The Method of Engine Fault Diagnosis Based on Improved SVM

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Abstract: The paper aimed at the common reasons of engine fault, established the membership matrix between the symptoms of the engine fault and the fault modes, and used optimized fault diagnosis model established to perform intelligent fault diagnosis, the simulation analysis proved the effectiveness of proposed method.

1 INTRODUCTION

Because of the excellent performance and strict theoretical basis of SVM, many improved SVM algorithms have been proposed[1-3]. The paper used GA algorithm to optimize the parameters of SVM, then made the fault diagnosis model based on classified SVM, to diagnose the engine fault, finally examples were used to verify the effectiveness of model.

2 FAULT DIAGNOSIS MODEL BASED ON REGRESSION SUPPORT VECTOR MACHINE

For regression-type support vector machines, we first consider using a linear regression function $f(x) = w \cdot x + b$ to fit the data $\{x_i, y_i\}$, $i = 1, \ldots, n$, $x_i \in R^d, y_i \in R^d$, so that the function regression problem can be described as how to find a function $f \in F$ that minimizes the loss function. The commonly used loss functions[4] are: quadratic loss function, Huber loss function, and ε-insensitivity loss function, where the ε-insensitivity loss function is an approximate form of the Huber loss function proposed by Vapnik due to its unique sparseness. In general, the solution to the ε-insensitivity loss function has the least number of support vectors used in the expansion of the solution and is therefore widely used.

ε-Insensitive loss function is defined as:

$$l = \begin{cases} 0 & |y - f(x,w)| \le \varepsilon \\ |y - f(x,w)| - \varepsilon & Other \end{cases} \quad (1)$$

Among them, w for the parameters to be identified, ε given accuracy.

The regression estimation problem is defined as the problem of minimizing the risk of a loss function. When using the SRM principle to minimize the risk, the optimal regression function is to minimize the functional under certain constraints, when using - insensitive loss For functions, the minimization constraint is

$$\begin{cases} y_i - w \cdot x_i - b \le \varepsilon \\ w \cdot x_i + b - y_i \le \varepsilon \end{cases} \quad i = 1, \cdots, n \quad (2)$$

The optimization goal is minimization $\frac{1}{2}\|w\|^2$, and statistical learning theory points out that under this optimization goal, better promotion ability can be achieved. Considering the case where the fitting error is allowed, if the relaxation factor $\xi_i \geqslant 0$ and $\xi_i^* \geqslant 0$, are introduced, the above equation becomes

$$\begin{cases} y_i - w\cdot x_i - b \le \varepsilon + \xi \\ w\cdot x_i + b - y_i \le \varepsilon + \xi \end{cases} \qquad i = 1,\cdots,n \qquad (3)$$

The optimization goal is minimized: $\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i + \xi_i^*$, where the constant C > 0, C denotes the degree of penalty for samples that exceed the error ε . This is a convex quadratic optimization problem, introducing the Lagrange function:

$$L(w,\xi_i,\xi_i^*) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{r}(\xi_1+\xi_i^*) - \sum_{i=1}^{r}a_i(\varepsilon+\xi_i+y_i-w\cdot x_i-b) - \sum_{i=1}^{r}a_i^*(\varepsilon+\xi_i+y_i-w\cdot x_i-b) - \sum_{i=1}^{r}(\eta_i\xi_i+\eta_i^*\xi_i^*) \qquad (4)$$

Where, a_i and a_i^* are Lagrange factors. Using the optimization method can get its dual problem

$$Max{:}W(a,a^*) = -\varepsilon\sum_{i=1}^{n}(a_i^*+a_i) + \sum_{i=1}^{n}y_i(a_i^*-a_i) - \frac{1}{2}\sum_{i=1}^{n}(a_i^*-a_i)(a_j^*-a_j)(x_i\cdot x_j) \qquad (5)$$

$$s.t. \quad \sum_{i=1}^{n}(a_i^*-a_i)=0,\ \ 0\le a_i, a_i^* \le C,\ \ i=1,\cdots,n$$

The aggression function is:

$$f(x) = w\cdot x + b = \sum_{i=1}^{n}(a_i^*-a_i)(x_i\cdot x) + b^* \qquad (6)$$

Among them, a_i and a_i^*, only a small part is not 0, their corresponding sample is the support vector.

