Solenoid Valve Fault Diagnosis Based on Genetic Optimization MKSVM

Wenhao Guo, Jinjun Cheng, Yangbo Tan and Qiang Liu

College of Aeronautics Engineering, Air Force Engineering University, Xi'an 710038, China

Abstract. In order to realize the accurate diagnosis of the solenoid valve fault and the accurate identification of the fault type, a fault diagnosis method of solenoid valve based on MKSVM (Multi-Kernel Support Vector Machine) is proposed. Firstly, through the analysis of support vector machine theory, a multiple-kernel learning support vector machine model is built, and the genetic algorithm is used to optimize the multiple-kernel learning weight coefficient and kernel parameter configuration. Then, the current signal of the solenoid valve driving terminal under the six common failure modes of the solenoid valve is obtained experimentally, and the characteristic information is extracted by EMD (Empirical Mode Decomposition) based on the current change rate. Finally, the multi-kernel learning SVM model was used to diagnose the state of the solenoid valve corresponding to each data, and its accuracy rate reached 98.9%. The comparison with the single-core diagnosis method shows that the method can accurately detect the solenoid valve fault Diagnosis, for similar studies with reference value.

1. Introduction

As a key action element of the control system, the solenoid valve is widely used in the aircraft's power system. Its performance is directly related to the flight safety of the aircraft [1]. Therefore, how to achieve rapid detection and positioning of its fault is an urgent task requirement in the ground support work.

The traditional disassembly detection can deeply check the feature of the solenoid valve, but it means high cost, complicated operation and introduction of new faults [2]. With the development of technology, non-disassembled solenoid valve fault diagnosis methods based on signal and data analysis have become the mainstream of modern fault detection technology. And with the rise of intelligent algorithms, expert systems, fault tree analysis, fuzzy reasoning and support vector machines are playing important roles in the classification of fault pattern recognition [3]. Literature [4] proposed a method based on the combination of EMD and the field rough set to solve the fault feature extraction of electromagnetic valve, but it can be improved in the accuracy of fault pattern recognition. The method based on LS-SVM, proposed by literature [5], realizes the fault detection of the pneumatic actuator, but its kernel parameter setting needs abundant experience, and its single-kernel learning restricts the generalization of this method.

This paper proposes a electromagnetic valve fault diagnosis method based on multi-kernel SVM whose kernel parameters are optimized by the genetic algorithm .The multi-kernel ensures the classifier's learning ability and generalization ability. Genetic methods, used to optimize kernel

parameters, make it more accurate to diagnose solenoid valve faults.**Multi-Kernel Support Vector Machine:**

2.1. Support Vector Machine

Support Vector Machine (SVM) is a two-class classification model based on statistical theory of VC dimension theory and structural risk minimization principle, and its basic model is defined as the largest linear classifier in feature space. Its learning strategy is to maximize the interval and to transform the original problem into a convex quadratic programming problem eventually [6].

For the linear inseparability problem in practical applications, a kernel function can be introduced to map the sample data from the original input space to the new feature space, making it linearly separable in the new feature space and then implementing sample classification [7]. The introduction of the kernel function avoids the explicit expression of the mapping. The computation in the low-dimensional space can achieve the classification in the high-dimensional feature space, effectively avoiding the "dimension explosion" problem [8] caused by directly performing explicit mapping and calculating in the high-dimensional space. The typical kernel functions and their expressions are shown in Table 1. According to the characteristic, they can be divided into two categories: local kernel function and global kernel function. The former has strong learning ability but weak generalization ability, linear kernel and radial basis kernel function (RBF) are the typical. The latter has strong generalization ability, but weak learning ability, such as polynomial kernel and sigmoid kernel.

