Smart Structures and Systems, Vol. 6, No. 4 (2010) 405-421 405
DOI: http://dx.doi.org/10.12989/sss.2010.6.4.405

Early warning of hazard for pipelines by acoustic recognition using principal component analysis and one-class support vector machines

Chunfeng Wan[1]* and Akira Mita[2]

[1]*International Institute for Urban Systems Engineering, School of Civil Engineering, Southeast University, Nanjing 210096, China*
[2]*System Design Department, Keio University, Hiyoshi, Yokohama 223-8522, Japan*

(Received July 29, 2009, Accepted October 6, 2009)

Abstract. This paper proposes a method for early warning of hazard for pipelines. Many pipelines transport dangerous contents so that any damage incurred might lead to catastrophic consequences. However, most of these damages are usually a result of surrounding third-party activities, mainly the constructions. In order to prevent accidents and disasters, detection of potential hazards from third-party activities is indispensable. This paper focuses on recognizing the running of construction machines because they indicate the activity of the constructions. Acoustic information is applied for the recognition and a novel pipeline monitoring approach is proposed. Principal Component Analysis (PCA) is applied. The obtained Eigenvalues are regarded as the special signature and thus used for building feature vectors. One-class Support Vector Machine (SVM) is used for the classifier. The denoising ability of PCA can make it robust to noise interference, while the powerful classifying ability of SVM can provide good recognition results. Some related issues such as standardization are also studied and discussed. On-site experiments are conducted and results prove the effectiveness of the proposed early warning method. Thus the possible hazards can be prevented and the integrity of pipelines can be ensured.

Keywords: pipeline; possible hazard; principal component analysis; one-class support vector machines; standardization.

1. Introduction

In modern cities, many important pipelines are laid underground and are often referred to as lifeline infrastructures. Some pipelines are very dangerous due to the perilous content they are carrying, such as gas or high pressure oil, etc. However, damage accidently happens sometimes. Recent reports (Eiber *et al.* 1987) show that most damages to these pipelines are usually caused by third-party activities, mainly the surrounding constructions, rather than material failure and corrosion. According to the statistics of American gas pipeline industry during 1985 to 2000, pipeline failure accidents due to the third-party activities prove to be the most dominant cause, resulting in as high as more than 200 accidents, occupying nearly 30% of all the pipeline failure causes. Fig. 1 shows the percentage of pipeline failures respected to different causes.

Although damages due to constructions might be considered as rare events, a single incident may

*Corresponding Author, Associate Professor, E-mail: chunfengwan@gmail.com

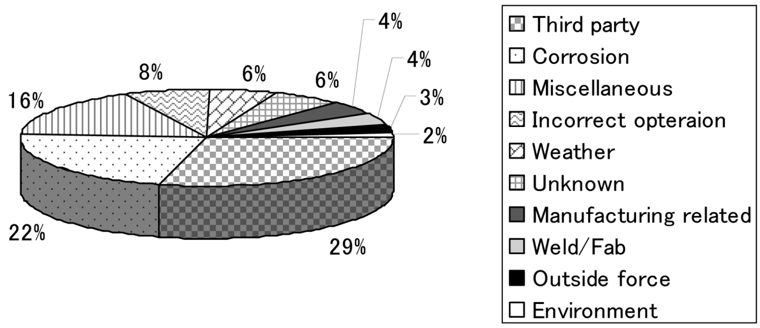

Fig. 1 Percentage of American gas pipeline failures respected to different causes

have catastrophic consequences due to the dangerous nature of those pipelines. A typical example could be found at the Ghislenghien gas pipeline explosion disaster in Belgium on July 30, 2004, which resulted in 24 deaths and over 120 injuries. As far as the risk is considered, risk is regarded to be proportional to both the probability of the structure failure and the degree of loss due to the failure consequences. Larger event likelihood and larger loss result in larger overall risk. Since the third-party activities are the main reason for pipeline failure and they often result in sudden and catastrophic accidents, the overall risk of the third-party activities is no doubt the largest. Therefore, for safety consideration, preventive measures to detect potential hazards from the third-party activities are becoming indispensable.

Since the third-party activities are mainly the constructions, constructions around pipelines are therefore often focused for early warning of impending hazards. In actual practices, dangerous pipelines are regularly patrolled by special personnel, either on foot, by vehicles, or even by helicopters. However, this kind of manual checking is laborious, economically expensive and is not seen to be efficient or necessarily effective. Therefore, there is an increasing necessity for automatic, continuous and low cost pipeline monitoring systems. In Europe, an early warning system based on image processing technology and Unmanned Aerial Vehicles (UAV) is under development (Hausamann *et al.* 2003). However, this system is expensive and requires the tight integration of several complicated technologies. Furthermore, the tendency for false alarms is still not low enough. In the United States, Gas Technology Institute (GTI) is developing another early warning system with the objective of preventing construction hazards (Huebler 2004). This system uses optical fibers, buried between the ground surface and the pipelines, to detect vibrations in the ground. The magnitude and profile of the vibrations are then used to determine the existence of construction equipment nearby. However, this system is only applicable in the case where the pipeline is under the soil ground. For pipelines under an asphalt or concrete road, which is the most common case in Japan, this system is not effective.

Bearing in mind the availability of these systems, Wan and Mita (2008, 2009) proposed a pipeline monitoring system based on acoustic information. Construction work near pipelines is supposed to be identified by the sounds emitted from the construction machines used. In those researches, Mel Frequency Cepstral Coefficients (MFCC), Linear Prediction Coding Cepstrum(LPCC) and Mel residual were used for the feature vectors and Euclidian distance was used for the classifier. Captured sound samples were segmented into many short-time sound frames. The acoustic recognition was based on the initial recognition of each single tiny sound frame. A tag-train post-process was proposed for the final decision making. In this paper, however, the acoustic recognition which is the key issue of the potential damage detection will be fulfilled with the recognition of a whole sound sample using PCA and one-class SVM, rather than with the two-step decision making approach in previous researches. Thus the sensor processor does not need initially process and recognize each sound frame from time to time any longer. The feature vectors are simply the truncated eigenvalues. Robustness to noises due to the denoising ability of PCA, and thus accurate decision making, is supposed to be realized. Meanwhile, high performance support vector machines are also supposed to bring high recognition accuracies. This research will be very useful for the later considering of real implementation of such early warning system in the future to prevent hazards and accidents for pipelines.