3 SUPPORT VECTOR MACHINE PARAMETER OPTIMIZATION

In order to improve the classification performance of SVM, training and testing samples are needed to determine the kernel parameters and penalty factors of the optimal SVM. The use of genetic algorithm can quickly search out the globally optimal parameter value, which not only saves the search time, but also improves the classification performance. In the process of classification using support vector machines, the main parameters affecting the classification performance of the support vector machine include: penalty function C and kernel function parameters[5].

3.1 Genetic Coding And Fitness Function Design

3.1.1 Coding Method And Coding Range

The loss function parameter ε, the penalty factor C, the kernel width σ of the radial basis kernel function, and the embedding dimension p of the time series are all coded using floating-point number coding. The coding interval is the value interval of each parameter.

3.1.2 Design of fitness function

In order to evaluate the prediction effect and accuracy of the model, the root mean square relative error (RMSRE) can be used to measure the accuracy of the prediction. The smaller the root mean square relative error, the higher the accuracy of the prediction.

$$RMSRE_l = \sqrt{\frac{1}{N-n_{tr}}\sum_{t=n_{tr}}^{N}\left(\frac{y_t-\hat{y}_{t,l}}{y_t}\right)^2} \qquad (7)$$

In the formula, n_{tr} is the number of training samples, N is the sample size, and $\hat{y}_{t,l}$ is the prediction result of the department l . The fitness function is expressed as

$$Fit(\varepsilon、C、\sigma、P) = \frac{1}{RMSRE_l} \qquad (8)$$

3.2 Genetic Operation

3.2.1 Select Operation

Use fitness sorting method. First, the individuals in the population are sorted according to the fitness value. Then determine the probability of the i th individual being selected by

$$P_i = \frac{1}{M}\left[a-(a-b)\frac{i-1}{M-1}\right] \qquad (9)$$

In the formula, M is the number of individuals in the population, P_i is the individual's probability of selection, satisfies $\sum_{i=1}^{M}P_i$ = 1, and P1⩾P2⩾P3⩾P4

≥...≥PM, i is the serial number of the individual, 1 ≤a≤2 , b=2-a.

3.2.2 Cross Selection

The crossover operation uses a linear combination. When you cross-operate a certain probability on a certain two chromosomes X1 and X2, you can use the following method:

$$X_1 = uX_1 + (1-u)X_2; \qquad (10)$$

$$X_2 = (1-u)X_1 + uX_2; \qquad (11)$$

In the formula, μ=U(0,1) is a random number between 0 and 1.

3.2.3 Mutation Operation

The mutation operator used is as follows: randomly select a mutation bit j in the chromosome to be mutated, and set it as a normalized random number U(a_i, b_i). a_i, b_i is the upper and lower limits of the corresponding mutation:

$$X_j = \begin{cases} U(a_i, b_i) & if\ \ i = j \\ x_i & otherwise \end{cases} \qquad (12)$$

4 SIMULATION

There are six common automatic engine fault symptoms for an engine, namely, exhaust temperature over-temperature (F1), vibration (F2), speed drop (F3), oil warning light (F4), and large oil consumption (F5) and speed does not go up (F6), there are 5 causes of failure, namely centrifugal valve axis (S1), turbine blade fracture (S2), oil pipeline rupture (S3), oil pump follow-up piston stuck (S4 And the drive shaft is broken (S5). After establishing the membership matrix between the fault symptoms and the failure modes, the intelligent fault diagnosis is performed using the optimized fault diagnosis model established in this paper.

After obfuscation and determination by experienced experts, the membership relationship between the symptoms of the failure and the cause of the fault is shown in Table 1. After the feature information is obtained, the support vector can be trained. At the same time, in order to verify its robustness and anti-jamming performance, different Gaussian noises were added. The classification results obtained are shown in Tables 2 and 3. (Table 2 shows the network diagnostics when the noise reaches 0.15, where 1,2,3 , 4, 5 for the indication of the corresponding failure mode). Figure 1 shows the error curve for network training. From Table 2, Figure 1 can be seen: 1 in the case of noise, the classification accuracy of the classification support vector machine is higher; 2 convergence speed is very fast (11 steps to reach the error requirements).

Table 1: Engine fault training samples.

Samples	F1	F2	F3	F4	F5	F6
S1	0.50	0.76	0.00	0.60	0.70	0.30
S2	0.45	0.55	0.00	0.72	0.48	0.00
S3	0.90	0.00	0.66	0.57	0.80	0.50
S4	0.38	0.40	0.70	0.40	0.90	0.74
S5	0.88	0.60	0.78	0.90	0.80	0.69

Table 2: The training result under the 0.15Gaussian noise.

