Aircraft Engine Gas Path Fault Diagnosis Based on Hybrid PSO-TWSVM

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Abstract: Twin support vector machine (TWSVM) is a new development of support vector machine (SVM) algorithm. It has the smaller computation scale and the stronger ability to cope with unbalanced problems. In this paper, TWSVM is introduced into aircraft engine gas path fault diagnosis. The generalization capacity of Gauss kernel function usually used in TWSVM is relatively weak. So a mixed kernel function is used to improve performance to ensure that the TWSVM algorithm can better balance a strong generalization ability and a good learning ability. Experimental results prove that the cross validation training accuracy of TWSVM using the mixed kernel function averagely increases 2%. Grid search is usually applied in parameter optimization of TWSVM, but it heavily depends on experience. Therefore, the hybrid particle swarm algorithm is introduced. It can intelligently and rapidly find the global optimum. Experiments prove that its training accuracy is better than that of the classical particle swarm algorithm by 5%.

Key words: aircraft engines; fault diagnosis; twin support vector machine (TWSVM); hybrid particle swarm optimization (HPSO) algorithm; mixed kernel function

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0 Introduction

The aircraft engine is an important equipment of an aircraft, and it is the power source of the aircraft. Modern aircraft engines work in a very harsh environment with high temperature, high pressure, strong vibration, and variable load, etc., so it is very easy to damage aircraft engine components. Therefore, it is imperative for fault diagnosis of aircraft engines. According to the statistical data, most of faults occur in gas paths[1] and gas path faults are often potential and difficult to judge[2], so researching on fault diagnosis of gas paths is important.

Classical support vector machine (SVM) algorithm has been introduced to complete aircraft engine gas path fault diagnosis, and a lot of papers[3-5] have reported it. Classical SVM has achieved good classification accuracy in fault diagnosis of aircraft engines. In this paper, a new SVM, i. e., twin support vector machine (TWSVM)[6] is introduced, and it is a new development of SVM theory. It is a novel SVM based on non-parallel support hyper-plane and its performance is mature. Compared with the traditional SVM, the size of TWSVM quadratic programming problem is quarter of that of SVM [6-7], so the operation velocity of TWSVM is accelerated. In addition, TWSVM also shows higher ability in dealing with imbalanced problems.

This paper introduces TWSVM algorithm to complete aircraft engine gas path fault diagnosis, uses a new optimization algorithm termed as hybrid particle swarm optimization (HPSO)[8] to optimize parameters of TWSVM and adopts a mixed kernel function to improve performance of TWSVM.

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1 Aircraft Engine Gas Path Fault Diagnosis

The modern aircraft turbofan engine is generally composed of air inlet, fan, high pressure compressor, main combustion chamber, high pressure turbines, low pressure turbines, afterburner, nozzle, etc. Their faults are known as aircraft engine gas path faults, and if any of them occurs, the performance of the whole machine will decline.

In the working process of aircraft engine, there are various faults, such as oxygen corrosion, damage collided by foreign objects on surface of engine parts and blade fracture because of collision, and so on. These faults will cause damage to the gas path components of aircraft engine, and structure damage can lead to the saltation of engine performance parameters, such as pressure, temperature of high and low compressor import and export, efficiency of high and low compressors, speed of high and low pressure rotor and fuel flow rate. The principle of aircraft engine gas path fault diagnosis is to deduce backwards and find out engine component states, and finally find locations of engine faults based on the changes of engine part performance parameters. The usual method of aircraft engine gas path fault diagnosis is that according to multiple state variables of gas path components, comprehensively analyze these variables and make an evaluation so as to deduce the performance of this engine.

Aircraft engine faults mainly include three aspects:

(1) Engine structure component damage.

(2) The engine system or some components have lost their original function.

(3) Performance degradation exceeds the design requirements of an engine.

At present, methods of performance status monitoring and fault diagnosis for aircraft engines are divided into the following classes: (1) The status monitoring technique based on the small deviation linearization fault equation; (2) Fault diagnosis methods based on the artificial intelligence algorithms; (3) Fault diagnosis methods based on knowledge learning rules. The SVM algorithm for aircraft engine fault diagnosis belongs to machine learning that is a part of artificial intelligence algorithms.