Table 1. Typical Kernel Function and Their Expressions

Kernel category	Kernel function expression
linear kernel	$K_{lin} = \langle x_1, x_2 \rangle$
polynomial kernel	$K_{POL}(x_1, x_2) = (x_1 \cdot x_2 + c)^d, c \geq 0$
RBF	$K_{RBF}(x_1, x_2) = \exp(-\sigma\|x_1 - x_2\|^2), \quad \sigma \geq 0$
Sigmoid kernel	$K_{Sig}(x_1, x_2) = tanh(\kappa(x_1 \cdot x_2) + v), \quad \kappa > 0, v < 0$

2.2. Construction of Multi-Kernel Support Vector Machine

There is no perfect theory to illustrate how to choose the optimal kernel function for different data forms in the practical application. The traditional single kernel function has poor mapping ability, which restricts the generalization of the model. According to Mercer's theorem, a set of base kerneles can be selected for linear combination to obtain a fused kernel function to improve the flexibility of selection of the kernel function [9]. The kernel function constructed by this method is:

$$K(x_i, x) = \sum_{k=1}^{M} d_k K_k(x_i, x)$$

$$s.t. \sum_{(k=1)}^{M} d_k = 1, d_k \geq 0 \tag{1}$$

Using the linear combination of the base kernel in the test (1) to obtain a multi-kernel learning support vector machine model:

$$\min_{\{f_m\},b,\xi,d} J(d) = \frac{1}{2} \sum_{m=1}^{M} \frac{1}{d_m} \|f_m\|^2 + C \sum_{i=1}^{l} \xi_i$$

$$s.t. \quad y_i \sum_{(i=1)}^{n} f_m(x_i) + y_i b \geq 1 - \xi_i, \xi_i \geq 0, \forall i$$

$$\sum_{(m=1)}^{M} d_m = 1, d_m \geq 0, \forall m \tag{2}$$

Use the Largrange multiplier method and the Karush-Kuhn-Tucker (KKT) condition to convert the above equation into a dual problem:

$$\max_{\alpha} \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j \sum_{m=1}^{M} d_m K_m \ (x_i, x_j)$$

$$s.t. \ \sum_{(i=1)}^{l} \alpha_i y_i = 0, 0 \leq \alpha_i \leq C, i = 1, \ldots, l$$

$$s.t. \ \sum_{(m=1)}^{M} d_m = 1 \tag{3}$$

From this, the classification function is:

$$f(x) = \sum_{(i=1)}^{l} \alpha_i^* y_i [\sum_{k=1}^{M} d_k^* K(x, x_i)] + b^* \tag{4}$$

3. MKSVM method based on GA optimization

The key to the construction of multi-kernel SVM is the selection of the kernel category, kernel weight factor and kernel parameters. Through the linear combination of a polynomial kernel function and a Gaussian radial basis function into a new kernel, a multi-kernel support vector machine with both strong learning ability and generalization capability can be obtained[10]. How to determine the weights of each core and their respective kernel parameters is the key to determine the performance of multi-kernel SVM classification recognition. The gradient descent method is used to solve the weight coefficient problem in multi-kernel learning. Although the algorithm is simple, it is easy to fall into the local optimal solution [11]. The genetic algorithm can start the search with multiple starting points in the solution space at the same time randomly, and then realize the global optimization. In this paper, polynomial kernels and Gaussian kernels are used as the basis kernels. By dynamically adjusting the weight coefficients and kernel parameters of the two, different new cores are assembled. Using the new verification experiment data to classify, and then iteratively adjust according to the classification accuracy calculation, finally get the best combination of kernel parameters and kernel weight.

3.1. Genetic algorithm design

3.1.1. Coding strategy. The choice of parameters determines the learning speed and classification performance of the support vector machine [12]. The GA algorithm can be used to optimize the kernel parameter weight coefficients, penalty parameters, and kernel parameters. The initial population vector X is constructed with the weight coefficients, penalty parameters, and kernel function parameters of MKL:

$$X = [\alpha_{i1}, \alpha_{i2}, \alpha_{i3}, \alpha_{i4}]$$

Among them, $[\alpha_{i1}, \alpha_{i2}, \alpha_{i3}, \alpha_{i4}]$ respectively correspond to the i-th individual's weight coefficient of the Gaussian kernel α, the penalty parameter c, and the kernel function parameters d and σ.

3.1.2. Determination of fitness function. Using genetic algorithm is to obtain a set of optimal kernel weights and kernel parameter combinations. The evaluation criterion is the classification accuracy of

the classifier. Therefore, the accuracy of the sample classification is selected as the fitness function. The classification accuracy of the model is defined as:

$$fit(\alpha) = \frac{Number\ of\ correctly\ classified\ samples}{Total\ number\ of\ samples} \tag{5}$$

3.1.3. Genetic manipulation. Genetic operators mainly include replication, crossover and mutation, which are the key to the optimization of genetic algorithms.

