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Fault diagnosis model of Multi-LS-SVM classifiers for electric machine based on modified PSO

Qi-Fan Yang[2,3], Ke Fang[2,3,4], Yong-Jun Xie[2,3], Yuan-Liang Huang[2,3]

Abstract. The modified PSO is proposed in the model, which is aimed at adjusting inertia weight and thus accelerating the training speed through convergence of swarm and individual fitness. By iteratively solving the matrix in LS-SVM through adaptive PSO, the problem of solving inverse matrix is avoided and the memory is saved. In order to classify 4 faults of electric machine quickly and accurately, one-against-rest LS-SVM multiple classifiers structure is applied in the model to construct 4 LS-SVM classifiers based modified PSO. Diagnosis test results show that the proposed method has high classification accuracy, which proves its effectiveness and usefulness.

Key words. Fault diagnosis, electric machine, least squares support vector machine (LS-SVM), particle swarm optimization (PSO), multi-classifier.

1. Introduction

There are many reasons of electric machine faults, including supercharge and long term continuous operation; meanwhile the faults also have close relation with electric machine type and operational state. There are many factors that affect the accuracy of electric machine fault diagnosis, which make it difficult to distinguish the faults of electric machine by traditional method [1–4].

In recent years, based on artificial neural network, fuzzy mathematics, clustering principle and grey systems theory, people obtained many practical achievements of electric machine faults diagnosis [5, 6]. Support Vector Machine (SVM) is based on Vapnik-Chervonenkis dimension theory and structural risk minimization principle,

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[2]Institute of Rail Transportation, Jinan University, Zhuhai, 519070, China

[3]Electrical and Information college, Jinan University, Zhuhai, 519070, China

[4]Corresponding to: Ke Fang e-mail: `fangke@jnu.edu.cn`

which can solve many practical problems such as small-sample problem, nonlinear system problem, high-dimension problem, local minimum problem and so on. It has been successfully applied to various problems. What's more, it can effectively avoid over-fitting [7, 8]. Least square support vector machine (LS-SVM) [9, 10] proposed by Suyken improves work efficiency and overcomes the shortcoming of long training time through solving large scale problems. It transforms inequality constraint into equality constraint, and converts the deviation of empirical risk from linear to quadratic. Learning problem of classical SVM is transformed into solving the linear equations of the system so as to avoid quadratic problems and increase the computing speed. But LS-SVM always has to calculate the inverse of matrices in calculating process, which leads to the difficult in solving large scale problems in practical engineering. The particle swarm optimization (PSO) algorithm is used to solve linear equations in any dimension, which can avoid matrix inversion and speed up the calculation.

This paper proposes a multi-class LS-SVM motor fault diagnosis model based on modified PSO algorithm, and compares the results processed by multi-class LS-SVM based on modified PSO with the results processed by LS-SVM based on standard PSO respectively.

2. Algorithm improvements

2.1. Modified PSO algorithm

Kennedy et al. proposed the particle swarm optimization algorithm (PSO) to simulate the flight of birds [11]. Each bird represents a particle, and its position represents a basic solution of the problem space. In this paper, particle operation is carried out according to the PSO algorithm.

There are m particles in the N-dimensional space. The particle i has current position $x_i = (x_{i1}, x_{i2}, \cdots, x_{in})$ and current velocity $v_i = (v_{i1}, v_{i2}, \cdots, v_{in})$. The best position of the particle i achieved so far is defined as $p_i = (p_{i1}, p_{i2}, \cdots, p_{in})$and $g_{\mathrm{best_i}}$ is the best place of all the particles in the particle swarm achieved so far. The velocity and position of particles can update for next iteration according to (1)–(3).