In this paper, the TWSVM algorithm is introduced to carry out the fault diagnosis of aircraft engine. Because directly obtaining test data and fault data of engines is difficult, this paper uses gas turbine simulation program (GSP) software for modeling and simulation of the PW4056 engine developed by Pratt & Amp Group[9]. Then according to the thermodynamic parameters of each section in different working conditions, the influence matrix of fault diagnosis is generated by establishing an influence matrix equation.

Fig. 1 shows the principle of using HPSO-TWSVM to carry out fault diagnosis, in which training data are used to train TWSVM classification model and HPSO is used to optimize parameters of TWSVM. Then, the test accuracy of this classifier is obtained.

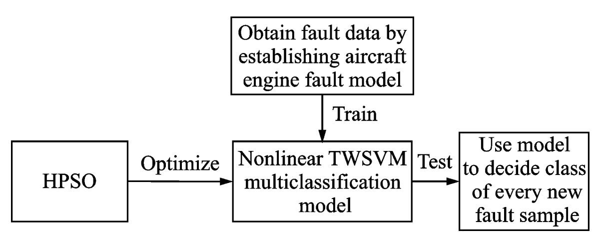

Fig. 1 Simple flow chart of HPSO-TWSVM fault diagnosis

2 Basic Principle of TWSVM

TWSVM was proposed by Jayadeva et al. based on the generalized eigenvalue SVM (GESVM) in 2007[6]. Both of TWSVM and GESVM change the model structure from two parallel support hyper planes to a pair of nonparallel hyper planes, which extends SVM to a wider and more complex field. So TWSVM can process some data distribution styles that the SVM is difficult to deal with. Especially, the size of convex quadratic programming optimization problems of TWSVM is only one fourth of that of SVM′s, and it improves training speed in theory.

TWSVM, like SVM, was originally designed for a binary classification, and its basic principles are as follows.

Assuming that the training sample set is $T=\{(x_1,+1),\cdots,(x_p,+1),(x_{p+1},-1),\cdots,(x_{p+q},-1)\}$. $\boldsymbol{x}_i\in\mathbf{R}^n, i=1,\cdots,p+q$. Let $\boldsymbol{A}=(x_1,\cdots,x_p)^{\mathrm{T}}\in\mathbf{R}^{p\times n}, \boldsymbol{B}=(x_{p+1},\cdots,x_{p+q})^{\mathrm{T}}\in\mathbf{R}^{q\times n}$ and $l=p+q$.

In this paper, the nonlinear TWSVM is used, so its brief introduction is given here. Since the linear TWSVM could not be extended to the nonlinear case directly like standard SVM, we need kernel functions for the nonlinear case. The kernel-generated plane is

$$K(\boldsymbol{x}^{\mathrm{T}},\boldsymbol{C}^{\mathrm{T}})\boldsymbol{u}_{+}+b_{+}=0$$
$$K(\boldsymbol{x}^{\mathrm{T}},\boldsymbol{C}^{\mathrm{T}})\boldsymbol{u}_{-}+b_{-}=0 \tag{1}$$

Two primal problems of nonlinear TWSVM are

$$\min_{\boldsymbol{u}_{+},b_{+},\xi_{-}}\frac{1}{2}\|K(\boldsymbol{A},\boldsymbol{C}^{\mathrm{T}})\boldsymbol{u}_{+}+\boldsymbol{e}_{+}b_{+}\|^2+c_1\boldsymbol{e}_{-}^{\mathrm{T}}\xi_{-}$$
$$\text{s.t.}\ -(K(\boldsymbol{B},\boldsymbol{C}^{\mathrm{T}})\boldsymbol{u}_{+}+\boldsymbol{e}_{-}b_{+})+\xi_{-}\geqslant\boldsymbol{e}_{-},\xi_{-}\geqslant 0 \tag{2}$$

and

$$\min_{\boldsymbol{u}_{-},b_{-},\xi_{+}}\frac{1}{2}\|K(\boldsymbol{B},\boldsymbol{C}^{\mathrm{T}})\boldsymbol{u}_{-}+\boldsymbol{e}_{-}b_{-}\|^2+c_2\boldsymbol{e}_{+}^{\mathrm{T}}\xi_{+}$$
$$\text{s.t.}\ (K(\boldsymbol{A},\boldsymbol{C}^{\mathrm{T}})\boldsymbol{u}_{-}+\boldsymbol{e}_{+}b_{-})+\xi_{+}\geqslant\boldsymbol{e}_{+},\xi_{+}\geqslant 0 \tag{3}$$

where $\boldsymbol{C}=[\boldsymbol{A};\boldsymbol{B}]\in\mathbf{R}^{l\times n}$.

