

Chapter 70

Study on Fault Classification of Power-Shift Steering Transmission Based on ν -Support Vector Machine

Yuan Zhu, Ying-feng Zhang and Ai-yong Du

Abstract This paper focused on the condition monitoring problem of the Power-Shift Steering Transmission (PSST). Spectrometric oil analysis is an important way to study the running state of PSST. Because of complicated nonlinear relationship in oil analysis data, a model of PSST' fault classification based on ν - Support Vector Machine (ν -SVM) is proposed. The fundamental of ν -SVM is researched. The influence of model parameters for performance of ν -SVM is analyzed. Experimental results show that, comparing with C-support vector machine and BP neural network, the ν -support vector machine has good properties in research of fault classification of PSST.

Keywords Fault classification · ν -support vector machine · Power-shift steering transmission

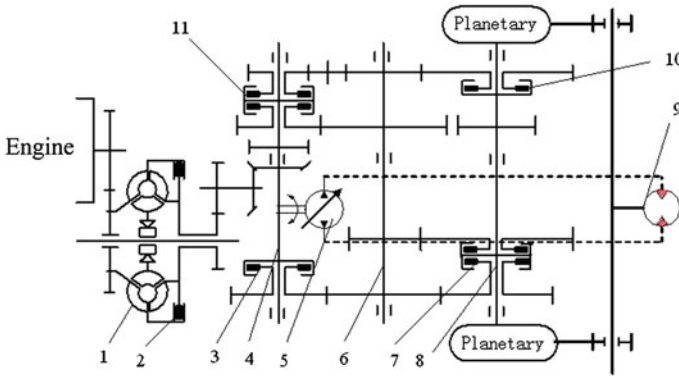
70.1 Introduction

As the rapid development of mechanical technology, the equipments become more sophisticated. The real-time status of equipment is important problem in condition monitoring. Spectrometric analysis of oil liquid model is a valid method in condition monitoring (Zheng et al. 2009; Li et al. 2009; Hongbo et al. 2006; Bing et al. 2006).

PSST is sophisticated equipment which is often used in hostile environment. The configuration of PSST is shown in Fig. 70.1. The failure of any part may leads to very serious consequences. Therefore, people want timely to know the status of PSST. From the lubrication system of the equipment regularly to obtain oil

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1. Hydraulic Torque Converter; 2. CV Clutch; 3. CH Clutch;
 4. First Shaft; 5. Steering Pump; 6. Second Shaft; 7. C1C2 Clutch;
 8. Third Shaft; 9. Steering Motor; 10. C3 Clutch; 11. CLCR Clutch

Fig. 70.1 The configuration of PSST

samples and spectral analysis, we can get the quantitative information of component wear without dismantling and identify the potential failures and timely maintenance. Therefore, we want to build a fault classification model using the samples that have been obtained during the running of PSST.

In this paper, a fault classification model of power-shift steering transmission based on ν -Support Vector Machine is proposed. The correct rate of the model has been proved to be very high with limited fault samples.

70.2 ν -Support Vector Machine

Basic classification approach of SVM is an issue of dichotomies (Boser et al. 1992; Vapnik 1998). For nonlinear problems, C , a penalty factor is introduced in order to obtain relatively good classification performance. In SVM training process, C , the penalty factor plays two roles: maximize classification interval and minimize training errors (Li et al. 2003; Zhai et al. 2003). The aforementioned roles are competing in the way that maximizing classification interval will inevitably lead to the increased training errors while minimizing training mistakes will result in the declined classification interval. In the training process, C mainly plays a compromised function (Hu et al. 2007). As a result, difficulty is in existence for selection of C . Hence, Schölkoph et al. (2000) propose an improved approach, namely, substituting parameter ν for C .

Assume that sample set $X = \{x_i\} \in R^d$ is composed of two types of points. In case of x_i belongs to the type 1, it can be concluded that $y_i = 1$. In case of x_i belongs to the type 2, it can be concluded that $y_i = -1$. Therefore, the training

sample set $\{x_i, y_i\}$ can be obtained, among which $i = 1, 2, 3, \dots, n$. Map x from original space to F , a high-dimensional feature space through applying a nonlinear mapping function:

$$\phi : x \rightarrow \phi(x), R^d \rightarrow F \tag{70.1}$$

Thus, corresponded optimization problem of dichotomies issue is:

$$\min J(\omega, \xi, \rho) = \frac{1}{2} \omega^T \cdot \omega - v\rho + \frac{1}{n} \sum_{i=1}^n \xi_i \tag{70.2}$$

$$\text{s.t. } y_i [(\omega^T \cdot \phi(x_i)) + b] \geq \rho - \xi_i \tag{70.3}$$

$$\xi_i \geq 0, i = 1, 2, \dots, n, \rho \geq 0 \tag{70.4}$$

where ξ_i reflects distance between y_i , actually indicates value and SVM output. Compared with C -SVM, there contains no parameter C , which is replaced by parameter v . In addition, the parameter of ρ is also added in. In case that $\xi_i = 0$, condition (70.3) means that the two types of points are separated by the interval of $2\rho/\|\omega\|$ (Boser et al. 1992; Naiyang and Yingjie 2004).