$$v_i^{k+1} = w \times v_i^k + \varphi_1 \times r_1 \times \left(p_i^k - x_i^k\right) + \varphi_2 \times r_2 \times \left(g_{\mathrm{best_i}}^k - x_i^k\right) , \tag{1}$$

$$x_{i+1} = x_i + v_{i+1} , \tag{2}$$

$$\begin{cases} v_i^{k+1} = v_{\max} , & \text{if } v_i^{k+1} > v_{\max} , \\ v_i^{k+1} = -v_{\max} , & \text{if } v_i^{k+1} < -v_{\max} , \end{cases} \tag{3}$$

where w is the weight coefficient, φ_1 and φ_2 are the acceleration constants which are set to 2, k and $k+1$ respectively represent the current iteration times, $r_1$and $\mathrm{r}_2$are random numbers in the interval [0, 1], and $v_{\max}$ is the maximum flying speed. It has been found that if the values of w, φ_1 and φ_2 are not set correctly in the iterative particle swarm optimization model, the particle swarm will be iterated indefinitely which leads to miss the optimal solution. In the case of finite iterations, the global optimal solution is obtained which makes the late iteration efficiency drop significantly and can't further improve the accuracy [12, 13]. In order to solve this problem, weight coefficient w can be adjusted according to the particle fitness. In the initial stage of the algorithm, w is given a larger positive value in order to avoid falling into local optimal solution. In the later stages of the algorithm, the algorithm gives w a smaller value when the iteration into global optimal range which makes the algorithm much easier to meet the accuracy requirement.

This paper proposes a modified PSO algorithm which can dynamically adjust the weight coefficient and modify the weight coefficient w according to the efficiency and precision of the iterations of the particle group. The specific methods are as follows:

(1) When $f\left(g_{\mathrm{best_i}}\right) < f\left(x_i\right) < f\left(p_{\mathrm{best_i}}\right)$, the particles tend to be more efficient in iterations. They usually jump over local optimal solutions and have high precision. w is iterated by the following form:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{K} k\,, \tag{4}$$

where $w_{\max}$ is the largest w at the beginning of the search which is set to 0.92; $w_{\min}$ is the smallest w at the end of the search which is set to 0.39; k is iterative steps and K is the maximum of the iterative steps. In this modified PSO algorithm, w will decrease linearly with the iterations of the algorithm which will improve the convergence performance of the algorithm significantly, speed up the convergence speed, and improve the accuracy.

(2) When $f\left(x_i\right) < f\left(g_{\mathrm{best_i}}\right)$, the particles have already entered into the range of the global optimal solution. The weight coefficient should be reduced to improve the efficiency of convergence to the global optimal. The weight coefficient of w is adjusted according to the fitness of particles which is shown as the following form:

$$w = w - \left(w - w_{\min}\right) \left| \frac{f\left(x_i\right) - f\left(p_{\mathrm{best_i}}\right)}{f\left(g_{\mathrm{best_i}}\right) - f\left(p_{\mathrm{best_i}}\right)} \right| \,, \tag{5}$$

where $w_{\min}$ is the minimum of w which is set to 0.39. The smaller the weight coefficient of the particle and the shorter the step are set, more easily the local optimal solution can be found.

2.2. LS-SVM solution based on modified PSO algorithm

The training set is $S = \left\{\left(x_i, y_i\right) \mid i = 1, 2, \cdots, l\right\}$, where $x_i \in R^n$ and $y_i \in R$ are input and output data respectively. LS-SVM minimizes the objective function using SRM criterion and its constraints are as follows:

$$\begin{aligned} &\min \;\; J\left(w, e\right) = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^{l} e_i^2\,, \\ &s.t. \;\; y_i = w^T \Phi\left(x_i\right) + b + e_i,\; i = 1, 2, \cdots, l\,, \end{aligned} \tag{6}$$

where w is the weight vector, γ is constant, b is the error constant.

Equation (1) can be regarded as an optimization problem which is usually converted to the following linear equations:

$$\begin{bmatrix} 0 & \boldsymbol{L}^T \\ \boldsymbol{L} & \boldsymbol{Q}+\gamma^{-1}\boldsymbol{I} \end{bmatrix} \begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix}, \tag{7}$$

where $\boldsymbol{y} = [y_1, y_2, \cdots, y_l]^T \in \boldsymbol{R}^l$, $\boldsymbol{L} \in \boldsymbol{R}^{1\times l}$ is the unit matrix of element 1, $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \cdots, \alpha_l]^T \in \boldsymbol{R}^l$, $\boldsymbol{Q} = \lfloor q_{ij} \rfloor_{l\times l}$, $q_{ij} = y_i y_j K(x_i, x_j)$.