After solving their corresponding dual problems

$$\max_{\boldsymbol{\alpha}}\boldsymbol{e}_{-}^{\mathrm{T}}\boldsymbol{\alpha}-\frac{1}{2}\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{R}(\boldsymbol{S}^{\mathrm{T}}\boldsymbol{S})^{-1}\boldsymbol{R}^{\mathrm{T}}\boldsymbol{\alpha}$$
$$\text{s.t.}\ 0\leqslant\boldsymbol{\alpha}\leqslant c_1\boldsymbol{e}_{-} \tag{4}$$

and

$$\max_{\boldsymbol{\gamma}}\boldsymbol{e}_{+}^{\mathrm{T}}\boldsymbol{\gamma}-\frac{1}{2}\boldsymbol{\gamma}^{\mathrm{T}}\boldsymbol{S}(\boldsymbol{R}^{\mathrm{T}}\boldsymbol{R})^{-1}\boldsymbol{S}^{\mathrm{T}}\boldsymbol{\gamma}$$
$$\text{s.t.}\ 0\leqslant\boldsymbol{\gamma}\leqslant c_2\boldsymbol{e}_{+} \tag{5}$$

where $\boldsymbol{R}=[K(\boldsymbol{B},\boldsymbol{C}^{\mathrm{T}})\ \boldsymbol{e}_{-}]$, $\boldsymbol{S}=[K(\boldsymbol{A},\boldsymbol{C}^{\mathrm{T}})\ \boldsymbol{e}_{+}]$.

The solutions of Eq.(2,3) are obtained by

$$(\boldsymbol{u}_{+}^{\mathrm{T}},b_{+})^{\mathrm{T}}=-(\boldsymbol{S}^{\mathrm{T}}\boldsymbol{S})^{-1}\boldsymbol{R}^{\mathrm{T}}\boldsymbol{\alpha} \tag{6}$$
$$(\boldsymbol{v}_{-}^{\mathrm{T}},b_{-})^{\mathrm{T}}=-(\boldsymbol{R}^{\mathrm{T}}\boldsymbol{R})^{-1}\boldsymbol{S}^{\mathrm{T}}\boldsymbol{\gamma} \tag{7}$$

Thus a new test point is predicted to its own class by

$$\text{classlabel}=\arg\min_{k=+,-}|K(\boldsymbol{x}^{\mathrm{T}},\boldsymbol{C}^{\mathrm{T}})\boldsymbol{u}_k+b_k| \tag{8}$$

The classical SVM algorithm is based on the principle of the distance maximum between two kinds of sample points to find all support vector points, and then find a classification hyper plane in middle of the two classes. The innovation of TWSVM is to find a relatively independent support hyper plane for either class. Thus, TWSVM has a new model structure and some new abilities. But a good TWSVM classifier is heavily relies on parameter optimization, so a fine parameter optimization algorithm is important. In this situation, the HPSO is introduced.

3 TWSVM Based on HPSO

3.1 Characteristics and principles of HPSO

The particle swarm optimization (PSO) is proposed by an American electrical engineer Eberhart and a social psychologist Kenndy in 1995[10]. This algorithm is one of common methods for parameter optimization of SVM. The key of this method is how to ensure that particles land at the optimal solution. In order to achieve this goal, the PSO algorithm cleverly simulates bird foraging behaviors, and forms a model about social and individual nature. By regulating two weight coefficients of personality and society, particles land in objective[10-11].

