DETECTION OF LEAKAGE SOUND BY USING MODULAR NEURAL NETWORKS

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Abstract: *It is important to detect the leakage of the gas to be flammable or poisonous from the cracks in pipes of petroleum refining plants or chemical plants. We examined the application of modular neural networks to the acoustic diagnosis technique for the leakage sound. The modular neural network has the ability to adapt its structure according to the environment. Experiments were performed for an artificial gas leakage device with various experimental conditions to imitate the change of environment for a long term. The discrimination accuracy with the proposed network was observed to be about 93%, which was better than 83% with the simple network. From the results, we confirmed the effectiveness for the application of the modular neural network to the detection of the leakage sound for the practical use.*

Keywords: Acoustic Diagnosis, Leakage Sound, Neural Networks

1 INTRODUCTION

The detection of gas leakage sound from pipes is important in petroleum refining plants and chemical plants, as oftentimes the gas used in these plants are flammable or poisonous. Gas sensors can also detect the gas leakage, but it is not always suitable for the early detection of the gas leakage. The ability of the detection is strongly influenced by the direction of the wind, the force of the wind, the density of the gas, and by other factors. On the other hand, if the leakage sound of the gas was used, we could detect the leakage as soon as it happened. Furthermore, the acoustic diagnosis uses the sound detected by microphone, and therefore has the excellent features of non-contact detection and easy handling.

We have already evaluated the detection performance with the neural network for short-term experiment [1]. The applied network is the multi-layered feed-forward model whose learning algorithm is the error back-propagation (BPN). However, the stable diagnosis for the long term is needed in order to establish the acoustic diagnosis for the practical use. It is supposed that the background noise varies every season and the deterioration of the equipment also affects the background noise. Such change of background noise influences the reliability of diagnosis results. Therefore, it is necessary to examine the diagnostic method that is able to adapt to the change of environment. The simplest method is to re-train the network, but diagnosis result would change before and after the re-training even for the same data. The examination of a new neural network model is necessary to overcome this difficulty.

The purpose of this study is to establish the acoustic diagnosis technique for the gas leakage from defects in pipes for the practical use. We propose modular neural networks to adapt the change of the environment and examine the effectiveness of the proposed network for the data imitated long-term experiment.

2 OUTLINE OF MODULAR NEURAL NETWORKS

The modular neural network consists of an initial module and some supplementary modules as shown in Figure 1. Outputs of each module are "Normal", "Abnormal", and "Unknown". "Normal" means no leakage, "Abnormal" means the leakage, and "Unknown" means that the input sound differs from the training data and the module can not discriminate to be "Normal" or "Abnormal". The initial module is trained using the data collected in various conditions. The supplementary module is added to the initial module when the output of the initial module is "Unknown" for many observed data. Similarly, the outputs of all modules are "Unknown", a new module is supplemented with the networks.

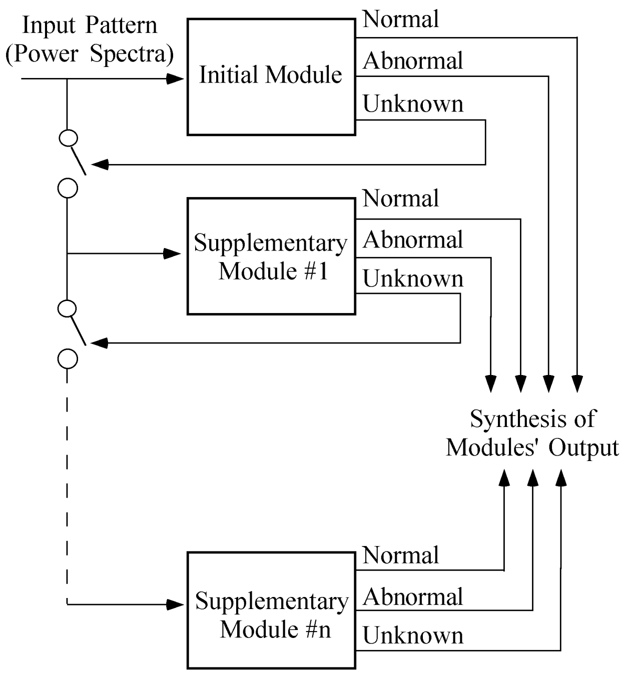


Figure 1. Structure of modular neural network

Hence, the modular neural network adds the new modules to the initial module according to the environment.

