Classifying Abnormal Conditions of Railway Point Machines Using Texture Information of Sound Data

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Abstract—Failure of railway point machines frequently leads to service delays and/or dangerous situations. Therefore, early detection and classification of the abnormal conditions in railway point machines (RPMs) is critical. In this paper, we propose a new method for classifying abnormal conditions of RPMs by converting sound signals into two-dimensional gray images and extracting texture information in noise environment with a convolutional neural network. Based on the experimental results, we show that the proposed method can accurately and stably classify the abnormal conditions of RPMs with robustness of noise.

Keywords—texture analysis; railway point machine; dominant neighborhood structure; convolutional neural network

I. INTRODUCTION

Nowadays, due to environmental problems and the congestion on the roads, the use of railways has continued to increase worldwide [1-2]. The railway point machine (RPM), an important component that constitutes the railway road, is one of the railway components that controls the course of the train. Since RPM defects can cause serious accidents, such as derailment and collision of trains, early detection of abnormal conditions of RPMs is very essential.

Recently, several studies have reported the diagnosis methods for the RPMs using electrical and sound signals. For example, Asada et al. [1-2] showed that combining discrete wavelet transforms (DWT) and support vector machine (SVM) enabled for a quite accurate detection and diagnosis of misalignment faults on RPMs using voltage and current sensors. Sa et al. [3] proposed a method for replacement condition detection of RPMs using shapelet algorithm by means of current signals. Interestingly, Lee et al. [4] worked on fault detection and classification of RPMs using mel-frequency cepstrum coefficients (MFCC) features of sound signal. However, they did not considered the sound signal with noise. In fact, the sound signals of RPMs are naturally exposed to a noise environment, because they are installed outdoors. Therefore, the sound signals collected from the sound sensor of RPMs are susceptible to noise.

On the other hand, in the image processing research community, we can find a novel global texture feature (i.e., dominant neighborhood structure (DNS)), which is highly robust to noise by considering the similarities in intensity between various pixels [5-6]. By applying DNS to an image, the de-noising effect for mixed noisy images and distinct texture information between different classes can be obtained.

In this paper, we propose a new method for classifying abnormal conditions of RPMs by converting sound signals into two-dimensional gray images and extracting texture information using DNS in noise environment with a convolutional neural network. Moreover, we show that the proposed method can accurately and stably classify the abnormal conditions of RPMs with robustness of noise by experimental results. To the best of our knowledge, this is the first report on using texture information of sound signal for classifying abnormal conditions of RPMs.

The remainder of this paper is structured as follows. Section 2 describes the proposed system architecture for classifying abnormal conditions of RPMs using texture information. Section 3 presents the simulations results. Finally, conclusions are drawn in Section 4.

II. SYSTEM STRUCTURE FOR CLASSIFYING ABNORMAL CONDITIONS OF RPMs

Figure 1 shows the overall system structure of the proposed method. The system consists of sound acquisition module, preprocessing module, texture extraction module, and railway conditions classification module.
A. Sound Acquisition Module

Sound acquisition module acquires sound signal from the sound sensor of RPMs when the RPMs are operated.

B. Preprocessing Module

The sound signal collected from sound acquisition module is converted into a two-dimensional gray scale image.

C. Texture Extract Module

To extract the texture information from the converted two-dimensional gray scale image, the DNS algorithm is applied. In the first step, the Euclidean distance between neighborhood window $N_i$ and searching window $S_j$, as in (1), is computed.

$$d^2(i, j) = ||v(N_i) - v(S_j)||_2^2$$  (1)

In the second step, compute an estimate for the global dominant image neighborhood structure for the underlying texture image, as in (2).

$$\text{DNS}(i) = \frac{1}{2} \sum_{k,l} d^2(k,l)$$  (2)

D. Railway Conditions Classification Module

Convolutional Neural Network (CNN) is used to classify abnormal conditions of RPMs using the extracted texture information. Using the CNN model that has been learned in advance, it decides whether or not there is any abnormal condition in the sound signal of RPMs coming in real time and notifies the administrator of it.

III. EXPERIMENTAL RESULTS

A. Experimental Data

In this experiment, the sound sensor (SHURE SM137) was placed in front of the RPM to collect the sound generated whenever the RPM switched. The sound data were collected from RPM, which is a NS-AM type located in Sehwa Company, Daejeon, South Korea, on January 1, 2016. The waveforms and spectrograms of the sound signals were manually edited to be used in the experiments, and each piece of sound data was composed of 4.5 to 5.7 seconds. The sound data used in the experiment are 150 normal condition data and 438 abnormal data (142 for graveled condition data; 141 for ice-covered condition data; and 155 for unscrewed condition data). In addition, a white noise was added to the collected sound signals in order to create a noisy data set, as far as a noisy environmental experiment is concerned.