(1) Copy: *size* defines the size of the population, the fitness of the individual α_i is $fit(\alpha_i)$, and the probability of being copied to the next generation is:

$$p(\alpha_i) = size \times fit(\alpha_i) / \sum_{i=1}^{size} fit(\alpha_i) \tag{6}$$

(2) Crossover: In the design of the genetic algorithm, the range of crossover probability is [0.60, 1.0], and a pair of individuals are randomly selected from the population for crossover operation. (3) Mutation: The mutation can obtain new individuals, which is beneficial to maintain the diversity of the population; the definition of the variation degree function is $f(g)$, and its concrete expression is:

$$f(g) = \exp(-3.6g / G_{\max}) \tag{7}$$

Among them, g is the genetic algebra of the population, and G_{max} is the largest genetic algebra. The method for designing the mutation of the j-th gene of the i-th individual in combination with the degree of variation function $f(g)$ is:

$$\alpha_{ij} = \alpha_{ij} + [\frac{(r_2+1)}{2r_2}(\alpha_{\max}^{(j)} - \alpha_{ij}) + \frac{(r_2-1)}{2r_2}(\alpha_{\min}^{(j)} - \alpha_{ij})]r_1 f(g) \tag{8}$$

In the formula, r_1 is a random number between 0.5 and 1, and r_2 is a random number taken from {-1, 1}. $\alpha_{max}^{(j)}$ and $\alpha_{min}^{(j)}$ are the maximum and minimum values of the corresponding genes in the jth gene position. When r_2 is 1, it is a positive mutation, and when it is -1, it is a negative variation. The degree of variation function $f(g)$ is a decreasing function of the genetic algebra g. From this definition, it can be known that the variation is non-uniform, and that the initial mutation operator is large, which is favorable for the initial global optimization and the reduction of the later mutation operator can ensure the Local optimization fine-tuning ability. The random number r_1 makes the trend of variation get rid of the regular change of the mutation degree function $f(g)$ to a certain extent, which ensures its local randomness under the global decreasing feature.

3.2. System Model Design

Based on the genetic algorithm optimization process and multi-kernel support vector machine architecture, the specific algorithm flow of designing a multi-kernel learning support vector machine based on genetic algorithm is shown in Figure 1.
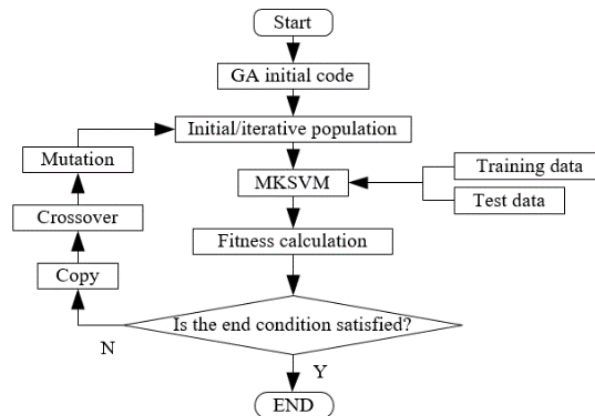
Figure 1. Flow chart of Genetic Optimization MKSVM model algorithm

The specific implementation steps are described as follows:

Step1: Initialize the data, randomly generate the initial population based on the range of values of each gene bit data, and set the population capacity to 30;

Step2: Enter the training data set, according to the formula (2)-(5) can solve the SVM model corresponding to the individuals. Enter the test data set, calculate the fault diagnosis accuracy rate of the model;

Step3: Determine whether the termination condition is met, stop if satisfied. Otherwise perform genetic operations Step4-Step6;

Step4: (replicate) Produce offspring using optimal preservation strategy and tournament selection;

Step5: (Cross) Randomly select pairs of individuals for cross-operation;

Step6: (Mutation) According to the formula (9) for mutation operation, transferred to Step2.

The termination condition of the algorithm is to reach the maximum number of iterations or $fit^i(\alpha) - Fit(\alpha) \leq \varepsilon$, where $fit^i(\alpha)$ represents the fitness that has evolved to the i-th generation. In this formula, $Fit(\alpha)$ is the preset ideal fitness, ε is a given small positive number.