The mathematical description of the PSO algorithm is as follows: assume a n-dimensional search space, m particles compose of a particle swarm $\boldsymbol{x}=(x_1,x_2,\cdots,x_m)^{\mathrm{T}}$, where $\boldsymbol{x}_i=(x_{i,1},x_{i,2},\cdots,x_{i,n})^{\mathrm{T}}$ is a position of particle i, and its velocity is $\boldsymbol{v}_i=(v_{i,1},v_{i,2},\cdots,v_{i,n})^{\mathrm{T}}$. The individual optimal position of particle i is $\boldsymbol{pbest}_i$ and it can be described as $\boldsymbol{pbest}_i=(pbest_{i,1},pbest_{i,2},\cdots,pbest_{i,n})^{\mathrm{T}}$. The global optimal position of this swarm is $\boldsymbol{gbest}=(gbest_1,gbest_2,\cdots,gbest_n)^{\mathrm{T}}$. After particle swarm finds the two optimal positions in the current iteration, they will update their own velocity and position according to the following equations

$$v_{i,d}^{k+1}=\omega\cdot v_{i,d}^{k}+c_1\cdot\text{rand}()(pbest_{i,d}^{k}-x_{i,d}^{k})+c_2\cdot\text{rand}()(gbest_{d}^{k}-x_{i,d}^{k}) \tag{9}$$
$$x_{i,d}^{k+1}=x_{i,d}^{k}+v_{i,d}^{k+1} \tag{10}$$

where c_1,c_2 are acceleration constants; rand( ) generates a random number in (0,1); $v_{i,d}^{k}$ and $x_{i,d}^{k}$ are the velocity and position of particle i at dimension d and iteration k; $pbest_{i,d}^{k}$ is the individual optimal position of particle i at dimension d and iteration k; $gbest_{d}^{k}$ is the global optimal position of particle swarm at dimension d and iteration k, and ω is the inertia weight.

From the above particle evolution equations, it can be find that c_1 and c_2 adjust the step size of a particle to flight forward its own best position and the global best position, respectively. For the PSO algorithm, exploration is that particles leave the original optimized track by a larger extent. Then exploitation is that particles search more detail on the original track. Ref. [11] pointed out that ω was a proportional parameter for exploration and exploitation of the PSO and the influence of ω on algorithm performance was researched. From experimental results, it can be find that a larger ω is good for the algorithm to jump out of the local optimum, and a smaller ω is good for the local deep optimization, in other words, the converging speed of the algorithm is accelerated.

However, the performance of the classical PSO algorithm needs to be improved to deal with the optimization problems with high complexity. Recently, evolutionary algorithms, traditional optimization algorithms or other techniques are used to improve the PSO. Among the improved methods, HPSO is one of the most effective algorithms. The improvement principle is that algorithms enhance global exploring ability by enriching the diversity of particles or enhance the convergent speed and accuracy by improving the PSO local exploitation ability. There are two general mixed strategies: (1) Use other optimization techniques to self-adaptively adjust shrinkage factor/inertia weight/acceleration constant, etc. (2) Combine PSO with other evolutionary algorithms or other techniques. HPSO belongs to the first kind. The hybrid concept is from the genetic algorithm (GA). In each time of iteration, according to the hybridization rate, the algorithm puts a part of particles into the hybrid pool, particles in this pool arise randomly pairwise hybridization to produce progeny particles with the same number compared with their father particles, and then progeny particles replace parent particles. The position of the progeny is obtained by the crossover of the parent positions

$$\boldsymbol{x}_n = i \times \boldsymbol{x}_m(1) + (1-i) \times \boldsymbol{x}_m(2) \tag{11}$$

where $\boldsymbol{x}_n$ is the position of progeny, $\boldsymbol{x}_m$ the position of father particles, and i the random number in (0,1).

Velocity of progeny can be computed by

$$\boldsymbol{v}_n = \frac{\boldsymbol{v}_m(1) + \boldsymbol{v}_m(2)}{|\boldsymbol{v}_m(1) + \boldsymbol{v}_m(2)|} |\boldsymbol{v}_m| \tag{12}$$

where $\boldsymbol{v}_m$ is the velocity of father particles, and $\boldsymbol{v}_n$ the velocity of progeny.

Fig. 2 is the 3-D graph of one of universal standard functions named Rastrigin. The minimum of Rastrigin is 0.

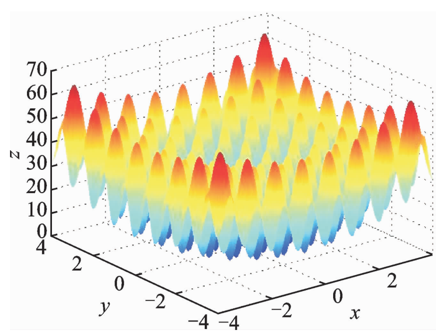

Fig. 2 3-D graph of Rastrigin function

In the paper, Rastrigin is used to test the performance of PSO and HPSO briefly. From this simple test, we could find that HPSO algorithm can find the global optimal value in almost the same time. Through many experiments, we find that HPSO has better ability on finding global optimal value than PSO (Fig. 3), though they are stochastic algorithms. HPSO needs more time to compute, but when the dimension of a problem is big enough, this disadvantage can be ignored.

