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A novel acoustic emission detection module for leakage recognition in a gas pipeline valve

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ABSTRACT

Internal valve leakage in a natural gas pipeline seriously impairs the safe operation on pipelines, and the recognition of leakages has therefore been a major concern of the industry. In this study, a novel leakage detection scheme based on kernel principal component analysis (kernel PCA) and the support vector machine (SVM) classifier for the recognition of the leakage level is constructed. Using this approach, the acoustic signal of the leakage is obtained as the feature source using an acoustic emission (AE) sensor. The kernel PCA is used to reduce the dimensionality of the features and extract the optimal features for the classification process, and the SVM is applied to perform the recognition of the leakage levels. The performance of the classification process based on kernel PCA and the classifier are evaluated in terms of the accuracy, Cohen's kappa number and training time. The experimental results demonstrate that the intelligent recognition model based on kernel PCA and SVM classifier is very effective for recognizing the leakage level of a valve in a natural gas pipeline.

1. Introduction

The inevitable events of gas pipeline valve leakage during the gas transportation process pose serious problems to the availability, reliability, and economy of the pipeline. Thus, the possibly used safety measures focused on early detection of both small and large leakages is not only a guarantee for safer operation but also a help for reducing the costs of the industry. To monitor the valve yield condition for substantial cost savings and safer working conditions, a great number of methods have been developed. However, the currently available leakage detection methods provide little capability for the quantitative recognition of leakage levels.

One common measurement technique for measuring the leakage of valves is acoustic emission (AE) (Sharif and Grosvenor, 1998), which is a new non-destructive testing (NDT) technique with very high sensitivity that can be used to detect weak signals without hindering operations (Christian and Masayasu, 2008). A comprehensive review of the development history of acoustic emission was provided by Drouillard (1996). In recent years, researchers have studied the characteristics of AE signals in the process of valve leakage. Lee et al. (2006) provided a detailed summary of the acoustic emission signals indicating different characteristics of the check valve. Kaewwaewnoi et al. (2010) investigated the relationship between the internal fluid leakage of a valve and the acoustic emission signal, and a further study has been made by Prateepasen et al. (2011) for the development of intelligent portable noninvasive instruments. Meland et al. (2011) analyzed the frequency spectrum of internally leaking shutdown valves. All of the above studies indicated that the leakage of pipelines can be detected qualitatively using AE technology. On the other hand, it is also important to measure the leakage level quantitatively for the safer operation of the natural gas pipeline. In this study, an intelligent leakage recognition method for valve leakages in a gas pipeline using acoustic emission was developed. The process of intelligent leakage recognition includes the dimensionality reduction of the acoustic signal and the classification of the leakage. As a pattern recognition method, the support vector machine (SVM) has been extensively employed to solve classification and regression problems (Cortes and Vapnik, 1995). The SVM has been successfully used in many fields, including valve leakage (Yang et al.,

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Table 1 – Measured AE parameters for leakage recognition.

Time domain	Frequency domain
Mean value	Root variance frequency
Standard deviation	Peak value
RMS	Frequency center
Energy	
Entropy	

2005), mechanical fault diagnosis (Oh and Sohn, 2009), image and video processing (Ding et al., 2008), medical engineering (Gil and Johnsson, 2010), and chemical engineering (Kulkarni et al., 2005). To improve the accuracy of classification, several feature parameters were calculated in the time and frequency domains. Because large number of features may lead to the reduction of the dimensionality and thereby reduced performance of classification, in this study, the kernel principal component analysis (kernel PCA) based on the non-linear feature of the reduction of dimensionality was adopted to convert the existing features into a space of a smaller number of dimensions and thereby improve the classification performance.

In the present study, an intelligent model was constructed to quantitatively recognize the leakage level of valves in gas pipelines. The acoustic parameter features of different leakage levels were first obtained using an acoustic emission sensor. The kernel PCA was then employed to transform the features into a lower-dimensional space and extract the effective features. Typical kernel functions of important parameters used for indicating the performance of the kernel PCA were compared and analyzed. Then, the effective features were trained and tested using the SVM to determine the level of valve leakage. To verify the SVM models, the performance of the classifiers, including the accuracy, the Cohen's kappa number, and the training time, were compared to the corresponding data from the k-nearest neighbor classifier (k-NN) (Liao and Vemuri, 2002), neural network classifier (NN) (Yu and Junsheng, 2006), naive Bayes classifier (NB) (Jiang et al., 2012), and decision tree classifier (DT) (Sethi, 1997).