Procedure of the construction of the modular network is shown in the following:

1) The initial module is trained in the data collected before hand.
2) The data collected in the fixed sampling time is fed to the modular network.
3) If the output of the network is not "Unknown" for the fixed period, go to the 2nd procedure.
4) The new supplementary module is trained in the data judged "Unknown" and the new module is added to the modular network. Then, go to the 2nd procedure.

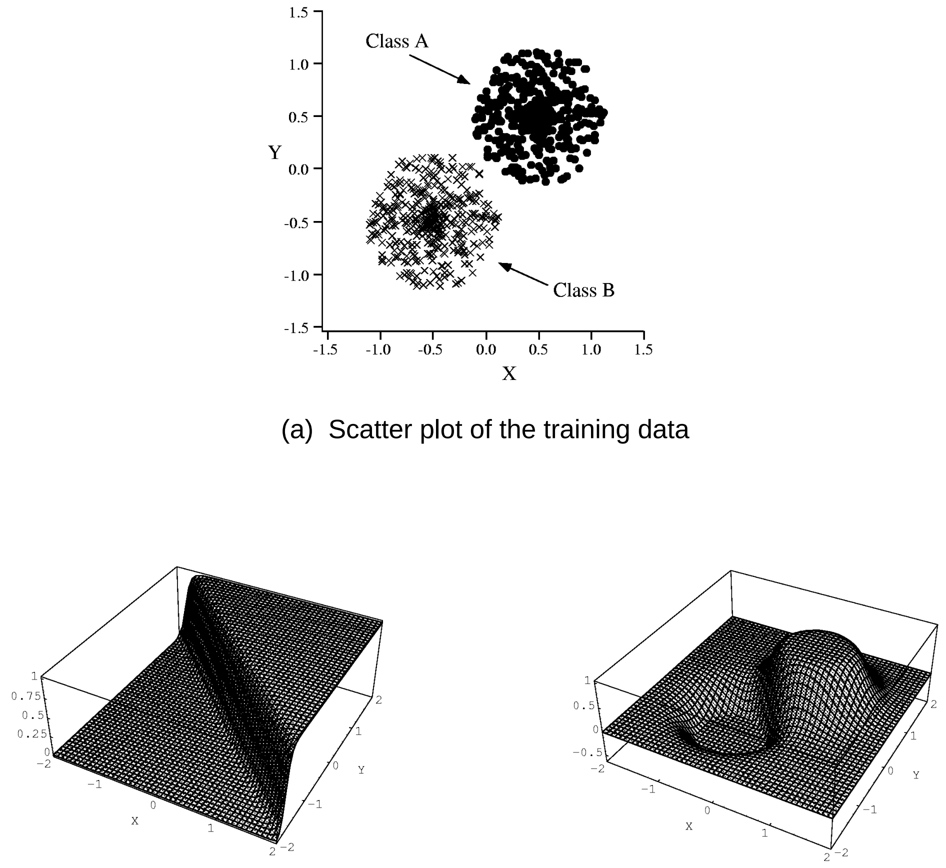
It would be able to precisely diagnose by the training the initial module using acoustic data collected beforehand. Then, in the case that diagnosis result of the "Unknown" continues over the fixed time, the supplementary module trained the data and it is added to the network. The reason that the addition criteria of the module is to continue over fixed time is for preventing the addition of the unnecessary module by the diagnosis of sudden noise, and etc.

In order to attain the output of module to be "Unknown", it is desired that the localization ability for the module is excellent. The localization ability is that the module responses only in the data which is similar to the training data. Therefore, we apply Gaussian Potential Network (GPN) [2] to the module. The GPN is a multi-layered feed-forward network that performs classification based on a set of potential fields synthesized over the domain of input space by a number of Gaussian potential function units.