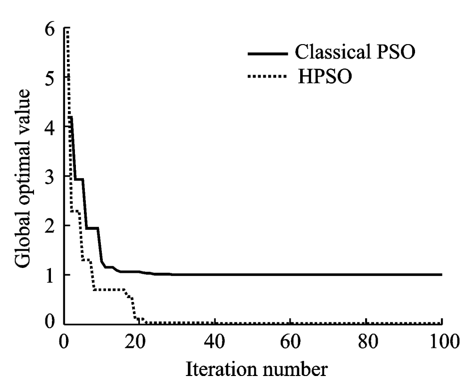

Fig. 3 Performance comparison of PSO and HPSO

3.2 Selection of kernel function

The essence of improving performance of TWSVM algorithm is to improve its learning ability and generalization ability. Eenhancing the performance of its kernel function is an important way to improve the performance of TWSVM algorithm. We often use the Gauss kernel function as the kernel function, which has a strong learning ability but relatively weak generalization ability. So the mixed kernel (MK) function[12] which can balance the generalization ability and learning ability well is introduced.

In this section, a simple polynomial kernel function and a Gaussian radial basis function are used to construct the mixed kernel function

$$K(x,x_i)=\gamma\cdot \mathrm{e}^{\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right)}+\theta\cdot(x\cdot x_i+1)^2 \quad \gamma>0,\theta>0 \tag{13}$$

where γ and θ are the proportions of the Gaussian radial basis function and the polynomial kernel function, respectively. In order to ensure that the mixed kernel function does not change the rationality of the original mapping space, generally make $0\leqslant\gamma,\theta\leqslant 1$ and $\gamma+\theta=1$. At the same time, make $s=\frac{1}{2\sigma^2}$, thereby the mixed kernel function is

$$K(x,x_i)=\gamma\cdot \mathrm{e}^{(-s\cdot\|x-x_i\|^2)}+(1-\gamma)\cdot(x\cdot x_i+1)^2 \quad 0\leqslant\gamma\leqslant 1 \tag{14}$$

The basic information of data sets used in the paper is shown in Table 1.

Table 1 Data sets

Data set	Account of sample points	Dimension of feature vector	Label number
Sonar	208	60	2
Iris	150	4	3
Vehicle	846	18	4

In these experiments, $c_1=c_2=0.01$ are fixed and then the grid search method is used to find optimal parameters. Variable parameters of MK-TWSVM are γ, s and that of TWSVM is s. The first two groups of comparative experiments use 5-fold cross validation to estimate accuracy, and the last group about Vehicle data uses a single accuracy rate to estimate accuracy for reducing the amount of calculation. In addition, the second contrast group uses the 1 v rest[13] multi-class classification algorithm, and the accuracy is not high for the third group after using this method, so the 1 v 1 multi-class classification algorithm is used.

Results of these experiments are shown in Table 2. Through the experimental verification, we can see that the mixed kernel function plays a significant role in performance improvement.

Table 2 Comparison results of MK-TWSVM and TWSVM

Data set	Accuracy/%		Optimal parameter	
	MK-TWSVM	TWSVM	MK-TWSVM(γ,s)	TWSVM(s)
Sonar	82.752 6	80.232 3	0.990 0, 0.270 0	0.095 0
Iris	96.666 7	94.000 0	0.500 0, 0.049 0	0.046 0
Vehicle	81.656 8	79.411 8	1.000 0, 0.006 1	0.007 0

3.3 Training algorithm of TWSVM

This paper introduces a fast calculation method named successive over relaxation (SOR)[14] as follow

$$\max_{\boldsymbol{\alpha}} \boldsymbol{e}_-^{\mathrm{T}}\boldsymbol{\alpha}-\frac{1}{2}\boldsymbol{\alpha}^{\mathrm{T}}\boldsymbol{G}(\boldsymbol{H}^{\mathrm{T}}\boldsymbol{H})^{-1}\boldsymbol{G}^{\mathrm{T}}\boldsymbol{\alpha}$$

$$\text{s.t.}\quad 0\leqslant\boldsymbol{\alpha}\leqslant c_1\boldsymbol{e}_- \tag{15}$$