B. Extracting Texture Information

The collected sound signal was sampled at 16,000 Hz and, since the lengths of sound signals were different from each other, the lengths of the sound signals were equalized by performing length normalization. The sound signals with the same length were converted into a two-dimensional image of 352 by 352 size (see Figure 2). As can be seen in Figure 2, it was difficult to identify the texture information of the images and, therefore, the texture information was extracted using DNS (see Figure 3). The extracted texture image size is 128 by 128.

Figure 3 (a)-(d) shows texture information of the normal condition, graveled condition, ice-covered condition, and unscrewed condition, respectively. As can be seen in Figure 3, each texture images can be distinctly recognized in terms of texture information. Figures 4 (a)-(b) show the images of normal condition and noise condition (SNR = 20), respectively, while Figures 4 (c)-(d) present texture information images extracted using DNS. By applying DNS to an image, we could confirm the de-noising effect for mixed noisy images in Figures 4 (d).
To design the optimized CNN model for the abnormal situation classification of the RPM, various parameters were adjusted. The parameters used for the CNN structure were dropout ratio 60% in hidden layer, 50% in fully connected layer, learning rate 0.0005, Rectified Linear Unit activation function, and 2000 times training epoch. The initial connection nodes were initialized using Xavier.

The performance of the proposed system was evaluated via abnormal detection rate (ADR), false positive rate (FPR), and false negative rate (FNR) in (3)-(5): True positive (TP: abnormal data correctly identified as abnormal data), False positive (FP: normal data incorrectly identified as abnormal data), True negative (TN: normal data correctly identified as normal data), and False negative (FN: abnormal data incorrectly identified as normal data) [8].

\[
\text{Abnormal Detection Rate (ADR)} = \frac{TP}{TP+FN} \times 100 \tag{3}
\]

\[
\text{False Positive Rate (FPR)} = \frac{FP}{FP+TN} \times 100 \tag{4}
\]

\[
\text{False Negative Rate (FNR)} = \frac{FN}{TP+FN} \times 100 \tag{5}
\]

A summary of abnormal detection results is shown in Table 1. According to the experimental results, when using CNN, the abnormal detection accuracy of the proposed system is 96.24%, that of FPR is 11.36%, and that of FNR is 3.76% when the clean data set was used. We also confirmed that the abnormal condition was stably detected in the data sets of white noise SNR=20.

<table>
<thead>
<tr>
<th>Test data sets</th>
<th>ADR (%)</th>
<th>FPR (%)</th>
<th>FNR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clean data set</td>
<td>96.24</td>
<td>11.11</td>
<td>3.76</td>
</tr>
<tr>
<td>Noise data set (SNR=20)</td>
<td>96.24</td>
<td>11.36</td>
<td>3.76</td>
</tr>
</tbody>
</table>

In the next step, we classified abnormal conditions of RPMs into the following four types: “normal condition”, “graveled condition”, “ice-covered condition”, “unscrewed condition”. In order to measure the classification of accuracy of the proposed method, the precision and recall are used as the performance measurements [8] in (6)-(7).

\[
\text{Precision} = \frac{TP}{TP+FP} \times 100 \tag{6}
\]

\[
\text{Recall} = \frac{TP}{TP+FN} \times 100 \tag{7}
\]

The experimental results are shown in Table 2. From the precision and recall of classifying abnormal conditions, we confirmed that the proposed method yields stable experimental results. After all, by means of the de-noising effect of DNS, we can claim that the proposed method can accurately and stably classify the abnormal conditions of RPMs with robustness of noise by experimental results.
TABLE II. CLASSIFICATION RESULTS OF ABNORMAL CONDITIONS

<table>
<thead>
<tr>
<th>Test data sets</th>
<th>Types of conditions</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clean data set</td>
<td>Normal condition</td>
<td>90.00</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Graveled condition</td>
<td>91.11</td>
<td>95.35</td>
</tr>
<tr>
<td></td>
<td>Ice-covered condition</td>
<td>97.56</td>
<td>93.02</td>
</tr>
<tr>
<td></td>
<td>Unscrewed condition</td>
<td>97.67</td>
<td>89.36</td>
</tr>
<tr>
<td>Noise data set (SNR=20)</td>
<td>Normal condition</td>
<td>90.00</td>
<td>97.78</td>
</tr>
<tr>
<td></td>
<td>Graveled condition</td>
<td>91.11</td>
<td>95.35</td>
</tr>
<tr>
<td></td>
<td>Ice-covered condition</td>
<td>97.56</td>
<td>93.02</td>
</tr>
<tr>
<td></td>
<td>Unscrewed condition</td>
<td>97.67</td>
<td>89.36</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

In this study, we proposed a new method for classifying abnormal conditions of RPMs by converting sound signals into two-dimensional gray images and extracting texture information using DNS in noise environment with a convolutional neural network. We also showed that the proposed method can accurately and stably classify the abnormal conditions of RPMs with robustness of noise by experimental results.

As a follow-up study, broader testing of the proposed system in commercial production conditions is a purposeful avenue. A complete real-time system in the real-world noisy environments is part of our ongoing research.

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References