Rewrite equation (2) as the form of the following matrix:

$$A_j = z(A \in \boldsymbol{R}^{m\times n}, z \in \boldsymbol{R}^m). \tag{8}$$

Equation (6) shows that in order to solve $j = (j_1, j_2, \cdots j_n)^T$, it is necessary to calculate the inverse matrix A. However, the efficiency of inversion is low due to a large dimensions of $A^T A$ for the large-scale problem of practical engineering, which means it is difficult to obtain result. To this end, this paper uses modified particle swarm optimization algorithm, adjusts the weight coefficient, and calculates the matrix equation. The flow of LS-SVM algorithm based on modified PSO is as follows:

(1) First, it is necessary to initialize the particle swarm. The particle size of the particle is set and the initial population $X(t)$ is composed of m particles $x_1, x_2, \cdots, x_m$ which are generated randomly in the N-dimensional space. The initial velocity of each particle is made of $v_{i1}, v_{i2}, \cdots, v_{in}$ which compose the velocity matrix $V(t)$. The initial value of the individual optimal solution of each particle $p_{\text{best}_i}$is the initial value of x_i.

(2) The second step is fitness calculation. Since the standard deviation can accurately display the dispersion degree of the data set, the fitness function in the iterations of equations is defined as follows:

$$f(x_i) = \frac{1}{n} \|z_i - A_i x_i\|^2. \tag{9}$$

(3) The current fitness $f(x_i)$ of each particle is compared with the fitness $f(p_{\text{best}_\text{i}})$ of best position of the history. If $f(x_i) < f(p_{\text{best}_\text{i}})$, $p_{\text{best}_\text{i}} = x_i$, and w is adjusted according to formula (4). The current fitness $f(x_i)$ of all particles is compared with the fitness $f(p_{\text{best}_\text{i}})$ of best position. If $f(x_i) < f(g_{\text{best}_\text{i}})$, global optimal solution $g_{\text{best}_\text{i}} = x_i$ and w is adjusted according to formula (5);

(4) New population $X(t+1)$ is generated after updating the velocity and location of particles. The speed adjustment rules are as follows:

$$v_i^{t+1} = \begin{cases} v_{\max}, & v_i^{t+1} > v_{\max}; \\ -v_{\max}, & v_i^{t+1} < -v_{\max}. \end{cases} \tag{10}$$

(5) Judge the termination conditions of iterations. If the iterative condition is satisfied, the result is considered as the optimal solution and the iteration is stopped.

Otherwise, $t = t+1$, the process go to (2) and continue the operation. The algorithm iterations are terminated by the maximum iteration number $t_{\max}$ or the accuracy of the iteration results which is satisfied.

(6) The output result is obtained by the least squares solution of the matrix equation, which is the optimal parameter $\{\alpha_i\}_{i=1}^{N}$ and b in the corresponding equation (2).

(7) $\{\alpha_i\}_{i=1}^{N}$ and b are substituted into

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b\,. \tag{11}$$

Then the sample is entered and diagnosed through the formula. This paper selects the radial basis function as kernel function which is defined by

$$K(x, x_k) = \exp\left(-\left\|x - x_k\right\|^2 / 2\sigma^2\right)\,. \tag{12}$$

2.3. Multi-class LS-SVM

LS-SVM was originally used for the 2-value classification problem. And for multi-value classification problems, there are one-against-rest (1-a-r) method, one-against-one (1-a-1) method, decision-tree-based multi-class SVM (DT-SVM) method and so on [14, 15]. Among them, 1-a-r and 1-a-1. 1-a-1 adopts a voting combination strategy to conduct multiple categories which has high precision. But the disadvantage is that for N classification problem, it must train $N(N-1)/2$ LS-SVM classifiers. The method must traverse all classifiers which means that the training is complex and has low classification efficiency. 1-a-r uses the "one against the others" method which only needs to train N LS-SVM classifiers. It uses the "maximum output" method to realize multi-classification. The number of LS-SVM classifiers is significantly smaller than that in 1-a-1 method, which improves the training speed.

Familiar faults of electric machine are mainly concentrated in stator, rotor, bearing and axle. Therefore they need four LS-SVM classifiers which can distinguish the different faults of electric machine in turn. After receiving the fault information, Classifiers run as shown in Figure 1.