The following function of formula (70.2) is obtained through introducing Lagrange function:

$$\begin{aligned} L(\omega, \xi, b, \rho, \alpha, \beta, \delta) &= \frac{1}{2} \|\omega\|^2 - v\rho + \frac{1}{n} \sum_{i=1}^n \xi_i \\ &\quad - \sum_{i=1}^n \{ \alpha_i [y_i [(\omega^T \cdot \phi(x_i)) + b] - \rho + \xi_i] + \beta_i \xi_i \} - \delta\rho \end{aligned} \tag{70.5}$$

Partial derivative of formula (70.5) is solved and the result is introduced into the function. Maximum value of α is worked out, and then dual problem of optimization issue (70.2) is obtained as follows:

$$\max -\frac{1}{2} \sum_i^n \sum_j^n \alpha_i \alpha_j y_i y_j (\phi(x_i)^T \cdot \phi(x_j)) \tag{70.6}$$

In other words, the minimum value of the following dual problem needs to be solved:

$$\min \frac{1}{2} \sum_i^n \sum_j^n \alpha_i \alpha_j y_i y_j (\phi(x_i)^T \cdot \phi(x_j)) \tag{70.7}$$

Calculating problem with similar shape of $\frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j \varphi(x_i)^T \varphi(x_j)$ will be encountered when solving optimization issue (70.7) with SVM. Direct calculation will be quite complicated due to the fact that φ function is nonlinear. In order to avoid the problem, Vapnik (Boser et al. 1992) puts forward kernel function

method, namely, replace $\varphi(x_i)^T \varphi(x_j)$ calculation with $K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j)$. RBF kernel function, which currently enjoys the most extensive application, is employed in the research with the following form:

$$K(x_i, x_j) = \exp\left(-\frac{|x_i - x_j|^2}{\sigma^2}\right) \tag{70.8}$$

After introducing kernel function, dual problem of dichotomies issue can be demonstrated as follows:

$$\min \frac{1}{2} \sum_i^n \sum_j^n \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{70.9}$$

$$\text{s.t. } \sum_{i=1}^n \alpha_i y_i = 0 \tag{70.10}$$

$$0 \leq \alpha_i \leq \frac{1}{n}, \quad i = 1, 2, \dots, n \tag{70.11}$$

$$\sum_{i=1}^n \alpha_i \geq \nu \tag{70.12}$$

70.3 Experimentation Research

Spectrometric oil analysis technology mainly detects the type and content of elements of oil. Different components may contain the same elements. According to Spectrometric analysis method, the same component elements are classified as the same type. The fault classification model of PSST is shown in Table 70.1.

The spectrometric analysis of oil liquid data shows in Table 70.2. We obtain these data in the vehicle road test and optimize these samples. Each group contains 8 elements such as Fe, Cr, etc.

Table 70.1 The fault classification model of PSST

Fault class	Component	Main elements
Clutch fault	Friction, Steel	Fe, Mn, Cu, Pb
Gear fault	Transmission gear, planetary	Fe, Cr, Ni
Sealing element fault	Sealing ring, Oil set	Fe, Si, Mn, Mo, Cr

Table 70.2 Spectrometric analysis of oil liquid data (unit: $\mu\text{g/mL}$)

Number	Cr	Cu	Si	Pb	Fe	Mn	Al	Mo
1	0.3	19.4	3.8	9.4	7.8	0.0	2.9	8.8
2	0.3	28.5	5.2	13.2	10.8	0.7	3.3	2.6
3	0.3	34.1	3.4	13.8	11.9	0.7	3.0	2.3
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
33	0.9	65.2	15.4	39.5	36.4	0.6	12.9	9.7

70.3.1 Selection of Parameters

Parameter selection occupies a significant status in SVM model training. RBF kernel function is put into application in the process of model training. Therefore, two parameters: σ and ν need to be confirmed in the process. Related researches indicate that numeric area of ν is supposed to be (0, 1) (Li and Xu 2005; Pawlak 1997; Swiniarski and Skowron 2003).

