Application of Support Vector Machines in Reciprocating Compressor Valve Fault Diagnosis

Quanmin Ren, Xiaojiang Ma, and Gang Miao

Key Laboratory for Precision and Non-traditional Machining Technology of Ministry of Education, Dalian University of Technology, Dalian 116023, P.R. China
renquanmin@163.com

Abstract. Support Vector Machine (SVM) is a very effective method for pattern recognition. In this article, a intelligent diagnosis system based on SVMs is presented to solve the problem that there is not effective method for reciprocating compressor valve fault detection. The Local Wave method was used to decompose vibration signals, which acquired from valves surface, into sub-band signals. Then the higher-order statistics were calculated as the input features of classification system. The experiment results confirm that the classification technique has high flexibility and reliability on valve condition monitoring.

1 Introduction

Machine fault diagnosis is a kind of pattern recognition for machine working conditions. It can increase reliability and decrease possible loss of production due to machine breakdown. The combined suction/discharge valves are the "hearts" of a secondary ethylene compressor that is the key element of the Low Density Polyethylene production plant [1]. Because valve faults are the biggest source of compressor failure, adding up to more than 30 percent of total faults, it is necessary to monitor working conditions of valves online during their lifetime.

The utilization of support vector machine classifiers has gained very popularity in the recent years. SVMs are discriminative classifiers based on Vapnik's structural risk minimization principle [2]. They can implement flexible decision boundaries in high dimensional feature spaces. The implicit regularization of the classifier's complexity avoids overfitting and leads to good generalizations.

In this article, SVMs have been used in automated diagnosis of valves conditions. The input features were extracted from vibration signals by Local Wave and higher-order statistical methods.

2 Support Vector Machines

The objective of SVMs learning is to find an optimal classification function that can classify all the training vectors correctly with high accuracy and good generalization, on the basis of the set of measures $\{\mathbf{x}_i,\mathbf{y}_i\}$, i=1,2,…N, where $\mathbf{x}_i$ is an input pattern, and $\mathbf{y}_i \in \mathbf{Y}=\{+1,-1\}$ is the corresponding target.

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In the case of nonlinear condition, the training points are mapped from the input space to a feature space through a nonlinear mapping. Thus, a simple linear hyperplane is used for separating the points in the feature space. Even if mapped in the high-dimensional feature space, it can't always be avoided that there are points misclassified. The SVM allows for some errors but penalizes their cardinality.

Therefore, the above description can be summarized as a CQP. By using the Lagrange multiplier theory, it is written in dual form as fellows:

$$\max_{\lambda}(\sum_{i}\lambda_i - \frac{1}{2}\sum_{i,j}\lambda_i\lambda_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j)) \ . \quad (1)$$

$$\text{subject to} \quad 0 \le \lambda_i \le C \ , \quad i = 1,2,\ldots,N \ . \quad (2)$$

$$\sum_{i}\lambda_i y_i = 0 \ . \quad (3)$$

The resulting classifier is

$$f(\mathbf{x}) = sign(\sum_{i=1}^{Ns}\lambda_i y_i K(\mathbf{x}_i, \mathbf{x}) + w_0) \ . \quad (4)$$

where $\boldsymbol{K}(\mathbf{x}_i,\mathbf{x})$ is a kernel function and N_s is the number of support vectors.

3 Fault Detection System

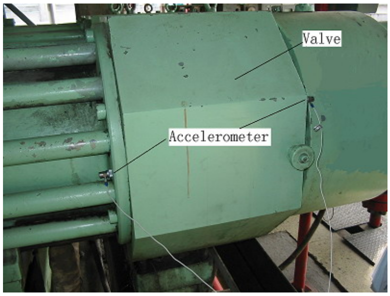
3.1 Vibration Measurements

Vibration signals from valves surface were acquired by accelerometers from three the secondary ethylene compressors as shown in Fig.1 (left). The maximum acquisition frequency was 25.6kHz and the number of sampled data was 16384.