3. Experiment

This paper collects 800 groups of typical faults records of electric machine to verify multi-class LS-SVM electric machine fault diagnosis model based on modified PSO algorithm.

The records were divided into 2 parts, the first 400 groups were training samples, and the other 400 were test samples. The experimental flow is as follows:

(1) Preprocessing and selecting of sample information

When the electric machine faults occur, there will be six types of symptoms including no-load current mismatch, excessive vibration, reduction of average torque,

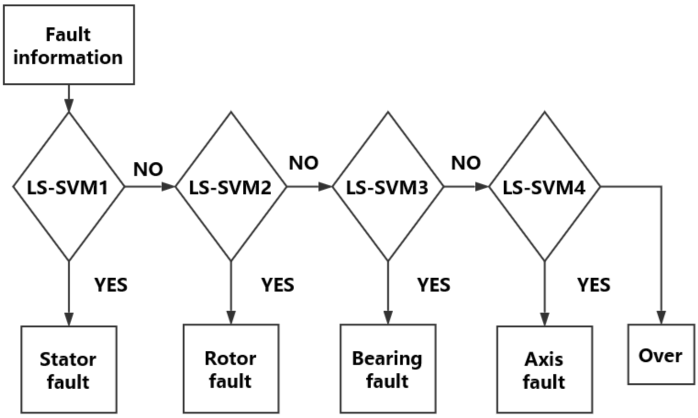

Fig. 1. Multi-fault classification based on 1-a-r SVM strategy

axle overheating and abnormal sound which can be monitored by current and vibration sensor. In order to reduce the influence caused by the difference between the measurement values and avoid the appearance of saturation, the normalized formula is as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \tag{13}$$

where $x \in [x_{\min}, x_{\max}]$ which makes the input sample data between $[0, 1]$.
(2) Finding the optimal solution by iterative method

During the iterations, scale of particle swarms is set to 25, solution space is 400 dimensions, maximum iteration number is 1000, acceleration constants φ_1 and φ_2 are defined as $\varphi_1 = \varphi_2 = 1.98$, and initial w is set to 0.92. Four LS-SVM classifiers were established and γ is set to 1000. The width parameter of radial basis function σ^2 is set to 0.125. The average error curve obtained by using standard PSO and modified PSO to solve the equation (3) in LS-SVM is shown in Figure 2. After the 100th iteration, the standard PSO algorithm error precision is 0.26, and the error precision of the modified PSO algorithm in the same number of iterations is 0.01. After 200 iterations, the error precision is improved to 0.001, which shows that the convergence rate and accuracy of modified PSO algorithm is better than that of standard PSO algorithm.
(3) Comparison of diagnosis results.

The prediction model obtained through the iterations of modified PSO is used to diagnose 400 fault samples. The result is compared with solution of standard PSO LS-SVM model. The weight coefficient w in LS-SVM model based on standard PSO is constant. The test parameters are training time, test time, accuracy and error of training set and accuracy and error of test set. Results of performance test are as shown in Table 1:

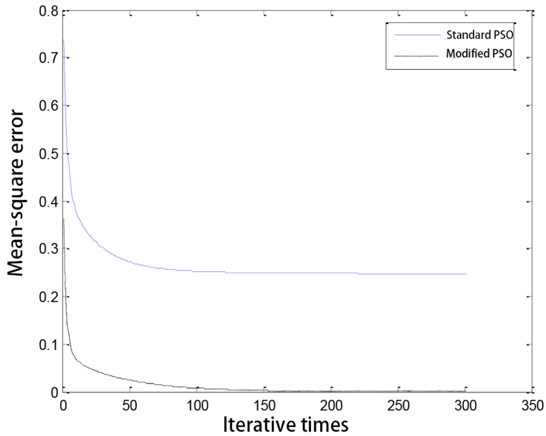

Fig. 2. Error curve of Standard PSO algorithm and modified PSO algorithm

Table 1. Comparison of algorithm performance

Algorithm	time/s		training set/%		test set/%	
	Training time	test time	accuracy	error	accuracy	error
Standard PSO's LS-SVM	0.261	0.203	85.472	2.161	85.926	2.835
Modified PSO's LS-SVM	0.160	0.136	89.461	1.417	88.012	1.923

50–400 groups training data samples and test date samples are used, and 400 groups test samples are used. With variance of sample number, training time and test time are shown in Figure 3 and Figure 4. 50–400 groups training samples of the accuracy test are also used, 400 groups test samples are used. The comparison of the accuracy change is shown in Figure 5.