2. Hazard early warning mechanism

Usually, it is the presence of surface construction activities that threaten the well-being of underground pipelines. The events of construction activities are the main source of the impending hazard. Therefore, detecting potential hazard and preventing accidents can be realized by detecting construction activities, especially by detecting the running of the construction machines. In modern cities, pipelines often run along underneath asphalt or concrete roads. In this case, a road cutter is often used before any other construction equipment according to the construction process. Furthermore, the operation of a road cutter is always accompanied with a very loud noise, which makes the recognition feasible and practical. For these two reasons, this paper focuses on detecting road cutters to determine if there are any construction activities near the pipelines. Fig. 2 shows a road cutter cutting the road.

A distributed computing sensor network could be deployed above ground along the pipelines and using smart sensors to "listen" for potential threats. Each sensor will have a microphone to capture sounds and a small chip to process the sound signals by using acoustic recognition methods. Once it detects a dangerous sound, it will send off an alarm and at the same time send a message to the control center so that immediate and relevant measures can be expediently executed. A sensor network may contain many pre-trained smart sensors. However, each sensor is able to do the work independently, including signal processing and acoustic recognition. Sensors will be connected to the control center either wired or wirelessly. For each of them, only a result symbol, such as "yes" or "no", is required to send to the control center from time to time. In this way, each sensor monitors a part of the pipeline and the whole sensor network can monitor the whole pipeline, as Fig. 3 shows.

Fig. 2 A road cutter is cutting the road

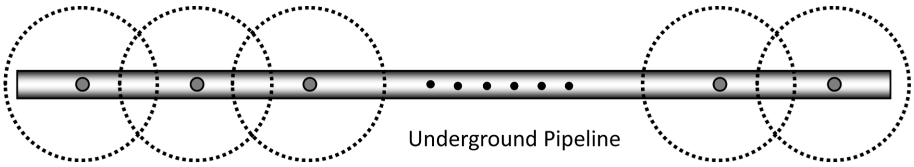

Fig. 3 A sensor network monitors the whole pipeline, the cycle refers to the sensing range of the smart sensor

Obviously, essential to the proposed hazard early warning approach is the acoustic recognition. Nearly all environmental sound recognition researches in literature use short audio clips, often lasting from 1s to 10s. For example, Lu *et al.* (2001) made a content-based audio classification based on a 1s sample, while Ma *et al.* (2006) recognized an environment sound based on a 3s sample. In this paper, a short period sound sample, lasting several seconds, is also applied to make the sound recognition. In simplicity, the sound-based road cutter detection on the whole can be described in 4 steps:

·Sound capture – capture an environmental sound signal.
·Sample extraction – extract a sound sample from the incoming sound signal.
·Sound classification – process sound samples and decide if they belong to road cutters.
·Alarm raising if necessary and further assessment – if a sound is classified to be that belonging to a road cutter, an alarm will be raised and a report will be sent to the control center so that further assessment can be made and measures taken.

Location of the potential hazard can be well identified by knowing which sensor is raising an alarm. Thus, when a sensor detects a road cutter, it will give off an alarm to caution the people nearby of the underground pipeline. Meanwhile, it will also send off a message to the control center to report the potential hazard so that relevant measures can be executed quickly. The whole early warning process is depicted in Fig. 4.

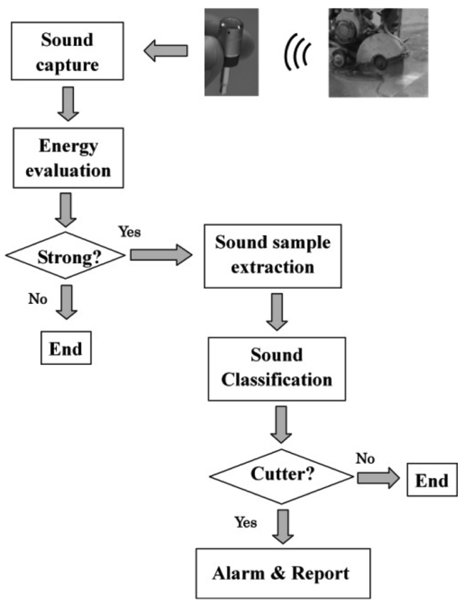

Fig. 4 Flow chart of the early warning of hazards

3. Acoustic recognition

Although most acoustic recognition techniques were developed initially for speech recognition, environmental sound recognition applications are mainly for the purpose of content-based classification, context awareness and ubiquitous surveillance.

For environment sound recognition, most researches focus on features of Mel Frequency Cepstral Coefficients (MFCC), Linear Prediction Coding Cestrum (LPCC), etc., and on classifiers such as Euclidean distance, Vector Quantization (VQ), Support Vector Machine (SVM), Hidden Markov Models (HMM), Gaussian Mixture Model (GMM), k-nearest neighbor algorithm (KNN) and Neural Network (NN). Gaunard *et al.* (1998) classified five types of noise events using LPCC feature combined with a HMM classifier and showed a good result. Later, Peltonen *et al.* (2002) used MFCC and GMM to classify 10 inside and outside environments for scene recognition. Lu *et al.* (2001) classified five classes of sounds using MFCC and SVM in his audio segmentation and classification with good classification resolution achieved. In his later research, Lu *et al.* (2003) further pointed out that SVM was much better than KNN and GMM. Toyoda *et al.* (2004) tried the multilayered Neural Networks for robotic audition. Krishna and Sreenivas (2004) compared MFCC and LPCC performance in musical instrument recognition and concluded that LPCC did better than MFCC. Ma *et al.* (2006) used the MFCC together with a HMM classifier to get a high resolution classification.

However, even though HMM showed a good performance, it usually requires large amount of training data to accurately train the models. Large computation cost makes it inconvenient for the small sensors. Above all, HMM, VQ as well, is a method for multi-class classification and it is hard to be applied to the one-class classification problem which is the case in our road cutter recognition. Neural Network method and GMM also has the problem of having a large computation burden. Since SVM was showed better than GMM and KNN (Lu *et al*. 2003), and could be much faster as the computation is only depends on small number of supporting vectors, a one-class SVM classifier is used for our proposed detection approach.