4. Electromagnetic valve fault diagnosis experiment analysis

4.1. Failure Mechanism Analysis and Fault Simulation Experiment

The electromagnetic valve constituent component can be divided into two major parts: electromagnetic component and mechanical component. The working process is mainly divided into five stages: pull-in touch, pull-in motion, power-on hold, release trigger and release motion. The mechanism which correspond to the five phases can be described by three principles: circuit, magnetic circuit and mechanics [13]. The failure of the electromagnetic valve is mainly manifested in the main components that determine its electromagnetic properties and mechanical properties. Common types of failures and their corresponding manifestations are shown in Table 2.

Table 2. Solenoid valve common fault types and corresponding manifestations

Fault type	Fault manifestation
Normal	Solenoid valve works normally
Coil abnormality	The coil insulating layer is aged, the equivalent resistance becomes smaller, and the current exceeds the limit
Electrical short circuit	Broken wire, short circuit to metal shield
Spring failure	Spring produces metal fatigue and cannot switch channels properly
Spool stuck	Accumulation of impurities, spool movement blocked

Using 16-bit AD acquisition card PCI9111A, computer, ATmege16 SCM, current sensor, DC power supply, solenoid valve and other necessary components, set up the data acquisition system of electromagnetic valve working status shown in Figure 2.
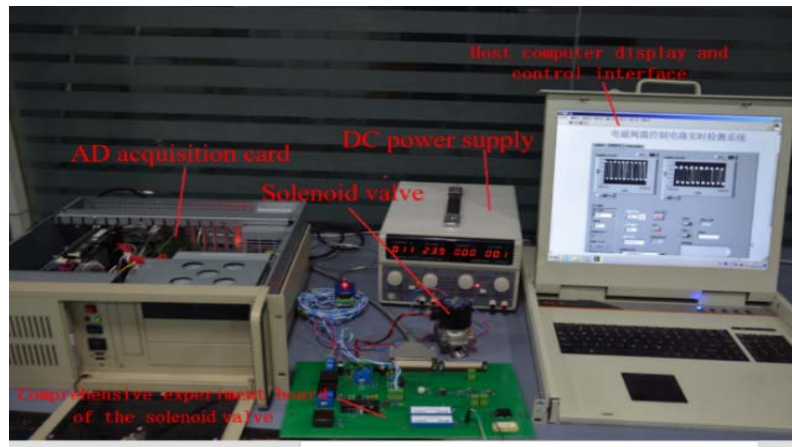

Figure 2. Data acquisition system of electromagnetic valve

During the experiment, the regulated power supply supplies power to the detection circuit and the solenoid valve circuit. The operating voltage and operating current of the solenoid valve are collected by the AD acquisition card and transmitted to the computer for storage. The microcontroller formed by ATmege16 controls the working state of the solenoid valve and realizes the indirect control of the solenoid valve's working status through the serial port communication. Select each type of fault solenoid valve to access, collect the corresponding drive current signal of their respective action phase, the specific experimental process shown in Figure 3.
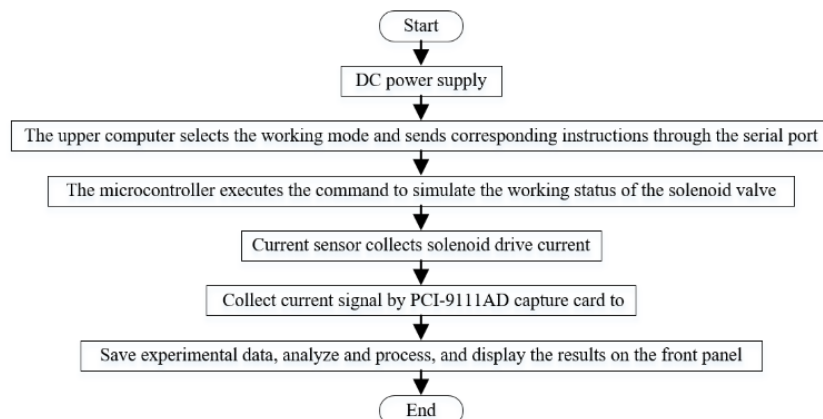

