulty of classification.

Therefore, we introduce the calculation of wavelet power pattern described in later section to reduce the size of the feature pattern.

3.2 Calculation Procedure of a Wavelet Power Pattern

To reduce the size of the feature pattern, that is wavelet components, first, we divide entire time region into N sections, called "frame" l_i $(i = 1, \ldots N)$. Each frame has K_i wavelet components. Next, we calculate the wavelet power $pw(j, l_i)$ for each frame l_i and level j as follows:

$$pw(j, l_i) = \frac{1}{K_i} \sum_{k=1}^{K_i} \left| w_k^{(j)} \right| \qquad (2)$$

The wavelet power $pw(j, l_i)$ represents the average power of a wavelet which has level(frequency) j in the frame l_i.

Finally, we combine all frame's wavelet power with specified level j $pw(j, l_i)$s into an N-dimensional vector $\boldsymbol{p}_j$ as follows:

$$\boldsymbol{p}_j = (pw(j, l_1), pw(j, l_2), \cdots, pw(j, l_N)) \qquad (3)$$

The vector $\boldsymbol{p}_j$ is now called "wavelet power pattern" of specified wavelet level j.

Examples of wavelet power pattern for different fatigue level of bill in case of $N = 20$ and each frame length is 4[ms] from wavelet levels 1 to 5 are shown in Fig.3. It shows the difference of power pattern in fatigue levels more remarkably. Though we can recognize the difference between fatigue level in wavelet power patterns, the distributions of wavelet power patterns are too complex to use simple classification algorithm.

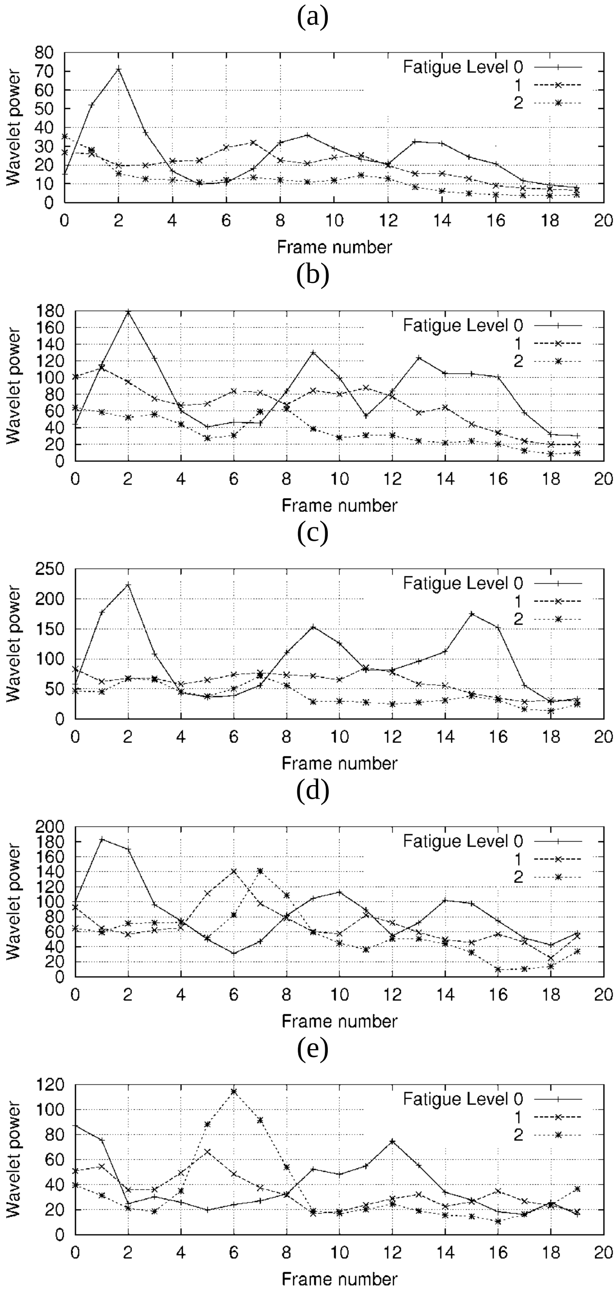

Fig. 3. Examples of wavelet power pattern for each fatigue level of bill: (a) wavelet level 1, (b) level 2, (c) level 3, (d) level 4, (e) level 5 .