As for the features, MFCC and LPCC are cesptrum based features and a little too complicated. Moreover, they can only be used for recognizing a single frame. In this paper, however, a PCA and one-class SVM based approach is applied so that a several second sound sample with dozens of frames can be recognized all at once as a whole. Simply truncated eigenvalues are used for the feature vector. This approach is introduced below in detail.

3.1 Mechanism of PCA and one-class SVM based sound recognition

In most conventional sound recognition processes, a several second sound sample is often segmented out for testing. In the signal processing, it is usually further segmented into many tiny frames, usually lasting from 20 ms to 30 ms, with an overlap between every two adjacent frames. Acoustic recognition will then be carried out according to the features of all overlapped frames. Ma *et al.* (2006) recognized an environment sound based on a 3s sample, with 25 ms frames and 15 ms overlap. Goldhor (1993) pointed out that the overlap usually should be more than 25% of the frame size. On the other hand, Lu *et al.* (2001) classified a 1s sample, with 40 evenly segmented non-overlapping 25 ms frames. Statistical characteristics over all 40 frame features were used to classify the sounds. Although Lu's method required only short samples and no frame overlapping, the computing cost and memory requirement is still quite significant for tiny smart sensors. Also their approaches suffer the same problem, i.e., the last decision cannot be made without extracting individual features for all frames. This means every frame needs to be processed

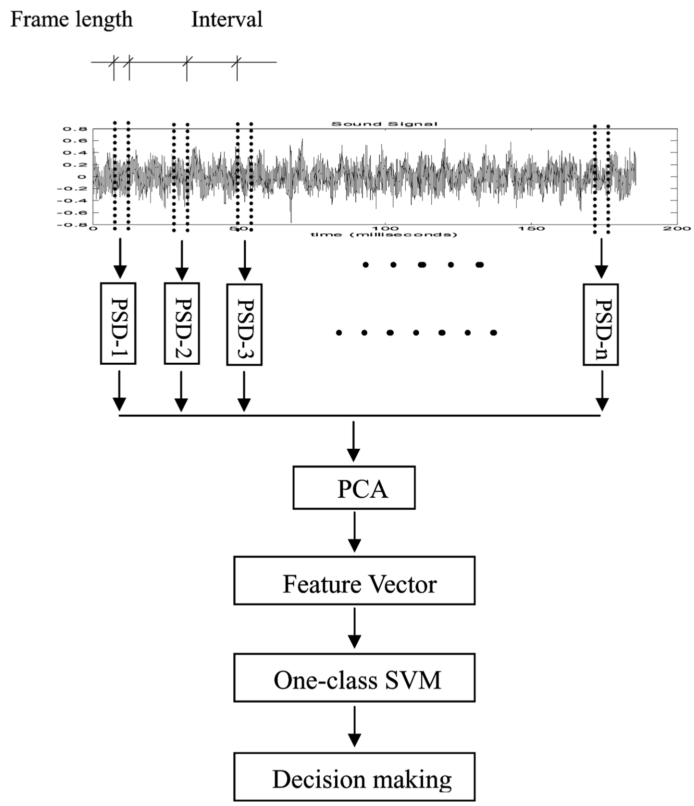

Fig. 5 PCA and one class SVM based sound recognition

individually at first. The acquired data also need to be reserved. However, a sound sample usually contains many of such frames so that both the computation and memory cost will be huge.

In order to lower the computational cost and memory requirement of the sensors, as well as its energy consumption, in this paper, however, another approach using PCA and one-class SVM is applied, which can make a decision for a sound sample as a whole. Moreover, some individual frames interfered by the noise will be avoided affecting the last decision, due to the denoising ability of the PCA. For further decreasing the computation cost, considering of the monotonous characteristic of the noise emitted from a road cutter in constant operation, we proposed a separated frame blocking mechanism. For each sound sample, all frames are segmented separately. An interval is set between every two adjacent frames instead of the overlap, as shown in Fig. 5. Then power spectral densities (PSDs) can be extracted from those separated frames and processed by PCA. After that, a feature vector, truncated eigenvalues, can be obtained. It is obvious that the acquired feature vector actually characterizes the whole sound sample, rather than the individual frames. Based on the obtained feature, a one-class SVM classifier can then be applied to make the classification and a decision can be made. The PCA and one-class SVM based sound recognition process is briefly depicted in Fig. 5.

3.2 Principal component analysis

Intuitively, PCA is a method that aids the gathering of important facts among a large amount of information. In statistics, PCA is a technique for simplifying a dataset, by reducing multi-dimensional datasets to lower dimensions for analysis. Technically speaking, PCA is a linear transformation that transforms the data to a new coordinate system in which the maximum variance can be achieved. In practice, PCA is a powerful tool to represent data and also a very useful method in pattern recognition (Jain *et al.* 2000).

From the incoming sound sample, n separated fames will be segmented out for analysis. For each frame, the signal is transformed into frequency domain by FFT transform, so that the power spectral density (PSD) can be obtained. For the purpose of pattern comparison, PSD of each frame is normalized into unit power within all frequency range. Thus n normalized PSDs can be obtained as

$$\mathbf{P}_i = (f_{i1}, f_{i2}, \ldots, f_{ik})(i = 1, 2, \ldots, n) \tag{1}$$

where: $\mathbf{P}_i$ is the PSD vector of the ith sound frame; k is the FFT point number; and $\sum_{j=1}^{k} f_{ij} = 1$.

The covariance matrix $\mathbf{C}$ can be expressed as

$$\mathbf{C} = E\{(\mathbf{P} - E(\mathbf{P}))(\mathbf{P} - E(\mathbf{P}))^T\} \tag{2}$$

From the obtained covariance matrix, a unit orthogonal basis can be obtained by finding its eigenvalues and eigenvectors. The eigenvalue vector $\mathbf{V}$ can be expressed as

$$\mathbf{V} = (a_1, a_2, \ldots a_n) \tag{3}$$

where a_i (i = 1,2...n) are obtained eigenvalues and

$$a_1 \geq a_2 \geq a_3 \ldots \geq a_n \tag{4}$$

In PCA analysis, usually only first several principal components are needed. Truncated eigenvalue vector $\tilde{\mathbf{V}}$ is therefore often used for the feature vector, which could be written as

$$\tilde{\mathbf{V}} = (a_1, a_2, \ldots a_m) \quad m < n \tag{5}$$

where m is the number of the retained eigenvalues and corresponds to the dimension of the subspace.