Here, we evaluated the localization performance of the neural network. Figure 2(a) shows the scatter plot of the training data. Figure 2(b) and (c) shows the output of the BPN and GPN, respectively. *x* and *y*-axis indicates coordinate of the input data and *z*-axis indicates the output of the network. Each network has 2 input units and an output unit. From these results, the BPN could not localize activation around the training data, but the GPN could localize it.

3 EXPERIMENTS FOR GAS LEAKAGE

Experiments were performed in the petroleum refining plants using an artificial gas leakage device, with experimental conditions being diameters of artificial defects, gas pressures, and distances between the microphone and the leakage device. Figure 3 shows the experimental set-up. A gas cylinder was connected to the artificial gas leakage device through the regulator. Three kinds of defect diameters, which were 0.5, 1.0, and 2.0 mm, were artificially processed in the stainless steel pipes of the leakage device. Since the end of the pipe was closed, the gas leaked only from the defect. Gas pressure was 10, 40, and 70 kgf/cm^2.



(a) Scatter plot of the training data

(b) Output of the BPN

(c) Output of the GPN

Figure 2. Localization performance of the neural networks

A microphone was placed at distances of 2, 5, and 10 m from the leakage device and picked up the sound. The signals from the microphone were recorded on a digital audio tape deck at 48 kHz sampling frequency. We collected the leakage sound and the background noise in various environments, which were near four very noisy pieces of equipment: screw compressor (SC), reciprocating compressor (RC), pump (PU), and reactor vessel (VE). Furthermore, the sound from a slightly quieter piece of equipment (heat exchanger (HE)) and a relatively quiet environment (gas storage tank (TK)) was also recorded.

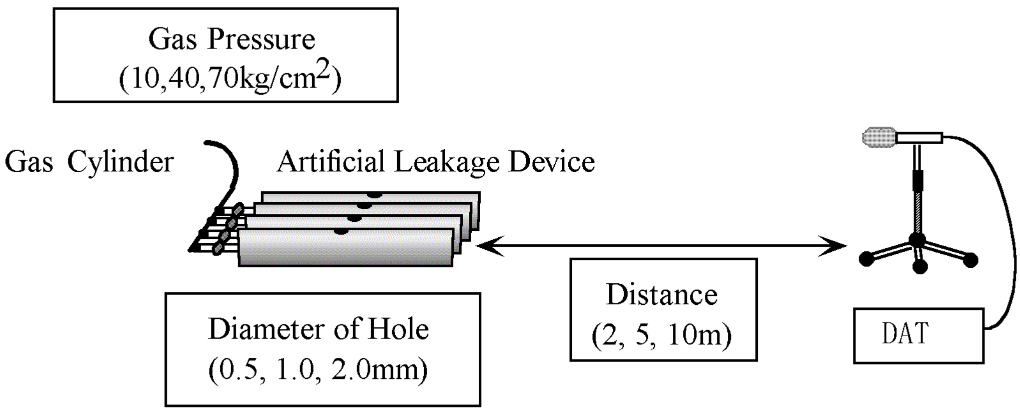


Figure 3. Experimental set-up

The leakage sound and the background noise were recorded in each environment for 180 and 900 seconds, respectively. We applied Fast Fourier Transform (FFT) to the pre-processing method and power spectra were used as the input information for the neural networks. The data were processed in the FFT analyzer. The FFT computation was carried out every 20 ms over Hanning-windowed frames with a 20 ms width. Logarithmic power spectra whose dimensions were 200 were calculated.

Figure 4 shows power spectra of the background noise in various environments. The frequency characteristics of the background noise varied in each environment. On the other hand, the power spectra for the leakage sound were higher than those for the background noise within the range from about 5 kHz to 20 kHz [1].

