Detection of Abnormal Signals in Gas Pipes Using Neural Networks

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Abstract

In this paper, we present a real-time system to detect abnormal events on gas pipes, based on the signals which are observed through the audio sensors attached on them. First, features are extracted from these signals so that they are robust to noise and invariant to the distance between a sensor and a spot at which an abnormal event like an attack on the gas pipes occurs. Then, a classifier is constructed to detect abnormal events using neural networks. It is a combination of two neural network models, a Gaussian mixture model and a multi-layer perceptron, for the reduction of miss and false alarms. The former works for miss alarm prevention and the latter for false alarm prevention. The experimental result with real data from the actual gas system shows that the proposed system is effective in detecting the dangerous events in real-time with an accuracy of 92.9%.

I. Introduction

The unintentional attack on a gas pipe by heavy things like hammer drills and breakers during the work such as digging the hole in the ground is one of the most dangerous situations that threaten the safety of the gas pipe. To prevent and cope with such events, a supervisor of the agency in charge of gas pipes is involved in the work having a possibility of contacting a gas pipe. Even though the presence of a supervisor can reduce the unintentional attacks to a certain amount, there still exists a possibility of unnoticeable attacks. Therefore, we need an automatic system to monitor the distant gas pipes in real-time. For this work, we consider the gas pipe system which has the audio sensors every several kilometers to produce signals form gas pipes.

In this paper, we concentrate on the attack event mentioned above and consider this event as an 'abnormal' one for the safety of gas pipes. Our goal is to detect abnormal events based on the signals which are observed through the sensors attached on the gas pipes in real-time. In the proposed system, the sensed signals are transferred to the central computing system continuously where features are extracted from the transferred signals and applied to the classifier to check whether abnormal event occurs or not in real-time. The difficulty of detecting the attack events is the existence of noise like background noise, car noise, nearby machine noise, etc.

II. Feature Extraction

The first step is the segmentation: a signal is divided into segments of 2 second duration by applying a window function proceeding by 0.5 second at a time. These parameters for the segmentation are determined based on the characteristics of the targets, i.e. attack events. Then, the Hamming window is applied to the segment to prevent the aliasing effect [1].

Next, for each segment, we perform discrete Fourier transform (DFT) using a filter bank which is designed as follows: the bank has 9 triangular filters whose center frequencies are linearly spaced from 100 Hz to 900 Hz. And, for the frequencies higher than 900 Hz, it has additional 4 triangular filters whose centers are spaced in the logarithmic scale [1] and the components over 2 kHz are suppressed.

The cepstral features, known to be good for robust recognition [1], are extracted from the outputs of the filter bank and the cepstral mean subtraction (CMS) is performed to remove the channel distortion caused by different distances between the sensor and the attack point [2].

Together with the 13 static features, we use the delta features defined by [3]. This feature contains the temporal properties of the signals. The use of the delta features along with the static features improves recognition performance in this work. The final feature vector consists of the 13 static features and the 13 delta features for every 0.5 second.

III. Classifier and Decision-Making

The classifier consists of the two complementary neural network models: a probability distribution model using a Gaussian mixture model (GMM) and a recognition model using a multi-layer perceptron (MLP). The former learns normal states and the latter the abnormal events. These two models are combined as a classifier for the reduction of miss and false alarms.

A. The Probability Distribution Model

What we have done first is to construct the probability density function of normal states using a GMM because of a lack of experimental data [4][5]. Given an input signal, we obtain its probability using this trained probability density function. If the probability is higher than a threshold, we make a decision that the event is normal. Otherwise, we conclude that the event may be abnormal. In order to prevent miss alarms, we use a slightly high threshold, which increases false alarms (Fig. 1(a)).

B. The Recognition Model

A MLP is used to recognize attack events [4]. It is trained by the supervised learning algorithm to produce 0 for the normal events and +1 for the attack events respectively. Compared to the probability distribution model, since the MLP learns the attack events directly, it prevents false alarms but has unexpected miss alarms (Fig. 1(b)).

C. Decision Rule

We should note that the MLP does not miss the whole sequence of attack events. As in Fig. 1(b), it misses the attack events by detecting them sparsely over the period of attacks. Therefore, the past results of several seconds are included for the decision of the current event. For the reduction of false alarms, we concentrate on the decision results of the MLP more than the probability distribution model, because the decision of the attack events from the latter is more likely to be false than the former. Finally, these two models are combined together to make a final decision.

We define an evaluation function of frame *i*, $d(i)$, for the final decision to be

$$d(i) = \frac{1}{15}\sum_{j=i-4}^{i}(g(j)+2m(j)), \qquad (1)$$

where $g(j)$ and $m(j)$ are outputs of the probability distribution model and the MLP respectively:

IV. Experiments

We use 8 data obtained from the actual gas pipe system for the experiments. Each of 8 data is from 60 seconds to 90 seconds long and contains the actual attack event which is about 10 seconds long. In our data set, attack events are generated from one source, the hammer drill attack on gas pipes. Each of data has various noises from the environment such as cars, machine related with gas pipes, and so on. In two of them, the distance between the sensor and the attack point is 13 km. And in the rest data, the distance is 6.5 km. We define three types of data set for experiments. In data set 1, we use 6 data whose distance, i.e. the distance between the sensor and attack point, is 6.5 km for the train and the rest for test. In data set 2, we use the 2 data where the distance is 13 km for the train and the rest for test. In dataset 3, we use 4 data, 3 of which are from 13 km and the rest from 6.5 km, for the train and the other 4 data for test.

The performance of data set 3 is the best among three data sets. When we use the full feature vector including the delta feature, the test accuracy reaches 92.9% (Table 1).

V. Conclusion

We have proposed the real-time monitoring system of gas pipes to determine whether an attack event which threatens the safety of gas pipes occurs on the pipes or not. We designed the robust feature extraction method from the signals recorded by a microphone attached on the pipe. To reduce the miss and false alarms together, the classifier is designed as the combination of two complementary neural network models: a probability distribution model and a MLP. Our experimental result shows that the best recognition accuracy was 100 % for training data and 92.9 % for test data. The developed method can be used in real-time operation, which is desirable for use in the real situation.

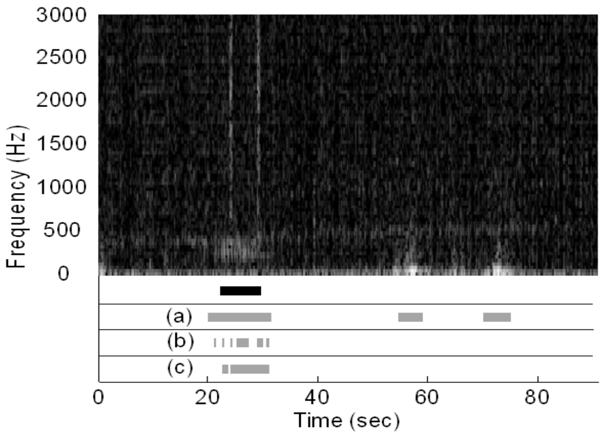

Fig. 1. Recognition results of the classification step. Black line represents the actual abnormal event and gray lines represent the results from the classification. (a) GMM (b) MLP (c) The final decision

Data set	test accuracy(%)		
	Filter Bank Analysis (FBA)	FBA + CMS	FBA+CMS+ Delta Feature
1	73.9 (92.7)	88.3 (96.6)	88.5 (94.0)
2	42.8 (54.1)	80.3 (91.9)	81.4 (88.2)
3	90.6 (97.4)	92.2 (96.8)	**92.9 (97.7)**

Table 1. Recognition Result. The number in the parentheses is the performance of the best case

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