The results of the performance test show that:

(1) Training and test time of multi-class LS-SVM based on modified PSO are significantly smaller than that of standard PSO LS-SVM. When dealing with relatively complex problems with real-time requirement, multi-class LS-SVM based on modified PSO has strong advantage;

(2) The accuracy of training set and test set of the multi-class LS-SVM based on modified PSO are slightly higher than that of LS-SVM based on standard PSO. The error is relatively small, indicating that the multi-class LS-SVM based on modified PSO has a better classification effect;

(3) With the increase of training samples number, the training time of the two kinds of classification algorithm increases significantly, and training time of multi-class LS-SVM based on modified PSO is significantly shorter than the LS-SVM based

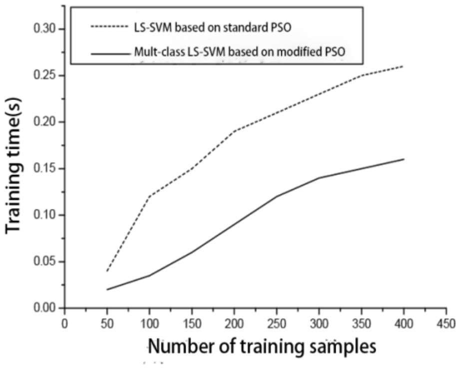

Fig. 3. Comparison curve of training time

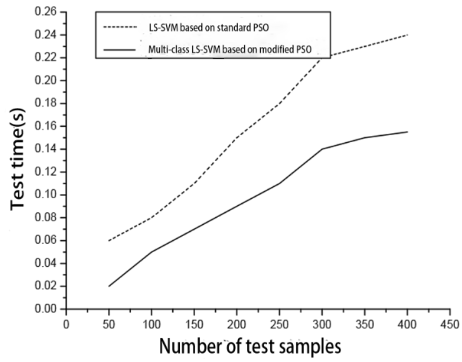

Fig. 4. Comparison curve of test time

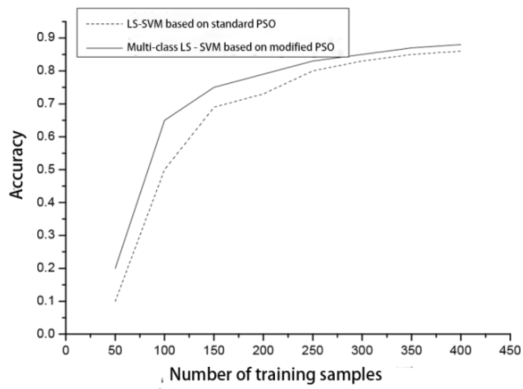

Fig. 5. Comparison curve of accuracy

on standard PSO, which shows that the multi-class LS-SVM based on modified PSO has good adaptability and fast learning process for different sample quantity, test conditions and test environment;

(4) The test of time of two algorithms both increases with the increase in quantity of test samples, while test time of multi-class LS-SVM based on modified PSO is significantly shorter than that of LS-SVM based on standard PSO, which shows that multi-class LS-SVM based on modified PSO has good real-time processing ability;

(5) Under the same conditions, The classification accuracy increases with the number of training samples, while multi-class LS-SVM based on modified PSO is slightly higher than that of LS-SVM based on standard PSO, which shows that modified PSO algorithm in the process of matrix iteration realizes higher precision, more accurate recognition.

4. Conclusion

Diagnosis of electric machine faults is very complicated and the traditional diagnosis methods have a variety of uncertainties. This paper proposed a multi-class LS-SVM based on modified PSO algorithm, which uses the LS-SVM algorithm to solve the problem such as the small samples, nonlinear, high dimensions and local minimum points. At the same time, the modified PSO algorithm is uesd to solve the problems of LS-SVM model, which can calculate high-dimension problem and improve computing speed. Based on the modified PSO, the model can always get the optimal solution and improve training speed and precision. The calculation example shows that the multi-class LS-SVM based on modified PSO algorithm is effective and reliable. The model has good practicability and generalization.

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