2. Methods

2.1. *Acoustic emission in valve application*

Acoustic emission is a spontaneous release of elastic energy during the deformation of a material and can be detected by an AE sensor in all directions. The main sources of acoustic emission are plastic deformation, crack growth, leakage, burning and fracture (Malhotra and Carino, 2003). Therefore, the acoustic signal induced by the internal leakage of the pipeline valve is a typical acoustic emission phenomenon. Gas leakage in the valve introduces a pressure difference in the gas space and then generates turbulence. The turbulence not only disturbs the normal flow of gas but also leads to an interaction between the frequency elastic wave (acoustic emission signal) and the valve wall. The leakage information spreads from the elastic wave to the surface of the valve, and the AE sensor can be used to pick up the acoustic emission signals. The degree of the pipeline valve leakage can then be evaluated through signal analysis and processing.

In signal analysis and processing, different parameters can be extracted from the signals. The AE signals of leakage are continuous waveforms that can be analyzed by several special techniques. In this study, the measured AE parameters selected to identify the leakage in the time and frequency domains are listed in Table 1.

The AE signal is very useful for studying the characteristics of valve leakage mechanism, because the measured AE parameters can be directly related to the level of leakage. Relative studies on valve frequency analysis showed that the AE signal obtained from valve leakage is usually in the frequency range of 100–300 kHz (Noipitak et al., 2011). The peak value and frequency center of the AE gradually increases with the leakage level. Consequently, the occurrence and levels of valve leakage can be evaluated by the parameters of the AE signal features in both the time and spectral domains.

2.2. *Kernel principal component analysis (kernel PCA)*

Principal component analysis (PCA) is probably the best known of the techniques of multivariate analysis, it's central idea is to reduce the dimensionality of data set in which there are large number of variables. The internal model of PCA is linear relationship, it focuses on the two order correlation between variables, which deals with the two order correlation between variables. PCA is less effective to extract the nonlinear characteristics of the acoustic parameters of leakage in valve, therefore, kernel PCA is proposed to extend the feature extraction method in the nonlinear case. The kernel principal component analysis is constructed from the traditional linear PCA in a high-dimensional space using a kernel function. Using the kernel PCA, the principal eigenvectors of the kernel matrix rather than those of the covariance matrix should be calculated. The reconstruction of the traditional PCA in kernel space is straightforward because of the similarity between the kernel matrix and the inner product of the data points that are used to construct the kernel function. The properties of constructing nonlinear mappings for kernel PCA can be provided by the application of PCA in the kernel space (Cho et al., 2005).

The idea of kernel PCA is to obtain linear operations by mapping the original non-linear input vectors x_k to a high-dimensional feature space $\phi(x_k)$ using a kernel function. A set of centered observed values, i.e., x_k ($k = 1\ldots M$, and $\sum_{k=1}^{M} x_k = 0$) are given for the kernel PCA model construction, and a multi-dimensional feature space is adopted. According to nonlinear mapping, namely, ϕ: $R_N \to F$, the observed values in the current space are converted into a high-dimensional feature space $\phi(x_k)$. The sample covariance matrix $\tilde{C}$ in the feature space can be expressed by

$$\tilde{C} = \frac{1}{M}\sum_{k=1}^{M} \phi(x_k)\,\phi(x_k)^T. \tag{1}$$

The eigenvalues and eigenvectors of the covariance matrix $\tilde{C}$ in feature space F can be calculated by the PCA solver as

$$\lambda \upsilon = \tilde{C}\upsilon = \frac{1}{M}\sum_{k=1}^{M} (\phi(x_k \cdot \upsilon))\,\phi(x_k). \tag{2}$$

In the above equation, λ and υ are an eigenvalue and eigenvector of the covariance matrix, respectively. All of the solutions for υ with $\lambda \neq 0$ lie in the span of $\phi(x_1)$–$\phi(x_M)$. A set of coefficients α_i ($i = 1,\ldots M$) that meet the following conditions exist, i.e.,

$$\upsilon = \sum_{i=1}^{M} \alpha_i \phi(x_i). \tag{3}$$