Figure 3. Experimental flowchart

4.2. Fault Diagnosis Method of Solenoid Valve Based on GA Optimization MKSVM
The electromagnetic valve drive current signal of each fault type was obtained from the electromagnetic valve fault simulation experiment. The drive current of the solenoid valve drives the current signal before and after the solenoid valve is opened and released as a stable signal, and its fault characteristic information is mainly concentrated during the movement of the valve core (the pull-in motion phase and the release motion phase). So the drive current signal of the pull-in process is selected as a research object [14]. The typical current signal during a single pull-in process under various fault modes is shown in Figure 4.
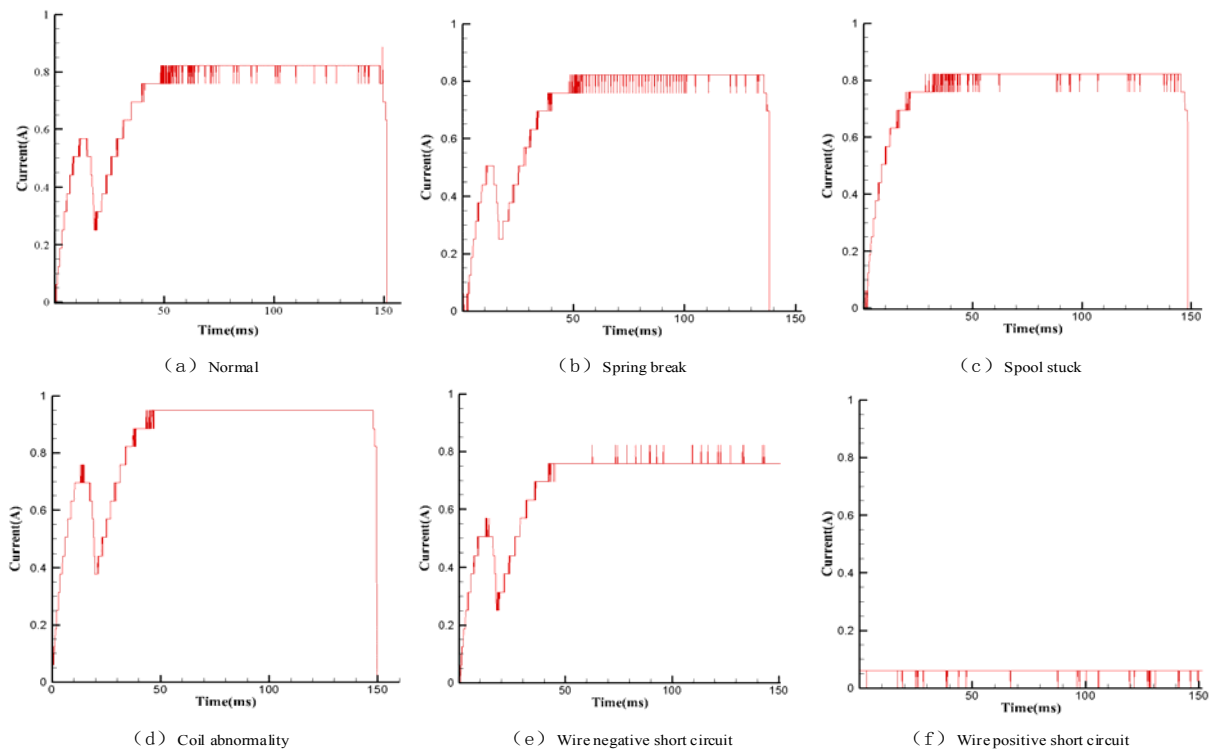
Figure 4. Electromagnetic valve pull-in phase drive current

In the drive current signal corresponding to the common 6 types of fault modes of the solenoid valve, the drive current signal is quite different from other types when the spool is stuck and the cable is short-circuited in the positive direction. But in the other four types of fault modes, it is difficult to determine the corresponding fault type from the drive current signal. What's more, to extract the current signal during the operation phase of the valve core is also difficult. Therefore, the change rate of the drive current can be selected as a feature. And the change rate of the drive current corresponding to each type of fault mode was obtained as shown in Figure. 5.
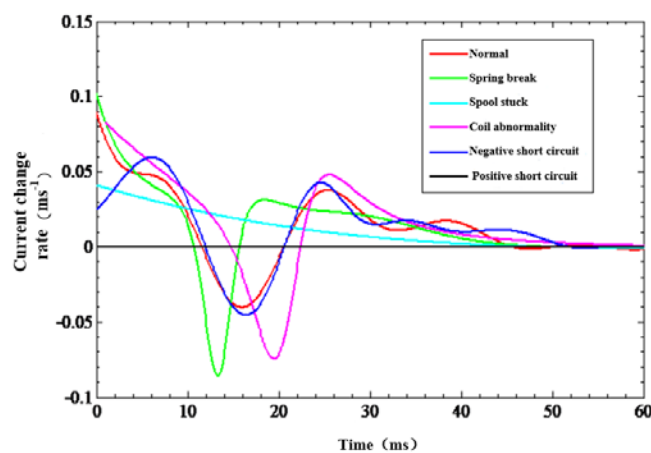