3.2 Feature Extraction

The reciprocating compressor is a very complexity system and the monitored signals are highly nonlinear and non-stationary. Local Wave method is a powerful method for analyzing nonlinear and non-stationary data [3,4]. Here it was used as filters. The signal was firstly decomposed into some 'intrinsic mode functions' (IMFs). Then four frequency sub-band signals were reconstructed according to the energy and frequency distribution of IMFs. They are as fellows: S1 being the IMF1, S2 being the IMF2, S3 being the sum of IMF3-IMF5, and S4 being the sum of others.

Higher-order statistics have been widely used in signal processing and system theory problems. Monitoring moments and cumulants of vibration signals can provide diagnostic information for machines [5]. Here the first four zero-lag cumulants of sub-band signals were used as input features. They were calculated as Fig.1 (right). So there were altogether 16 features that were obtained from sub-band signals. Table 1 shows the statistical parameters of sub-band signals (S1-S4) in healthy and faulty conditions, respectively.



$$x'(k) = \frac{x(k)}{Max[abs(x(k))]}$$

$$m_n = \frac{1}{N}\sum_{k=1}^{N} \left|x'(k)\right|^n \quad (n = 1-4)$$

$$\begin{aligned} C_1 &= m_1 \\ C_2 &= m_2 - m_1^2 \\ C_3 &= m_3 - 3m_2m_1 + 2m_1^3 \\ C_4 &= m_4 - 4m_1m_3 + 6m_1^2m_2 - 3m_1^4 \end{aligned}$$

Fig. 1. The picture of acquisition system (left) and calculation of higher-order statistics (right)

Table 1. Statistical parameters of sub-band signals in healthy and faulty conditions

Signal	C1		C2		C3		C4	
	Healthy	Faulty	Healthy	Faulty	Healthy	Faulty	Healthy	Faulty
S1	0.0400	0.0216	0.0052	0.0022	0.0019	9.3188e-004	0.0010	6.2754e-004
S2	0.0423	0.0255	0.0056	0.0026	0.0023	0.0010	0.0015	6.5694e-004
S3	0.0356	0.0195	0.0039	0.0014	0.0015	4.5429e-004	9.6415e-004	2.6668e-004
S4	0.1145	0.0617	0.0090	0.0040	0.0017	0.0013	9.9595e-004	9.3001e-004

3.3 Classification Results

For training and testing, 135 sets of data were used which consist of 90 healthy conditions and 45 faulty conditions. A total 90 sets of data were used for the training (30 data from each compressor) and 45 sets of data were used for the testing (15 data from each compressor).

Here RBF kernel was used as the kernel function of SVMs for its excellent performance for real-world applications. The training of SVMs was carried out using the algorithm proposed by [6]. The RBF kernel width σ was chose by experiments. From Fig. 2, an optimum value for best performance is σ=0.002(C=1000). In this condition, the classification rate is 100% and the number of SVs is 10.Thus these values were selected for the classification system.

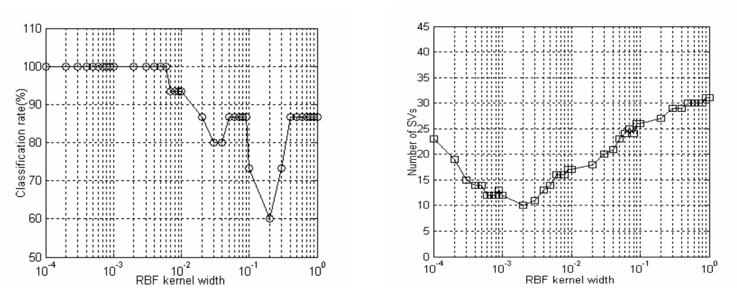


Fig. 2. The influence of RBF kernel width: classification rate (left) and number of SVs (right)

Neural networks were also used in experiments and Probabilistic Neural Networks achieved 100% classification rate. Due to having good performance for small samples, SVMs were finally selected as the classifiers of fault diagnosis system.

4 Conclusions

This paper presents a novel approach to detect faulty condition of combined valves online in the Low Density Polyethylene product lines. The vibration signals acquired from the surface of valves were decomposed into sub-bands by local wave method and the features from them were extracted by statistical method. The classification efficiency is much higher by using SVMs. It can effectively monitor valves working conditions. If other parameters are considered, such as temperature and pressure, this system will be more powerful and can be applied to other kinds of compressors.

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