It can be assumed that sounds from a same class have their own special pattern and thus have their own principal space. Eigenvectors actually can be referred as the direction vectors, while eigenvalues represent the weights for each direction. In most cases, the truncated eigenvalues can uniquely characterize the sound. Thus, using truncated eigenvalue vector $\tilde{\mathbf{V}}$ as the feature vector is feasible, practical and reasonable.

3.3 One-class SVM

SVM is a supervised learning method which can separate the data easily using a hyperplane by projecting them into a high dimension feature space. SVM was first introduced by Vapnik (1979, 1995) and soon became popular due to its strong power of classification and many successful applications.

SVM was initially used for classifying two classes. But it was soon extended to the use for multi-class and one-class classification. For one-class classification problems, they are often due to the lack of data

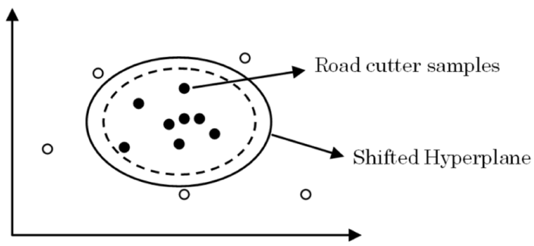

Fig. 6 Hyperplane shifted to increase recognition ability for road cutters

or incomplete information. In our road cutter recognition problem, considering that it is impossible for us to collect all kinds of environmental sounds to train them, it is reasonable to apply one-class SVM to make classification.

The one-class SVM classifier distinguishes other classes from a known class, depending on the decision hyperplane built on the support vectors and a Kernel function. The decision function for one class SVM has the form (Unnthorsson *et al*. 2003)

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i \cdot K(\Phi(X_i), \Phi(Z)) - \rho\right) \tag{6}$$

where: $\Phi(X_i)$ is a support vector, $\Phi(Z)$ is a data vector to be classified, K is a Kernel function, l is the number of the support vectors and ρ is the offset.

Usually, the hyperplane of the one class SVM is the geometric form of the decision function. However, for the pipeline monitoring, considering the ponderance of the accidents, we would like to decrease the rejection error (regarding it is not a road cutter but actually it is), even though it may increase the risk of acceptance error (regarding it is a road cutter but actually it is not). In this case, we could shift the hyperplane a little away from the road cutter class, as Fig. 6 shows, so that the margin for cutter class could be increased and could tolerate more suspicious samples.

An advantage of SVM is that it can project and group separated data to a higher dimensional space. Even though this paper focuses on the recognition of the road cutters, with the SVM, it could easily extend to include other construction machines, such as drills and backhoes.

3.4 Standardization

Standardization of the data is sometimes required. There are even some arguments that since the principal components are dependent on the units used to measure the original variables as well as on the range of the values they assume, standardization of the data is always necessary to be applied prior to using PCA (PCA lecture slides, University of Nevada). A common standardization method is to transform all the data to have zero mean and unit standard deviation. Here, considering the significant variation of the frequency, the effect of standardization is also tested. With standardization, the standardized PSD vector $\mathbf{P}^s$ becomes

$$\mathbf{P}_i^s = \frac{\mathbf{P}_i - \mu_p}{\sigma_p} \quad (i = 1, 2, \ldots, n) \tag{7}$$

where μ_p and σ_p are the mean and standard deviation of $\mathbf{P}$ respectively.

The covariance matrix will then have the form

$$\mathbf{C}^s = \begin{pmatrix} 1 & & \cdots & \vdots \\ & 1 & & \vdots \\ \vdots & & \ddots & \\ \vdots & \cdots & & 1 \end{pmatrix}_{k\times k} \tag{8}$$

4. Experiments and results

4.1 Experimental setup

In order to test the feasibility of deploying this hazard early warning approach to a real pipeline, on-site experiments were conducted. The experiments were conducted at several places in Tokyo at different times. Fig. 7 shows an experiment conducted at one place of Tokyo.

During the experiments, a microphone (Sony ECM-CR120) was used to capture the sound, and a digital recorder (Olympus IC recorder) was used for recording. The specification of the experiment equipments can be shown in Table 1. Considering the frequency sensing range of the unit, frequencies higher than 12 kHz were discarded for all captured acoustic signals.

With the experiments, totally 151 sound samples were collected, including road cutting sounds and other environmental sounds. As shown in Table 2, 10 road cutting sounds were picked up as the template cutter sounds which were used to build the one-class SVM for the road cutter class. 15 other sounds, including 5 cutting sounds and 10 non-cutting sounds, were used for the training sounds, to train and optimize the Gaussian kernel parameters of the one-class SVM, such as highest allowable fraction of the misclassification and the bandwidth of the Gaussian distribution. The rest of 126 sounds were used for testing.

Fig. 7 An experiment was conducted in Tokyo

Table 1 Specification of experiment equipment

Microphone		Digital Recorder	
Model	ECM-CR120	Model	Olympus V-60
Directivity	Omni-directional	Sampling frequency	44.1 kHz
Frequency range	100 Hz-12 kHz	Frequency range	50 Hz-13 kHz
Sensitivity	-46 dB±4 dB	Input level	-70 dBv

Table 2 Data collection

	Total sounds	Template sounds	Training sounds	Testing sounds
Cutter	51	10	5	36
Vehicle	15		1	14
Backhoe	44		7	37
Train	4			4
Wood cutting	7			7
Pionjar drill	5			5
Others	25		2	23
Total	151	10	15	126

4.2 Data analysis and acoustic recognition

For analyzing the sound, the power spectra of the road cutter samples were studied at first. Usually the sound contains two parts, the low frequency band sound from the engine of the road cutter and the high frequency band sound from the action of road cutting. It can be found that the frequencies vary significantly in different samples even though they all belong to the same class, i.e., road cutter, as shown in Fig. 8. The variation of the frequency can be explained by the working conditions. The material the blade is cutting is always changing, either the soft asphalt, or sand, or the hard carpolite or something else. Also, the pressure put on the cutter by workers can never be kept constant. The lubricant effect of the water, which is indispensable when the cutter is working, will change the frequency too. Thickness of the road also results in the frequency variation. At last, another fact requiring us to treat seriously is that the engine condition of different cutters varies significantly too. Usually, for a new cutter the low frequency component will be small while for an old one, the low frequency engine sound may be very large, making high frequency cutting sounds relatively trivial. All of these facts will cause problems for generalizing the classification process.

