Chapter 94
SVM-Based Multi-Sensor Information Fusion Technology Research in the Diesel Engine Fault Diagnosis

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Abstract According to engine's characteristics of running mechanism and prone to failure, using integration based on the sub-module decision-making output multi-sensor information fusion model, this paper discusses the use of SVM-based multi-sensor information fusion technology on the diesel engine fault diagnosis. As the real data of the fault vehicles experiment shows, compared to the traditional diagnostic methods, SVM-based multi-sensor information fusion technology is more effective on identifying the agricultural diesel failure type.

Keywords Diesel engine · Fault diagnosis · Multi-sensor information fusion · Support vector machine (SVM)

94.1 Introduction

The vigorous development of the automotive market has led to the improvement of diesel engine fault diagnosis technology has become the mainstream of diesel engine fault diagnosis, diagnostic techniques based on sensor signals. Traditionally, the relative maturity of the spectrum-based signal analysis algorithms, but such methods due to lack of time local analysis function, and is not suitable to analyze non-stationary signals. The diesel engine vibration signal contains a large number of high-frequency, low frequency and its harmonic components. By Vapnik's support vector machine (SVM) (Vapnik 1995) is a new learning machine

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based on statistical learning theory. Compared to the neural network, which will use heuristic learning methods in the implementation with a lot of experience in composition. SVM avoid the local minimum problem, and not overly dependent on the quality and quantity of the sample, greatly improving its generalization ability. Multi-sensor information fusion technology can improve the integration and integration of information between the different sensors, information redundancy, complementarity, timeliness and accuracy. The theory of SVM is introduced into the multi-sensor information fusion technology, and applied in the agricultural diesel engine fault diagnosis, and achieved good results.

94.2 Information Fusion Based on SVM

94.2.1 The Concept of Support Vector Machines SVM

For a linearly separable sample set N, N is $(x_i, y_i),\ldots,\ (x_k, y_k),\ x_i \in R^n$, $y_i \in (k,\ k),\ i = 1, 2, \ldots, k$. Seeking an optimal hyper-plane $\omega \cdot x + b = 0$ will be two types of separation and spacing of the $2 \big/ \|\omega\|^2$ largest. The relaxation factor $\xi_i \geq 0\,(i = 1, 2, \ldots, k), \sum_{i=1}^{k} \xi_i$ that allows the sample to the degree of misclassification, and its minimum. That is, solving: min $\frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{k} \xi_i, C$ penalty coefficient, to correct the misclassification sample caused by deviation in accordance with the degree of importance. When the sample linear non-time-sharing, decision function $K(x, x_i)$ can be divided into the data of high dimension space by kernel function, $g(x) = \sum_{SV} a_i y_i K(x, x_i) + b\ 0 \leq a_i \leq C$, a_i is the Lagrange factor. The decision output is that: $d(x) = \mathrm{sgn}[g(x)]$.

Through 1-on-1 to promote the SVM to multi-class classification: N Construction on the number of separator $N \cdot (N-1)/2$. Discrimination, the new test sample x can be obtained $N \cdot (N-1)/2$ discrimination results and vote. x belong to the highest classification. Token the category subscript class if appeared flat votes.

94.2.2 Fusion Method Based on the Output Sub-Module Decision-Making

Training of large-scale data is not only time-consuming and memory demanding on the hardware, there would be insufficient memory space training. Were solved using this small module based on SVM information fusion technology will be the number of large-scale data decomposition, the ultimate fusion. Assume that decomposition of the overall problem into K sub-module, each module containing the N type of data, including information fusion method based on SVM (Hu et al. 2005; Platt 1999; Hsu and Lin 2002): (1) decision-making output of the sub-module integration; (2) sub-module in N the decision function value on the class integration; integration of the weighted value of the decision function (3) sub-module in the class N; (4) sub-module the number of votes in the class N fusion.

This article taken the first category, the decision-making output of the sub-module integration:

$$d(x) = \arg\max\{V_1, V_2, \ldots V_k\}, V_j = \sum_{i=1}^{k} \delta_{ij,} \delta_{ij,}$$
$$= \begin{cases} 1, d_i(x) = j \\ 0, d_i(x) \neq j \end{cases}, (i = 1, 2, \ldots K; j = 1, 2, \ldots N)$$

such as the number of votes are p, discrimination in accordance with $d(x) = \arg\max\{\sum_{i=1}^{p} |f_{ij}(x)|\}$.

94.3 Diesel Engine Sensor Fault Diagnosis Application

According to characteristics of diesel engines, commonly used cylinder head vibration acceleration sensor, the instantaneous speed sensor, cylinder pressure sensor three types of sensors to collect the required information, the amount of feature extraction, and in accordance with the integration of decision-making output of the above sub-module fusion. Prone to the actual running of each cylinder power imbalance in the type of fault, for example. The failure of the cylinder power imbalance is a common fault. Cylinder head vibration sensors, in theory, the cylinder pressure sensor, instantaneous speed sensor fusion of the three diagnoses can get the best results. But in the actual diagnostic process, the high temperature and high pressure cylinder environmental damage the performance and life of the pressure sensor, greatly increasing the difficulty of the measurement of cylinder pressure. And by calculating the conversion speed is obtained by the instantaneous cylinder pressure, the conversion formula (Kennedy and Eberhart 1995; Coello and Lechuga 2002):

$$\left\{J + m_1 R^2 \sum_{k=1}^{N} [f(\theta - \phi_k)]^2\right\}\ddot{\theta} + \left\{m_1 R^2 \sum_{k=1}^{N} [f(\theta - \phi_k) g(\theta - \phi_k)]\right\}\dot{\theta}$$
$$= A_p R \sum_{k=1}^{N} [f_p^{(k)}(\theta) f(\theta - \phi_k)] - T$$

The test measured in normal and pipeline oil spill two states under the cylinder head vibration 5 signal for each, is calculated to extract diagnostic indicators such as Table 94.1.