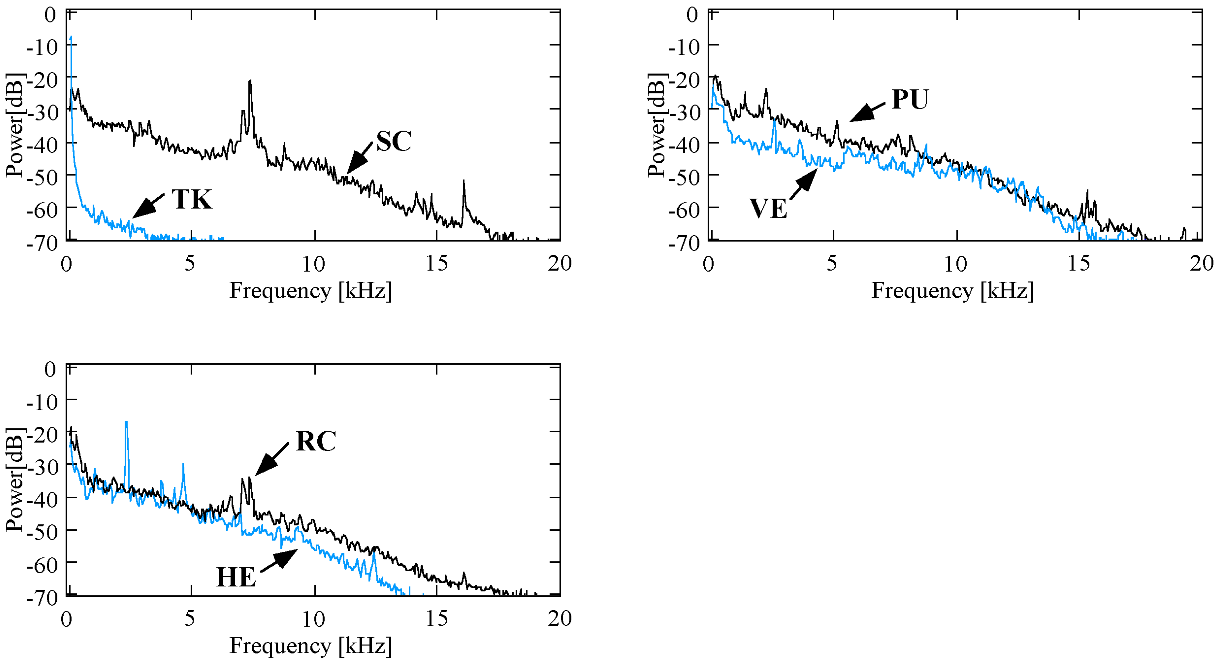


Figure 4. Power spectra of normal sound under various environments

4 RESULTS

Here, we evaluate the modular neural network using the above mentioned acoustic data. The input information was 200 dimensional logarithmic power spectra and the output of the network was the diagnostic result. The number of input units was 200 and the number of output units was 1. The target pattern was +1.0 for the background noise and -1.0 for the leakage sound. We used background noise and leakage sound collected in the different equipment as the data in which the environment changed.

First of all, we trained the initial module with the data collected in four kinds of equipment: SC, TK, PU, and VE. The discrimination accuracy for the test data collected in SC, TK, PU, and VE, using the initial module was about 92%. The input data was judged normal for the output being over +0.8, abnormal for the output below -0.8, and unknown for the other value.

Next, in order to imitate the change of the environment, we fed the data collected around different two kinds of equipment (HE and RC) to the initial module. Results are shown in Table 1. This table shows that the initial module could discriminate the sound in RC accurately, but most of the normal sound in HE was discriminated to be the unknown data.

Table 1. Discrimination accuracy for the data in HE and RC with the initial module

	Normal sound		Abnormal sound	
Output	HE	RC	HE	RC
Normal	0%	95.3%	0.6%	8.8%
Abnormal	0%	1.0%	80.0%	79.6%
Unknown	100%	3.7%	19.4%	11.6%

Therefore, we added a supplementary module to the initial module and trained only the new module using the unknown data. Consequently, the modular neural network, which consisted of the initial module and one supplementary module, could discriminate the unknown data as normal or abnormal. The discrimination accuracy for the test data in all equipment was 82.5% using only the initial module, 87.1% using the re-training network, and 93.1% using the modular neural network. The re-training network means the initial module being trained with the data collected around all kinds of equipment. These results indicate that the proposed modular network is capable of adapting its structure to the change of environments.

5 CONCLUSION

We have described the acoustic diagnosis for gas leakage from pipes for the long term. We have proposed the modular neural networks suitable for the practical use.

We have collected the sound under various environments to imitate the change of the sound for the long term. We confirmed the effectiveness of the modular neural network that can add the new module according to the change of the data.

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