Aiming at a quadratic programming problem above, SOR is written as

$$\alpha^{i+1}=(\alpha^i-t\boldsymbol{E}^{-1}(\boldsymbol{Q}\alpha^i-\boldsymbol{e}+\boldsymbol{L}(\alpha^{i+1}-\alpha^i)))_{\#} \tag{16}$$

where $\boldsymbol{Q}$ is the quadratic matrix of convex quadratic programming (Eq. (15)), and $\boldsymbol{L}$ and $\boldsymbol{E}$ are composed of elements of $\boldsymbol{Q}$. $\boldsymbol{L}$ is the strict lower triangular matrix, and elements located in lower left of the main diagonal correspond to the elements of same positions in $\boldsymbol{Q}$. $\boldsymbol{E}$ is the diagonal matrix, and diagonal elements are in one-to-one correspondence to the diagonal elements of $\boldsymbol{Q}$. $t\in(0,2)$. This algorithm starts with any $\alpha^0\in\mathbf{R}^n$, and through Eq. (16) unknown variables can be solved by iteration methods. The corresponding numerical solutions of convex quadratic programming problems of TWSVM are obtained until $\| \alpha^{i+1} - \alpha^{i} \|$ is enough small.

In addition, $()_{\#}$ is an operator

$$(\alpha_i)_{\#} = \begin{cases} 0 & \alpha_i \leqslant 0 \\ \alpha_i & 0 < \alpha_i < c_1 \\ c_1 & \alpha_i \geqslant c_1 \end{cases} \tag{17}$$

In particular, Eq. (16) is not the final iteration equation and there must be no α^{i+1} in right of the equation. Only in this way, it can be running on computers.

4 Gas Path Fault Diagnosis Based on HPSO-TWSVM

After obtaining the corresponding classification rules and the fault data, aircraft engine fault diagnosis becomes a pattern recognition problem. In this paper, the corresponding classification rules are introduced[9] and the method of resample is used to enrich data sets. After then, TWSVM with a mixed kernel function is used to carry out this pattern recognition problem. In this process, TWSVM classification model is a fitness function for HPSO. Through choosing suitable parameters for HPSO algorithm, an optimal classification model of HPSO-TWSVM is built.

Procedures of gas path fault diagnosis based on HPSO-TWSVM are as follows:

Step 1 Obtain the corresponding classification rules of gas path fault diagnosis and divide the fault data set into a training set and a test set according to a certain proportion.

Step 2 Use the training set to train MK-TWSVM classification model.

Step 3 Use HPSO to find the optimal parameters of MK-TWSVM. Set the position and velocity of each particle randomly.

Step 4 Calculate the fitness value of each particle. If the fitness function value is better, update the best individual position of the particle, i. e. ***pbest***. Compare all *pbest* and find the global optimal position ***gbest***.

Step 5 Choose a certain number of particles according to hybrid probability, and put them into the hybrid pool. The particles in the pool are randomly paired to produce offspring with the same amount of their father generation particles. The position and velocity of the offspring are computed by Eqs. (11,12) and updated by Eqs. (9,10).

Step 6 When this algorithm meets stop conditions, stop the search and give the output. Or return to Step 5 to continue.

Step 7 After obtaining the optimal classification model, use the test data set to get test accuracy and running time.

Fig. 4 gives the flow chart of HPSO-TWSVM algorithm.

5 Experiments

According to the procedure of obtaining the aircraft fault analysis rules in Section 2 and the procedure of gas path fault diagnosis based on HPSO-TWSVM in Section 4, experiments are carried out. In this paper, the decision rules for fault diagnosis in Ref. [9] are adopted. In Ref. [9], the decision rules for fault diagnosis are obtained in conditions: flight height $H = 10\ 700$ m, atmospheric pressure $p_0 = 0.237\ 23$ bar, atmospheric temperature $T_0 = 218.6$ K, atmospheric density $\rho_0 = 0.378\ 06$ kg/m^3, Mach number $Ma = 0.39$, thrust $F_N = 47.01$ kN. All programs in this paper are edited on MATLAB 2014a and computer configurations are Intel Core i5-4200M CPU with dominant frequency 2.5 GHz, RAM 8 GB, a 64 bit operate system of Windows 10.