4 Classification of Fatigue Level by Competitive Neural Networks

The proposed method uses a set of competitive neural networks to classify wavelet power patterns into three categories, each of which corresponds to a fatigue level of a bill. To get good classification performance, we choose the LVQ algorithm as the training method for competitive neural network[1]. Furthermore, we propose a new classification method to improve the classification performance. The new classification method consists of two techniques: one is called “wavelet level-wise classification”, and the other is called “α-nearest neighbor voting(α-NN voting)”. The outline of the proposed method that includes two new technique is shown in Fig.4.

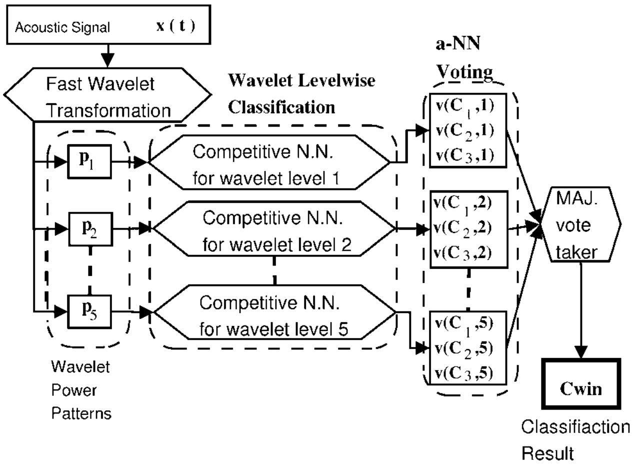

Fig. 4. Outline of the proposed classification method}

4.1 Wavelet level-wise classification

As shown in Fig.3, each wavelet level of wavelet power pattern has different feature structure. If we combine all wavelet levels' power pattern into a vector and classify the fatigue level, then we may lose partial information about each wavelet level feature. Therefore, we use a set of competitive neural networks as shown in Fig.4 to classify wavelet power patterns. The set consists five individual competitive neural networks. The *j*-th competitive neural network classifies only wavelet power pattern $\boldsymbol{p}_j$. The structure of each competitive neural network is two-layered; one is the input layer, the other is the competitive layer. The input layer consists of *N* neuron units, and each element of the wavelet power pattern $\boldsymbol{p}_j$ is fed to each unit. In the competitive layer, *i*-th neuron unit has the predefined category C_i, and has a codebook vector $\boldsymbol{w}_i$.

The competitive neural network classifies input vector based on the *j*-th wavelet level information. The network produces the partial classification result by using the “α-NN voting” technique as classification votes.

4.2 α-NN voting

In the classification examination of wavelet power patterns with taking the nearest codebook vector, we had often misclassification result. The misclassification is caused by the fact that the correct category's codebook vector is located at next nearest position from the input vector. This implies that pattern distributions of two different categories are very close, and the input vector is located at the boundary of the correct distribution. To reduce such misclassification, we introduce the new partial classification technique called “α-NN voting”. The concept of the technique is to keep the classification capability of next neighbor codebook vector. We achieve this function by casting vote according to distance between input vector and codebook vectors. Taking such a vote, the technique suspends making decision of the classification result, and obtains partial classification information instead. Final classification result is decided by taking majority vote among these votes. First, we calculate all distances between all codebook vectors and the input vector. Then each codebook vector casts a vote value $v(C_i, j)$ for its category according to the following equation.