Figure 5. Solenoid valve drive current rate of change

EMD is used to decompose the curve of the rate of change of the drive current. In order to circumvent the endpoint effect, the characteristic curve is mirror-extended and the continuation part of each IMF

component is removed after decomposing[15].Thus, the EMD decomposi--tion results of the electromagnetic valve drive current change under various types of fault conditions are obtained. The result of the EMD decomposition of the drive current change rate of the normal solenoid valve during the pull-in phase is shown in Fig. 6.
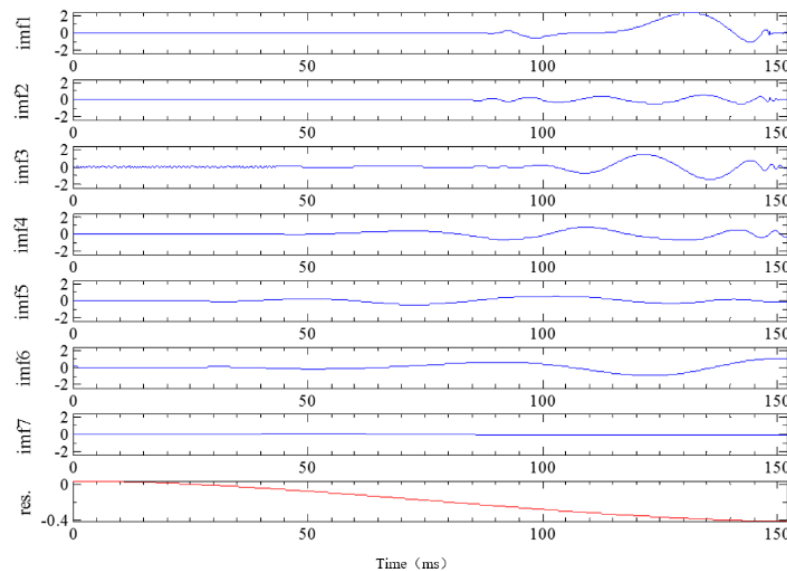

Figure 6. Normal solenoid valve pull-in current rate of change EMD decomposition

Changes in the state of the system are always accompanied by changes in the energy distribution. Therefore, the energy entropy can be solved for the input of the model for each IMF component of the various signals decomposed by the EMD. According to the information entropy theory [16], the energy entropy of the seven IMF components and the residual components of various fault types is calculated, and the corresponding typical partial values of each fault type obtained shown in Table 3.

Table 3. Electromagnetic valve drive current change rate IMF component energy entropy

Fault type	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	res
Normal	2365.833	115.162	1051.777	1670.235	864.061	7.318	30.149	42.038
Spring break	3241.958	852.106	4420.840	1157.863	5914.260	9389.43	6960.266	3141.841
Spool stuck	4039.618	808.403	2538.24	1046.723	20875.37	43423.4	15013.96	16004.19
Coil abnormality	367.644	31.000	57.151	50.505	12.658	16.264	7.699	2.151
Wire negative short circuit	0.003	0.014	0.043	0.312	0.029	0.239	0.046	0.052
Wire positive short circuit	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

In this experiment, 50 sets of solenoid valve drive current signals for each type of fault were obtained, of which 20 sets were used as training sets and the rest were used as test sets. The energy entropy of the IMF component obtained after the decomposition of the drive current in each group is decomposed by the EMD is used as a feature vector and input to the fault diagnosis model. Set the population number to 30 and the maximum evolution generation to 100 generations. At the same time, set the value range of the weight coefficient ɑ by [0, 1]. Set the penalty parameter c and the range of the kernel function parameters d and σ to be [0,100]]. The training set data is used to train the model. Figure 7 shows the iterative process of optimizing the multi-kernel SVM by the genetic algorithm. Finally, the weight coefficient and relevant parameters of the model were obtained shown in Table 4.