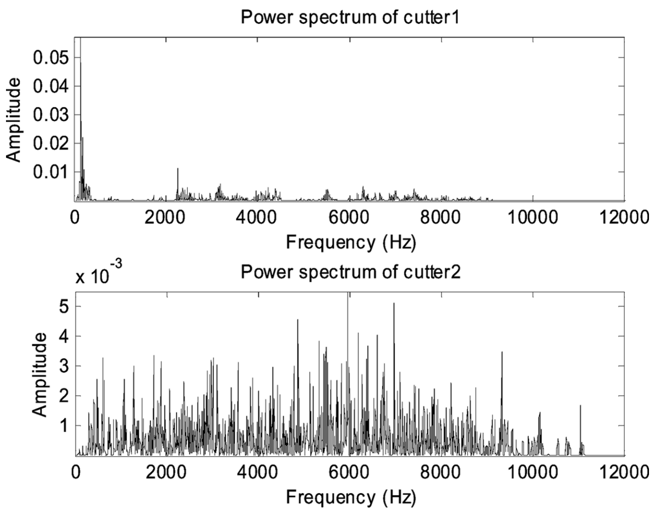

Fig. 8 Significant frequency variation of cutter sounds

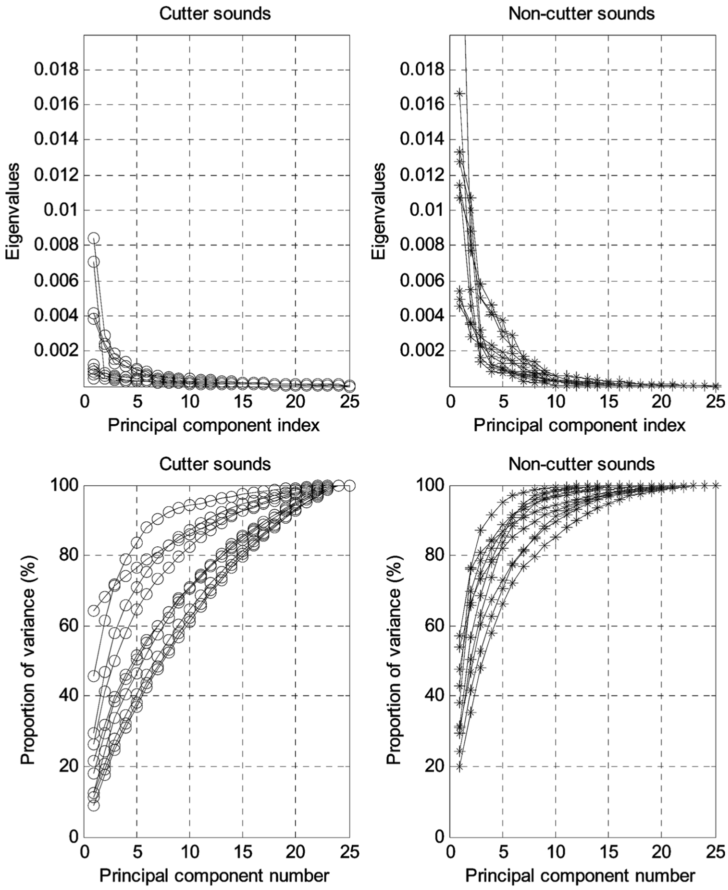

Fig. 9 Eigenvalues and proportions of variance (%), with low frequency engine sound included

Since most environmental noise sounds from the street have relatively low frequency components, such as engine sounds of vehicles and voices of pedestrians, etc., interference may easily happen in the low frequency band. Moreover, the actual danger to the pipeline is coming from the action of road cutting. It seems that the road cutting sound should be the deterministic sound that actually characterizes a road cutter. In this sense, it seems that in order to effectively recognize a dangerous road cutter, its engine sound and road cutting sound should be separated. As we found that the frequencies from the cutter engine were usually around 140 Hz, this paper studies the both effects for frequencies below 500 Hz being either remained or removed.

In the analysis, for each sound sample, 25 tiny frames were segmented out, each lasting 23 ms which corresponded to sample points of 1024. A 200 ms interval was set between every two adjacent frames. For each frame, the PSD was calculated and normalized into unit power. The normalized PSDs were further analyzed using PCA. Thus for each sound sample, the feature vector, i.e., truncated eigenvalue vector, could be obtained. Fig. 9 shows the eigenvalues (without being truncated) and the accumulated proportion of variance for template cutter sounds and non-cutter training sounds when low frequency engine sounds were remained. While Fig. 10 shows the case when low frequency engine sounds was removed. From Figs. 9 and 10, it can be found that the eigenvalues for cutter sounds are much different