$$v(C_i, j) = \begin{cases} 1, & (d(\boldsymbol{w}_i, \boldsymbol{p}_j) \le (1+\alpha)d_{\min}) \\ 0, & (otherwise) \end{cases} \quad (4)$$

where $d(\boldsymbol{w}_i, \boldsymbol{p}_j)$ denotes Euclidian distance between the codebook vector $\boldsymbol{w}_i$ and $\boldsymbol{p}_j$, $d_{\min}$ denotes the minimum distance among all $d(\boldsymbol{w}_i, \boldsymbol{p}_j)$. The concept of Eq.(4) is shown in Fig.5. In the α-NN voting technique, each codebook vector within the hyper sphere whose radius is equal to $(1+\alpha)d_{\min}$ has a right to vote for its own category as the capability of classification.

The vote value implies capability of classification result. The aim of the technique is to save and reflect capabilities of classification as possible. After counting votes of every wavelet level's competitive neural network by applying the above technique, the final classification result is decided by taking majority vote. Final classification result C_{win} is obtained by the following equation.

$$C_{win} = \arg\max_{C_i} (\sum_j v(C_i, j)) \quad (5)$$

If majority numbers of votes are the same in different categories, the input vector is regarded as unclassified.

The proposed technique is similar to the K-NN method in point of taking nearest plural codebook vectors for classification. But the proposed α -NN voting has an advantage of reducing misclassification risk by rejecting codebook vectors that are so far from the input vector among these ones.

By taking majority votes, we can classify the input vector safely, i.e., without misclassification. We can also obtain unclassifiable input easily when we had even votes. We can extract automatically each level's most characteristic point of wavelet power pattern which varies in different level and difficult to find by a heuristic feature extraction method.

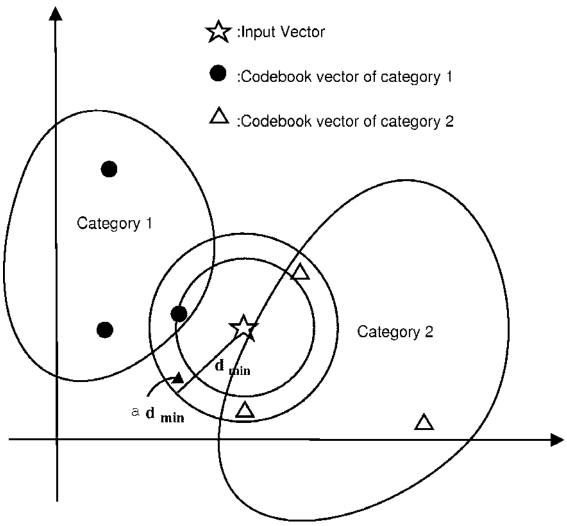

Fig. 5. α **-NN voting**

5 Training Method for Classification

5.1 Training algorithm of competitive neural network : LVQ1

The LVQ[1] algorithm trains each competitive neural network. Since the LVQ algorithm can train competitive neural networks effectively for the classification task based on vector distances, we adopt the LVQ algorithm. In the proposed method, LVQ1[1] that is a basic algorithm of LVQ algorithm is used. We illustrate the procedure of the LVQ1 algorithm below.

In the competitive layer, *i*-th neuron unit has the predefined category C_i, and has a codebook vector $\boldsymbol{w}_i$. Each element of the training pattern, that is, wavelet power pattern, $\boldsymbol{p}_j$ is fed to each input layer's unit. Then all distances between the all competitive unit's codebook vectors and the training pattern are calculated. The unit whose codebook vector is in the nearest distance to the training vector is called "winner unit", and has the codebook vector $\boldsymbol{w}_{win}$. In the LVQ1 algorithm, the codebook vector of the winner unit $\boldsymbol{w}_{win}$ is modified by the following equation:

$$\begin{aligned} \boldsymbol{w}_{win}(t+1) &= \boldsymbol{w}_{win}(t) + \alpha_{win}(t)(\boldsymbol{p}_j - \boldsymbol{w}_{win}(t)) \\ & \quad \textit{if } C_{win} \textit{ is correct category} \\ \boldsymbol{w}_{win}(t+1) &= \boldsymbol{w}_{win}(t) - \alpha_{win}(t)(\boldsymbol{p}_j - \boldsymbol{w}_{win}(t)) \\ & \quad \textit{if } C_{win} \textit{ is incorrect category} \end{aligned} \tag{6}$$

where t denotes the iteration number of the training cycle, and $\alpha_{win}(t)$ is the training factor for $\boldsymbol{w}_{win}$. In the LVQ1 algorithm, $\alpha_{win}(t)$ is set to a small number α_0 at start of training, and it is modified to decrease monotonically with the training iteration.

5.2 Adaptive allocation of competitive unit

To keep the size of competitive neural network compact, and make flexibility to classification, we allocate competitive unit, adaptively by using the procedure described below.

Step 1: Allocate two competitive units per each category.
Step 2: Train all competitive neural networks by the LVQ1 with a training pattern set.
Step 3: Examine classification accuracy by using the training pattern set.
Step 4: If every training pattern is classified into a correct category, then finish the training process.
Step 5: If misclassified training patterns are found, then allocate a new competitive unit which has a codebook vector is located at near of the training pattern, and go back Step 2.

Since this procedure starts with least number of competitive units, we can keep the entire network size compact, and can work every competitive unit with high contribution. We can also cope with misclassification effectively by adding a new competitive unit.

6 Classification Experiment

To verify the effectiveness of the proposed method, classification experiments have been carried out. In this experiments, we use three real bill samples as fatigue level 0 and 2 bills, and six real bills as fatigue level 1 bills. Fifty acoustic signals were measured for each bill. Totally, 150 acoustic signal data were taken for fatigue level 0 and 2, 400 data were taken for fatigue level 1. In this experiment, 50 patterns among these data for each fatigue level are used to train the competitive neural network. After training, the remaining 100 patterns for fatigue level 0 and 2, 250 patterns for fatigue level 1 are used as untrained patterns to obtain classification performance. Three classification methods defined below were taken for above training/untrained data to show effects by the proposed two new classification technique.

Method 1: Classification by using a single competitive neural network with all wavelet level combined power pattern(conventional method)[2].

Method 2: Classification by using the wavelet level-wise competitive neural networks, without using α -NN voting (Nearest neighbor classification).

Method 3: Classification by using the wavelet level-wise competitive neural networks, with using α -NN voting.

By comparing the results of Method 1 and Method 3, we can show the effect of introducing the wavelet level-wise classification in the proposed method. Comparing the results of Methods 2 and 3, we can show the effect of introducing the α -NN voting technique in the proposed method. In the experiments, we use $\alpha = 0.2$ for the α -NN voting.

The results of the experiments is indicated in Table 1 where values mean the correctly classification ratios for untrained patterns.

Table 1. Classification performance

	Fatigue Level 0	Fatigue Level 1	Fatigue Level 2	Entire
Method 1	84.4%	74.3%	82.8%	80.5%
Method 2	92.8%	83.6%	84.2%	86.9%
Method 3	96.4%	89.4%	91.4%	92.4%

From the result, the classification performance of the Method 2 is better than that of the Method 1. This fact implies that the proposed method, especially the wavelet level-wise classification part works effectively for classification of bill fatigue levels. We can also recognize the advantage of introducing the α -NN voting technique in classification process from the results of Methods 2 and 3.

7 Conclusion

A new method has been proposed to classify the fatigue levels of a bill based on the wavelet power pattern by a set of competitive neural networks. The result of classification experiment shows the effectiveness using the wavelet power pattern and the advantage using of the two new classification technique, one is the "wavelet level-wise classification", the other is the "α -NN voting", for the neuro-classification. Experimental results show that using both of two techniques improves the classification performance remarkably.

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