We choose all kinds of fault data in Ref. [9] and generate randomly samples obeying the normal distribution by using the variance and the mean of every original sample according to correlation methods of resampling[15]. Its formula is

$$x_i = x_i (1 + L * \sigma_{\text{fault}} * \text{rand}n) \tag{18}$$

where x_i is any sample, $L = 0.1$ is a constant, σ_{fault} is the standard deviation of x_i, and rand$n$ generates random number obeying the normal distribution. According to this method, we generate 200 samples, 100 of which are used as the training samples, and the other 100 as test samples. The 5-fold cross validation is used in training, the av-

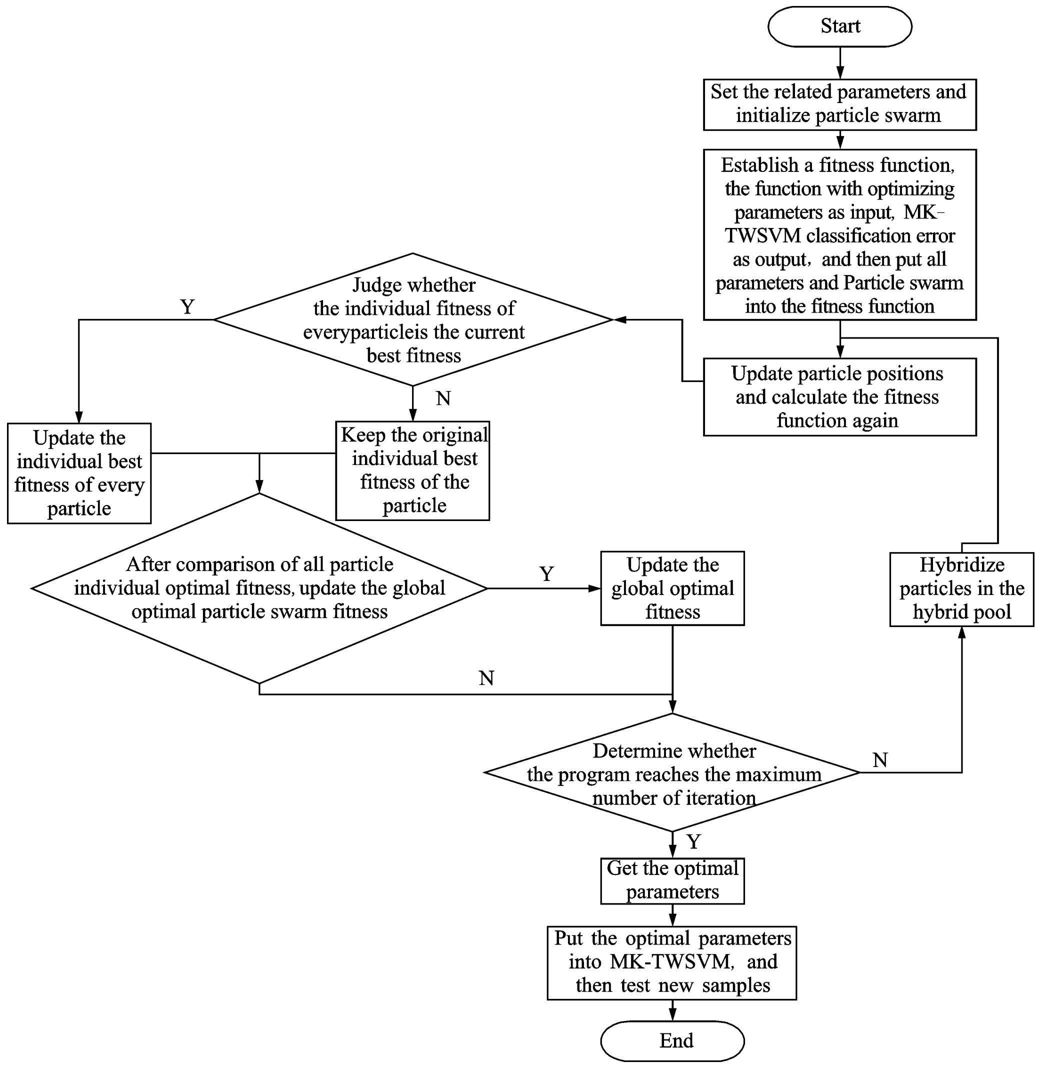

Fig. 4 Flow chart of HPSO-TWSVM algorithm

erage of which is adopted as the training accuracy, and the time of the whole training process is defined as the running time.