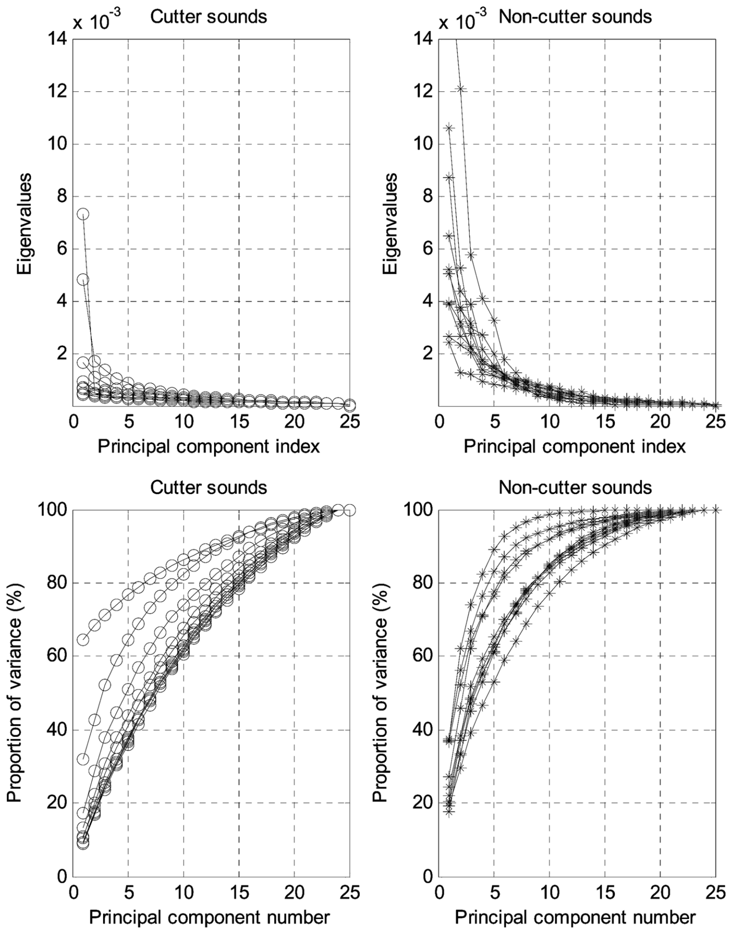

Fig. 10 Eigenvalues and proportions of variance (%), with low frequency engine sound excluded

with those for non-cutter sounds. Thus the eigenvalue vectors are feasible for the required acoustic classification.

For effective classification, the subspace dimension in principal component analysis should be selected carefully, striking a good balance between underfitting, overfitting and also computing cost. It is simply a problem of deciding how many principal components (PCs) should be retained. This problem, however, is still a big and open issue for principal component analysis. Basically, there are three popular criteria which indicate the terminating condition for gathering the PCs (Jolliffe 1986, Jackson 1991).

- Proportion of variance: it means the cumulative percentage of total variation in several PCs. The required number of PCs is determined to be the smallest value for which a chosen variance percentage is exceeded. However, there is no definite rule to decide exactly how much the percentage should be chosen. Jolliffe (1986) suggested a value between 70% and 90%.
- Scree test: it was proposed and named by Cattell (1966). It is a graphical technique. According to this criterion, the PCs, corresponding to the steepest part till the fairly sharp "elbow" in its eigenvalue graph, will be retained.
- Kaiser rule: Kaiser (1960) pointed out that only those PCs whose variances no smaller than 1 should

be retained. However, this method was for using with correlation matrices. For covariance matrices, Jolliffe suggested to use the average value of the eigenvalues to be the cut-off value, i.e., retaining those eigenvalues larger than the average value.

From the eigenvalues in Figs. 9 and 10, according to the scree test criterion, the number of PCs should be around 5. However, according to proportion of variance, about 20 PCs are needed for 90% of total variance. Thus the required PCs should be between 5 and 20. However, due to the significant eigenvalue variation caused by frequency variation between samples, it is very difficult for us to decide the exact dimension of the principal space for our case. In this case, we therefore tested 4 conditions, when the number of PCs was set to be 5, 10, 15 and 20.

After the truncation of the eigenvalue serials, the remained eigenvalues were used for the feature vector. The feature vector was then classified by the pre-trained one-class SVM classifier. By studying the discriminant values of the training samples, as shown in Fig. 11, it could be found that most training non-cutter sounds were well recognized and their distances to the hyperplane were very large, thus leave us large space for adjusting the hyperplane. Considering the discriminant values for road cutter sand non-cutters, the hyperplane was deliberately shifted a little away from the road cutter class, to be -0.03, to decrease the rejection error for road cutter samples.

With the PCA and one-class SVM classifier, all the testing sounds were classified and the recognition correctness rates were listed in the Table 3. The recognition correctness refers to whether cutter sounds can be correctly recognized as from road cutters and non-cutter sounds be recognized as not from road cutters. Results show that the PCA and one-class SVM based cutter recognition algorithm can do the work very well. For road cutters, the recognition correctness rate can be as high as 97.22%, while for overall, the correctness rate can still reach 95.24%. Even though it assumes that removing the low frequency band can improve the recognition, our result shows that there is no much difference between the cases when the low frequency band is remained and removed. The improvement is very small. However, it should also be noted, that with the low frequencies removed, only 5 PCs can lead to the

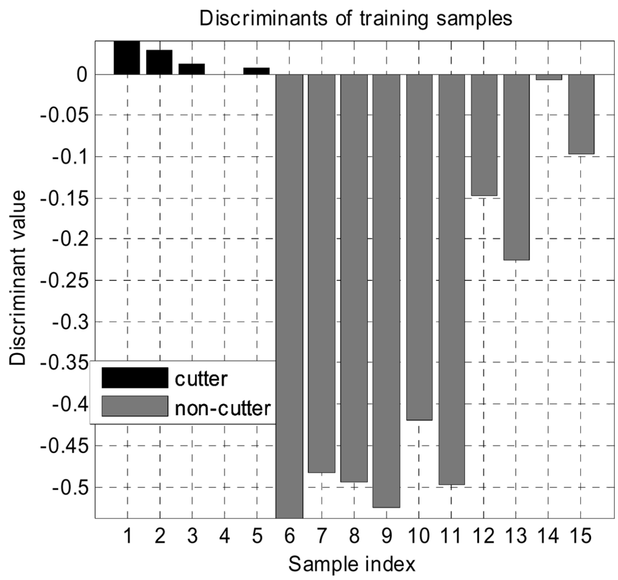

Fig. 11 Discriminant values for training samples with PCs being 10 and low frequency engine sounds remained

Table 3 Recognition correctness rate (%)

	All frequencies remained				Low frequencies removed			
	PC=5	PC=10	PC=15	PC=20	PC=5	PC=10	PC=15	PC=20
Cutter	97.22	97.22	97.22	97.22	97.22	97.22	97.22	97.22
Vehicle	85.71	85.71	92.86	92.86	100	100	100	100
Backhoe	91.89	94.59	94.59	94.59	97.30	97.30	97.30	97.30
Train	100	100	100	100	100	100	100	100
Wood cutting	100	100	100	100	85.71	85.71	85.71	85.71
Pionjar drill	80	80	80	80	40	40	40	40
Others	91.30	95.65	95.65	95.65	100	100	100	100
overall	92.86	94.44	95.24	95.24	95.24	95.24	95.24	95.24