Recourse to Table 94.1 data to establish a diagnostic model. Assume that the indicators in the state vector X = [X1, X2, X3] T in accordance with and other

Table 94.1 Sample data

Sample number	Detonation pressure of normal state 8.367 MPa			Detonation pressure of oil spill state 7.608 MPa		
	P_{1-1}	P_{1-2}	P_{1-3}	P_{1-1}	P_{1-2}	P_{1-3}
1	63.1677	8.2508	12.4569	51.3794	7.5608	10.9037
2	60.1160	8.9492	13.0616	50.6096	7.3252	10.6371
3	61.5950	7.8080	11.9880	50.6898	7.6953	11.1545
4	64.2261	8.8686	12.9638	52.4091	7.9606	11.7211
5	62.6066	9.9479	15.1454	52.5400	7.9170	11.5639

covariance matrix normal distribution, denoted as $X \sim N(\mu(\theta), \sum)$. Sample mean to estimate the μ (θ):

$$\mu(\theta = 8.365) = \begin{bmatrix} 62.342 \\ 8.7649 \\ 13.1231 \end{bmatrix} \quad \mu(\theta = 7.607) = \begin{bmatrix} 51.5256 \\ 7.6918 \\ 11.1961 \end{bmatrix}$$

To estimate the sample covariance matrices in the $\sum$:

$$\sum = \frac{1}{n-k-1} \sum_{l=1}^{k} \sum_{i=1}^{n_i} (X_1^l - \bar{X}_l)(X_1^l - \bar{X}_i) = \begin{bmatrix} 1.8874 & & \\ 0.1707 & 0.3926 & \\ 0.1595 & 0.5986 & 0.9834 \end{bmatrix}$$

94.4 Comparison with Other Traditional Diesel Engine Fault Diagnosis Results

The current methods commonly used in diesel engine fault diagnosis, including wavelet analysis, artificial neural network diagnosis, extended rough set theory, and so on. Each method has the characteristics for diesel engine operation of the law and prone to failure characteristics, compare the pros and cons of various methods in dealing with the diesel engine fault diagnosis is the key to promote the further development of diesel engine fault diagnosis technology.

Fault data processing capabilities of several methods for comparing the above, in the experiments from the actual testing of the diesel engine, select the total number of features for 1820, the normal signal, the total number of features for the 714's imbalance signal, the total number of features for the 1148 collision friction signal. From randomly selected 70 % of the characteristics of data for network training, the remaining 30 % for network testing. Therefore, training in normal working condition the signal characteristics for 1274, the imbalance in the number of signal characteristics for 497, collision friction signal characteristics 812. Signal characteristics of normal conditions in the test were 546, the number of features of the unbalanced signal 217, and collision characteristics of friction signal for 336. The experimental results of the training set and test set, respectively, as shown in Table 94.2.

Table 94.2 Test set classification comparison

Test set classification comparison		Normal	Unbalanced	Friction and collision
The total characteristic numbers		546	217	336
Artificial neural networks	Correct classification number	525	207	279
	Correct classification rate	96.15 %	95.39 %	83.04 %
Generalized rough sets theory	Correct classification number	539	217	294
	Correct classification rate	98.72 %	100 %	87.5 %
Wavelet analysis	Correct classification number	532	210	273
	Correct classification rate	97.44 %	96.77 %	81.25 %
SVM-based multi-sensor information fusion technology	Correct classification number	536	215	304
	Correct classification rate	98.17 %	99.08 %	90.48 %

From the experimental results can be seen, for diesel engine fault diagnosis, artificial neural network methods require a large amount of data is not dominant. The wavelet analysis method in the training set for the high recognition rate of the normal signal, but performance degradation is more obvious in the test set. And for the failure of the diesel engine, we put more weight on the test set under diesel imbalance signal and friction collision signal to identify the correct rate. The imbalance signal recognition, SVM-based multi-sensor information fusion technology and generalized rough set theory is almost equal, there are certain advantages in the identification of friction collision signal.

94.5 Conclusion

In this paper, we use the SVM-based multi-sensor information fusion technology for diagnosis of diesel engine failure. And with the example of the multi-cylinder power imbalance failure, acquisition failure diesel real vehicle data, using a variety of diagnostic methods for the comparison test. The results show that SVM-based multi-sensor fusion technology can effectively identify diesel engine operating status and faults category. And more focused subsequent posterior distribution compared to single sensor, compared with methods such as artificial neural network, the same confidence level confidence interval is smaller, higher accuracy.

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