Figure 70.2 indicates variation trend of classification accuracy rate with parameters of σ and ν . According to the figure, when σ enjoys certain numeric area, no significant variation of classification accuracy rate is witnessed with the increasing of ν ; when ν enjoys certain numeric area, classification accuracy rate decreases in a gradual manner with the increasing of σ . It can be seen from calculation that when $\sigma = 0.003$ and numeric area of ν is 0.36–0.5, the accuracy rate is 0.9, which also applies in case of $\sigma = 0.045$ and numeric area of ν is 0.42–0.55. However, another problem needs to be noticed, namely, number of support vector, for numeric area of ν is influenced by number of support vector.

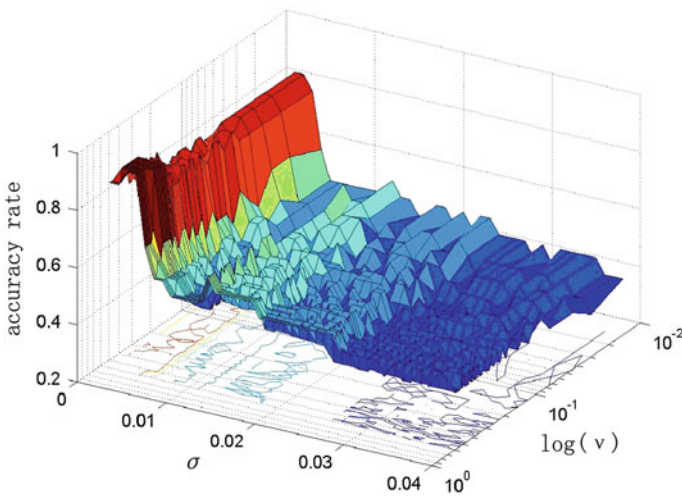


Fig. 70.2 Relationship of accuracy rate and parameters

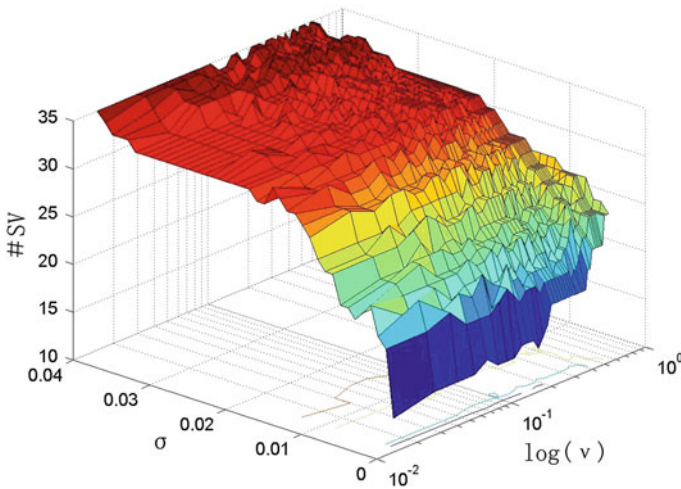


Fig. 70.3 Relationship of support vector number and parameters

Figure 70.3 indicates variation trend of support vector number with parameters of σ and ν . #SV represents number of support vector. The figure shows that parameter σ can pose significant influence on the number of support vector. No matter what the numeric area of ν is, number of support vector always increases sharply with the increasing of σ ; no significant variation of support vector number is witnessed when σ enjoys certain values, no matter how ν changes. With the increasing of σ , number of support vector also increases, while accuracy rate of the model declines, thus making popularization capacity of the model decrease. Therefore, selection of the parameter of σ is of great significance. Selection of the parameter of ν is supposed to be affected by the number of support vector; otherwise, it will pose influence on popularization capacity of the model.

Taking into comprehensive consideration influence of model parameters on accuracy rate and number of support vectors, the paper ultimately selects $(\sigma, \nu) = (0.045, 0.42)$ as the parameter for SVM model.

70.3.2 Experimentation

Through selecting, we pick out 33 group data for training and 10 group data as testing samples. During the training, the model makes only one error of judgment in test samples. The correct rate of judgment for the test group data is 90 %. Table 70.3 show that, comparing with C-support vector machine and BP neural network, the ν -support vector machine has good properties in research of fault classification of PSST.

Table 70.3 Correct rate of different classifiers

Classifiers	Parameters of model	Correct rate (%)
v-support vector machine	$\sigma = 0.045, \nu = 0.42$	90
C-support vector machine	$\sigma = 0.05, C = 0.2$	70
BP neural network	net.lr = 0.01, net.show = 500;	80

In most cases, the oil samples of the lubrication system of the equipment are normal. But, the components of the PSST may have a potential fault that could not be detected. The model of PSST' fault classification based on v-SVM can judge the status of PSST. The correct rate of the model has been proved to be very high with small samples.

70.4 Conclusion

In this paper, a model of PSST' fault classification based on v-SVM is proposed. The fundamental of v-SVM is researched. The influence of model parameters for performance of v-SVM is analyzed. The correct rate of the model has been proved to be very high with limited fault samples.

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