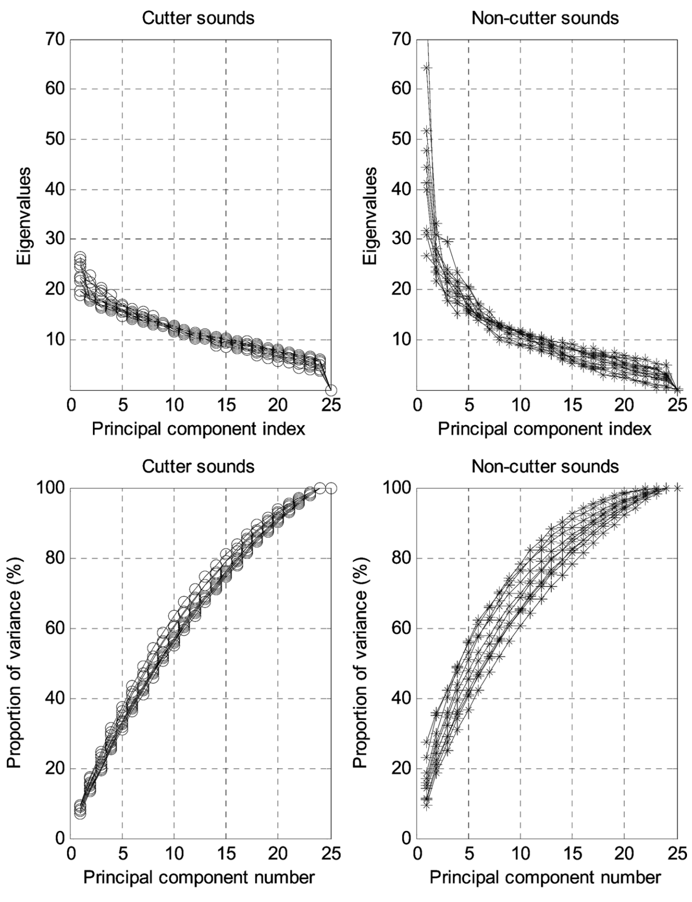

Fig. 12 Eigenvalues and proportions of variance with low frequency engine sounds remained and standardization applied

best result. When the low frequencies are remained, however, the recognition resolution for Vehicles is only 85.71%. While with the low frequencies removed, all vehicles are well recognized. Considering there will be many vehicles on the roads, removing the low frequency band to have a better recognition for vehicles will be practical and useful.

4.3 Sound recognition with standardization

In this research, standardization was also tested. This time, all the normalized PSD vectors were first standardized prior to the PCA analysis. The eigenvalues of the template cutter sounds after standardization are shown in Figs. 12 and 13. Obviously, the eigenvalues with standardization differ significantly from those without standardization. With standardization, the variation of the eigenvalues is strongly alleviated. It can also be found that, with standardization, the posterior eigenvalues become much closer between the cases of cutter sounds and non-cutter sounds, which will make the recognition much more difficult.

Figs. 12 and 13 also shows that with standardization, more variance energy is distributed into posterior principal components, so that the situation of variance condensing into few principal components becomes worse; in this case, it is very difficult for us to determine the number of PCs required using the scree test criteria. For the view of the accumulated variance proportion, 20 PCs contains about 90% of the total variance. In this case, we also tested the data for 4 conditions, i.e., the principal space dimension being 5, 10, 15 and 20 respectively. The final recognition results are listed in Table 4. It is

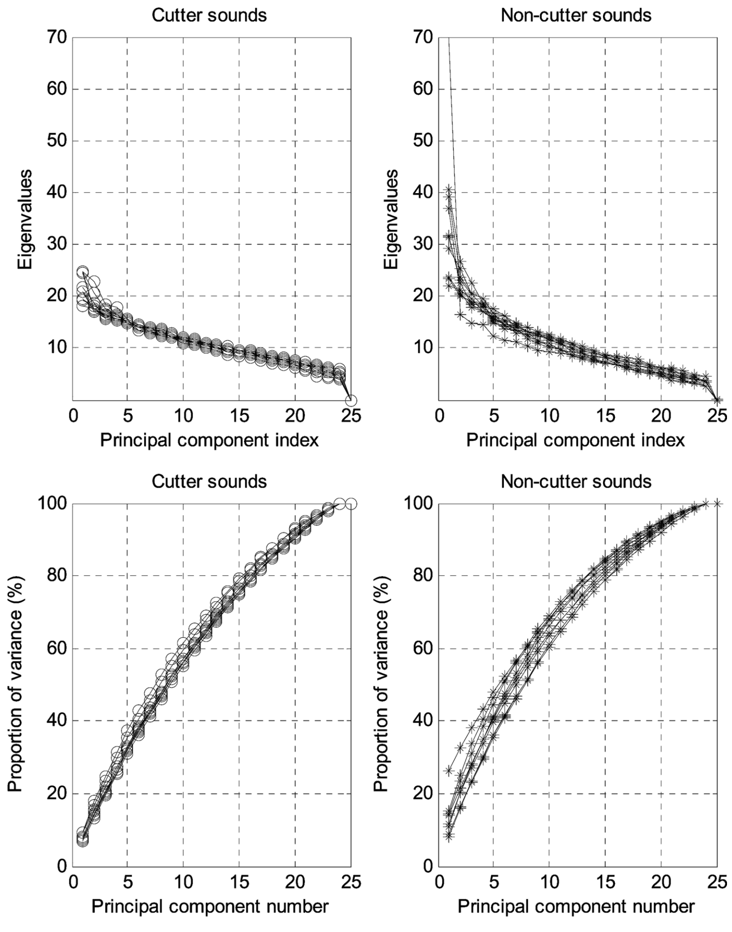

Fig. 13 Eigenvalues and proportions of variance with low frequency engine sounds removed and standardization applied

Table 4 Recognition correctness rate when standardization is applied (%)

	All frequencies remained				Low frequencies removed			
	PC=5	PC=10	PC=15	PC=20	PC=5	PC=10	PC=15	PC=20
Cutter	86.11	86.11	86.11	86.11	88.89	88.89	88.89	88.89
Vehicle	100	100	100	100	78.57	78.57	78.57	78.57
Backhoe	91.89	91.89	91.89	91.89	86.49	86.49	86.49	86.49
Train	100	100	100	100	100	100	100	100
Wood cutting	100	100	100	100	100	100	100	100
Pionjar drill	100	100	100	100	40	40	40	40
Others	91.30	91.30	91.30	91.30	91.30	91.30	91.30	91.30
overall	92.06	92.06	92.06	92.06	86.51	86.51	85.71	85.71

obvious that with standardization the results become much worse. Moreover, many errors are coming from the road cutter sound, which will lead to high risks for the pipeline. Therefore, standardization should not be applied in our case.