Table 4. The final parameter combination of the model obtained by genetic optimization

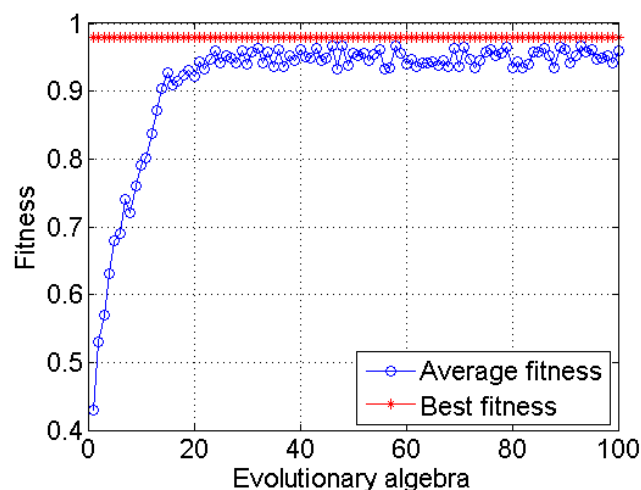| Category	proportion of RBF(ɑ)	Penalty parameter (c)	Parameter (d)	Parameter (σ)
Value	0.73	21.69	1.45	0.37

Figure 7. GA fitness curve for optimization of kernel parameters and kernel coefficients

The test set data is input into the trained model, and the classification result chart of the fault diagnosis model is shown in Fig. 8.
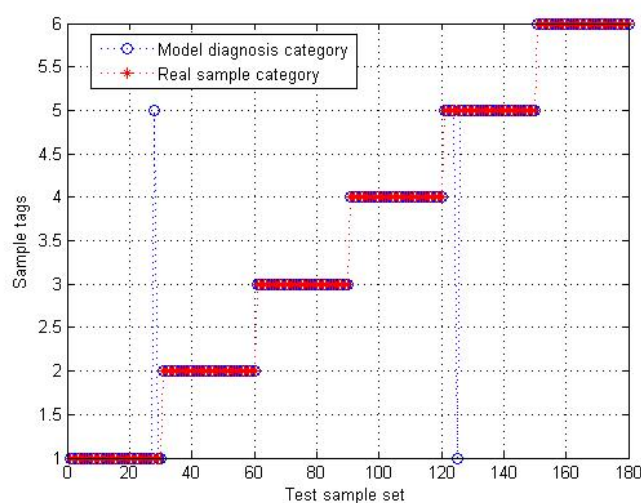

Figure 8. Model Classification Results

The decision tree model in literature [5] implements classifier construction by combining multiple linear partitions in the feature space, while support vector machine implements nonlinear classification in feature space by mapping feature space to high-dimensional space. Obviously, it is theoretically superior. The experimental results show that the classification effect of the model reaches 98.9%, which is obviously higher than the classification effect in the literature [5], and this effectively validates the classification accuracy of the model. Linear kernel, polynomial kernel, and Gaussian kernel were respectively selected to build single-kernel SVM models which were optimized by genetic algorithm using the same training set. After obtaining corresponding single-kernel classifier models, the experimental test data sets were classified with these various methods, and their classification effect is shown in Table 5.

Table 5. Classification effect of single-core SVM model

Kernel category	linear kernel	polynomial kernel	RBF
Accuracy (%)	81.6	87.2	90.6

By comparison, it can be known that the Gaussian kernel has the best classification effect when using a single-kernel classifier. However, compared with multi-kernel SVM, whose kernel is a combination of Gaussian and polynomial kernel, the test accuracy of the later one is obviously insufficient. The integration of polynomial kernel functions with global properties makes the new kernel better than the best performing Gaussian kernel. The resulting new kernel has both global and local characteristics, and its fault detection model constructed by it has obviously better detection performance than each single-core support vector machine.