Fig. 5 shows the parameter convergence of different algorithms in a simple experiment, and these two algorithms can find the best values within two steps. These experiments give us a

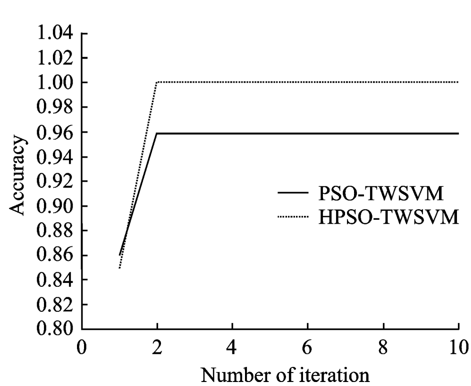

Fig. 5 Parameter convergence

guide and then we can use this result to complete the following research.

The following experiments are all carried out under the condition of mixed kernel function as Eq. (14). The first and second experiments are carried out in two different multiple classification methods. In last two experiments, we use PSO and HPSO respectively to optimize parameters of MK-TWSVM. In order to reduce the amount of computation, we set two penalty factors are equal, i. e. , $c_1 = c_2$, and fix the mixed kernel function parameter $\gamma = 0.5$. Accordingly, we need to optimize only two parameters. In order to better contrast the two optimization methods, the common parameters of the two algorithms are set as follows: the number of population is 10, two acceleration constants are all 2.05[11,16], initial inertia weight is 0.8, the maximum times of iteration is

2, and the dimension of any particle position is 2.

The experimental results are shown in Table 3. In dealing with the multi-class classification problem, 1 v 1 method has a higher accuracy. Because every two classes of samples need a binary classifier and all of the samples require $\frac{N(N-1)}{2}$ (N is the total number of categories) binary classifiers, and it needs to design more complex voting algorithm, the computation needs more time. In the case of adequate computing power, we usually choose the 1 v 1 multiple classification algorithm in 2—4 groups. However, parameter optimization methods used in 2—4 groups are different. They are respectively grid search, PSO and HPSO. Experimental results show that HPSO can find the global optimum, and PSO can find a group of local best parameters. In addition, grid search algorithm also finds the best parameters, but it excessively relies on experience.

The experiment that has four parameters to optimize is carried out, and results are shown in Table 4. From the results we can see that HPSO uses much less time in the case that there are more parameters need to be optimized, because it can intelligently find out the best parameters.

Table 3 Comparison of experimental results of different algorithms

Method	TWSVM		PSO-TWSVM	HPSO-TWSVM
	1 v rest	1 v 1	1 v 1	1 v 1
Training accuracy/%	97	100	95	100
The optimal parameter	$c_1=0.1$ $s=880.0$	$c_1=0.1$ $s=800.0$	$c_1=5.6951$ $s=5.2891$	$c_1=1.0293$ $s=0.8998$
Training time/s	141.740 4	222.806 0	545.082 2	619.129 7
Test accuracy/%	100	100	95	100

Table 4 Comparison results of TWSVM and HPSO-TWSVM

Methods	TWSVM	HPSO-TWSVM
Training accuracy/%	100	100
The optimal parameter	$c_1=0.1$ $c_2=0.6$ $s=800$ $\gamma=0.4$	$c_1=0.4043$ $c_2=0.8597$ $s=2.2219$ $\gamma=0.3545$
Training time/s	176 3.677 8	817.716 4

6 Conclusions

(1) The feasibility and effectiveness of TWSVM in aircraft engine fault diagnosis are verified through the experiments. This is a new exploration for SVM technology in aircraft engine fault diagnosis.

(2) It is proved that HPSO has better optimization performance than PSO though it needs slightly more time. HPSO is easier than PSO to find the global optimum.

(3) A mixed kernel function can improve the performance of a kernel function so as to ensure that the TWSVM algorithm can better balance the generalization ability and the learning ability.

(4) The 1 v 1 multiple classification algorithm[17] of TWSVM has better training accuracy.

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