Fault mode						Fault type
Fault1	0.8806	-0.5780	-0.4575	0.5147	-0.3570	4
Fault2	0.1264	0.3006	0.0142	0.6696	-0.5254	1
Fault3	0.2575	-0.1228	1.1453	0.1481	-0.0430	2
Fault4	0.2201	-0.4717	0.3056	1.2915	-0.4647	3
Fault5	0.8251	-0.5221	0.4017	0.4511	0.3236	4

Table 3: Testing fault samples.

Fault mode	F1	F2	F3	F4	F5	F6
T1	0.66	0.73	0.98	0.08	0.23	0.40
T2	0.20	0.57	0.60	0.77	0.25	0.66
T3	0.43	0.25	0.61	0.34	0.15	0.46

Table 4: Classified results.

Fault mode						Fault type
T1	0.2001	-0.1105	1.0145	0.1585	-0.1002	2
T2	0.8220	-0.5441	0.3996	0.4258	0.3002	4
T3	0.1002	0.3548	0.0787	0.6102	-0.5003	1

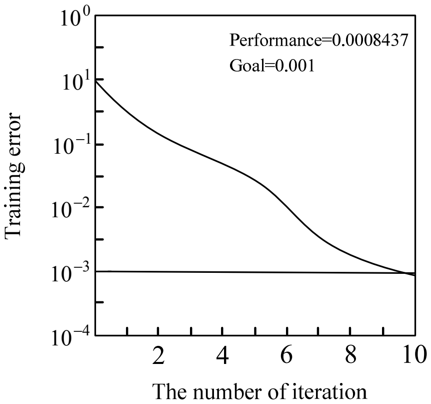

Figure 1: Training error curve.

In this type of engine, several times of automatic parking parameters were collected during several test runs. After filtering and processing, six symptom parameters are extracted. These parameters are subjected to fuzzy processing by the selected membership function (preprocessing of the input signal of the type-class support vector machine) to obtain the fuzzy feature vector as shown in Table 3 and substituted into the training. The test is performed in a good support vector network. The diagnosis results are shown in Table 4. These three faults were manually diagnosed by field experts and were diagnosed as: T1 centrifugal valve holding shaft (S1), T2 lubricating pipe vibration (S3) and T3 drive shaft broken (S5). It can be seen from the above that the accuracy of the fault diagnosis model based on the subdivision type support vector machine based on fault diagnosis is 100%, which shows that the model is really efficient and practical for fault diagnosis.

Finally, using training and test results, the data is divided into two groups: the first 60 data as training data, and the last 34 as test data. In the calculation process, in order to analyze the accuracy of the forecasting model of the optimized SVM state forecasting model, AR model, SVM model, and optimized SVM model are used to predict one step and three steps in advance. As shown in Figures 2 and 3, the prediction accuracy of the support vector machine optimized by the genetic algorithm is better than that of the support vector machine based on empirical selection of each parameter.

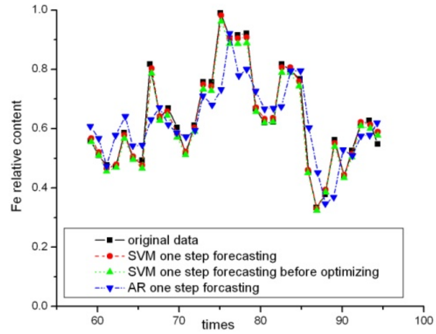

Figure 2: The prediction result of one step in advance.

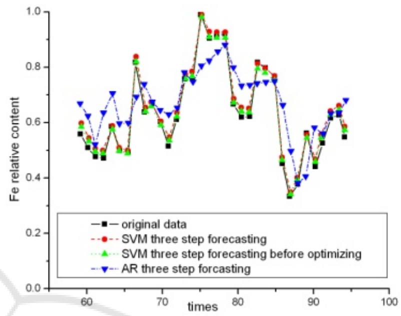

Figure 3: The prediction result of three step in advance.

5 CONCLUSIONS

The paper introduced the basic theory of SVM, constructed the fault diagnosis model based on classified SVM, used the GA algorithm to optimize and select the parameters of SVM, the simulation proved the proposed algorithm to be effective, robust and correct, provided a powerful guarantee for effective and real-time monitoring of the engine.

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