5. Conclusion

In order to realize the accurate diagnosis of the electromagnetic valve fault mode, this paper presents a genetic algorithm based optimization multi-core support vector machine construction method, and build a solenoid valve fault diagnosis model. Six types of electromagnetic valve fault models were obtained through experiments, and the EMD was used to decompose the rate of change of the drive current during the pull-in action stage. The energy entropy of each IMF component was calculated and used as the input of the fault diagnosis model to perform fault detection experiments.

The results show that compared with single-kernel SVM and decision tree-based classification methods, multi-kernel SVM has obvious advantages. In the experimental six types of fault detection, the diagnostic accuracy reached 98.9%, which provides a basis for the multi-kernel SVM in the diagnosis and maintenance of the solenoid valve fault, and has certain engineering value.

References

[1]   Cheng Jinjun, Xiao Mingqing, Liu Shuai, etc. Design and Implementation of an Engine Automatic Test System [J]. Computer Measurement & Control, 2016, 24 (2): 61-63.

[2]   CaiWei, Zheng Xianlin, Zhang Zhili, etc. Failure mechanism analysis and transient characteristic simulation of hydraulic electromagnetic valve [J]. Chinese Journal of Scientific Instrument, 2011, 32 (12): 2726-2733.

[3]   Zhu Bing, Hu Shuangjun. A New Method of Support Vector Machine (SVM) for Power Electronic Fault Diagnosis[J].Control Engineering of China, 2009, 5 (16): 206-208.

[4]   Tan Yangbo, Cheng Jinjun, Liu Shuai. Liquid solenoid valve fault diagnosis based on EMD and neighborhood rough set [J]. Computer Engineering and Applications, 2017, 53 (12).

[5]   Feng Zhigang, Zhang Xuejuan. Pneumatic Actuator Fault Diagnosis Based on LS-SVM and SVM [J]. Chinese Journal of Sensors and Actuators,2013, 26 (11): 1610-1616.

[6]   Tian Hailei, Li Hongru, Xu Baohua. Fault Diagnosis of Hydraulic Pump Based on D-S Evidence Theory and SVM [J]. Instrument Technique and Sensor, 2013 (5): 81-83.

[7]   Krebel H G. Pairwise classification and support vector machines [J]. Advances in Kernel Methods,

2010, 15: 255-268.

[8]   Mehdi Namdari, Hooshang Jazayeri-Rad. Incipient fault diagnosis using support vector machines based on monitoring continuous decision functions [J]. Engineering Applications of Artificial Intelligence 28 (2014) 22–35.

[9]   Xu Lixiang, Li Xu, Lv Wanli, etc. New model analysis method of combined kernel Support Vector Machine [J]. Computer Engineering and Applications, 2013, 49 (24): 112-115.

[10]   Ye Hui, Luo Qiufeng, Li Yong. Application of wavelet and multi-kernel SVM in UAV sensors fault diagnosis [J], Electronic Measurement Technology, 2014, 37 (1): 112-116.

[11]   Yu Qing, Zhao Hui. Parameter optimization of ε-Support Vector Machine by genetic algorithm [J]. COMPUTER ENGINEERING AND APPLICATIONS, 2008, 44 (15): 139-141.

[12]   Wang Yuan, Tong HengQin, Zhu Yingying. Parameters. Optimization of Multi-Kernel Support Vector Machine Based on Genetic Algorithm [J]. JOurnal of Wuhan University:Natural Science Edition, 2012, 58 (3): 255-259.

[13]   Liu Zhihao, Gao Qinhe, Niu Hailong,etc. The Fault Diagnosis of Electromagnetic Valves Based on Driving Current Detection [J], Acta Armamentarii, 2014 ,35 (7): 1083-1090.

[14]   Liu Shuai, Cheng Jinjun, Yan Zhizhong et al. Research on Fault Detection of Aircraft Servo Solenoid Valve [J], Journal of Projectiles, Rockets, Missiles and Guidance, 2017, 37 (1): 153-156

[15]   Huang Jun, Pan Hongxia, Du Heng. Gearbox Fault Diagnosis Based on EMD-Approximate Entropy and LSSVM [J]. Modular Machine Tool & Automatic Manufacturing Technique, 2014 (3): 111-113.

[16]   Zhang Chao, Chen Jianjun, Guo Xun. A gear fault diagnosis method based on EMD energy entropy and SVM [J]. JOURNAL OF VIBRATION AND SHOCK, 2010, 29 (10): 216-220.