5. Conclusions

In this paper, acoustic information is used to recognize dangerous construction machines that are potential hazards to the well-being of underground pipelines. An early warning approach is introduced to prevent hazards. A sound recognition method based on PCA and one-class SVM was studied and applied. With it, a sound sample can be recognized with many separated segmented frames. The abstracting ability of PCA could make it robust to noises. At the same time, one-class SVM classifier could provide good classification ability. Real-site experiments were conducted and data were analyzed. Results show that PCA and one-class SVM based algorithm can do the work very well. It can also be found that standardization will make the results much worse and therefore should not be applied prior to the PCA analysis. The potential hazard detection approach based on acoustic recognition for construction machines studied in this paper will be very useful for pipeline early warning systems in the future to prevent disasters and ensure the safety of underground lifeline infrastructures.

Acknowledgments

We would like to thank Mr. T. Kume and Dr. M. Tamura at Tokyo Gas Co., Ltd. for providing valuable experimental data.

References

Cattell, R.B. (1966), "The Scree test for the number of factors", *Multivar. Behav. Res.*, **1**(2), 245-276.

Eiber, R.J., Jones, D.J. and Kramer, G.S. (1987), "Outside force causes most natural gas pipeline failures", *Oil Gas J.*, **85**(11), 52-57.

Gaunard, P., Mubikangiey, C.G., Couvreur, C. and Fontaine, V. (1998), "Automatic classification of environmental noise events by hidden Markov model", *Proceedings of the IEEE International Conference on Acoustics, Speech* *and Signal Processing*, Seattle, WA , USA, May.

Goldhor, R.S. (1993), "Recognition of environment sounds", *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing,* Minneapolis, MN, USA, April.

Hausamann, D., Zirnig, W. and Schreier, G. (2003), "Monitoring of gas transmission pipelines-A customer driven civil UAV application", *Proceedings of the ODAS Conference*, Toulouse, France, June.

Huebler, J.E. (2004), *Detection of unauthorized construction equipment in pipeline right-of-ways*, Technical Report of Gas Technology Institute.

Jackson, J.E. (1991), *A user's Guide to Principal Components*, John Wiley & Sons, Inc.

Jain, A.K., Duin, R.P.W. and Mao, J. (2000), "Statistical pattern recognition: a review", *IEEE Trans. Pattern Anal. Mach. Intell.*, **22**(1), 4-37.

Jolliffe, I.T. (1986), *Principal Component Analysis*, Springer-Verlag New York Inc.

Kaiser, H.F. (1960), "The application of electronic computers to factor analysis", *Educ. Psychol. Meas*., **20**, 141-151.

Krishna, A.G. and Sreenivas, T.V. (2004), "Music instrument recognition: from isolated notes to solo phrases", *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing,* Montreal, Quebec, Canada, May.

Lu, L., Li, S.Z. and Zhang, H.J. (2001), "Content-based audio segmentation using support vector machines", *Proceedings of the IEEE International Conference on Multimedia and Expo*, Tokyo, Japan.

Lu, L., Li, S.Z. and Zhang, H.J. (2003), "Content-based audio classification and segmentation by using support vector machines", *Multimedia Syst.,* **8**(6), 482-492.

Ma, L., Milner, B. and Smith, D. (2006), "Acoustic environment classification", *ACM TSLP*, **3**(2), 1-22.

Peltonen, V., Tuomi, J., Klapuri, A., Huopaniemi, J. and Sorsa, T. (2002), "Computational auditory scene recognition", *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing*, Orlando, Florida, USA, May.

Toyoda, Y., Huang, J., Ding, S. and Liu, Y. (2004), "Environmental sound recognition by multilayered neural networks", *Proceedings of the 4th International Conference on Computer and Information Technology*, Wuhan, China, September.

Unnthorsson, R., Runarsson, T.P. and Jonsson, M.T. (2003), "Model selection in one class nu-SVMs using RBF kernels", *Proceedings of the 16th Conference on Condition Monitoring and Diagnostic*, April.

Vapnik, V. (1979), *Estimation of Dependences Based on Empirical Data (in Russian)*, Nauka, Moscow, Russia (English translation: Springer Verlag, New York, 1982).

Vapnik, V. (1995), *The Nature of Statistical Learning Theory*, Springer-Verlag, New York.

Wan, C., Mita, A. and Kume, T. (2008), "An automatic pipeline monitoring system using sound information", *Struct. Contr. Health Monit*., published online., Available at http://www3.interscience.wiley.com/journal/121552603/abstract.

Wan, C. and Mita, A. (2008), "Recognition of potential danger to buried pipelines based on sounds", *Struct. Contr. Health Monit*., published online., Available at http://www3.interscience.wiley.com/journal/121575104/abstract.

Wan, C. and Mita, A. (2009), "Pipeline monitoring using acoustic PCA recognition with Mel scale", *Smart Mater. Struct.*, **18**(5).

Principal Component Analysis (PCA), Lecture slides at Computer Science Department of University of Nevada, Available at http://www.cse.unr.edu/~bebis/MathMethods/PCA/lecture.pdf.

Principal Component Analysis, notes from Indiana University, Available at http://rguha.net/writing/notes/stats/node7.html.

Principal Components and Factor Analysis, electronic statistics textbook, StatSoft, Inc., Available at http://www.statsoft.com/textbook/stfacan.html.

JK