Fault Detection of Liquid-Propellant Rocket Engines Based on LSSVM

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Abstract. In terms of fault diagnosis of liquid-propellant rocket engine, the fault diagnosis accuracy of the traditional method is low because the characteristics of engine fault data are small sample and nonlinear variation. In order to improve the accuracy of sensor fault diagnosis and overcome the scarcity of related samples, the particle swarm optimization (PSO) with strong global searching ability is used to optimize the LS-SVM parameters, and the LSSVM optimal parameter values are obtained by iteration to improve the model fitting accuracy and generalization ability. At the same time, the traditional support vector machine and BP neural network model are used for the detection. The simulation results show that the least squares support vector machine (SVM) detection method based on particle swarm optimization has the advantages of high precision and high speed. It has certain effect and positive significance for improving the safety of liquid-propellant rocket engine test and engine failure loss.

Introduction

Aerospace technology is one of the most important achievements in the development of human science and technology in the 20th century. With the development of science and technology, more and more countries have joined the research on aerospace technology [1]. The United States, Russia, China and Europe have all launched their own manned space projects and space station construction projects, while Japan and India have also made great efforts to develop launch vehicle technology. Aerospace engineering involves many fields of technology and production. It is a concrete manifestation of a country's comprehensive national strength. The development of aerospace industry is of great significance to the comprehensive development of each country.

In recent years, with the development of artificial intelligence technology, a large number of intelligent methods such as artificial neural networks, fuzzy theory, mixing algorithms, genetic algorithms, rough set theory, etc. have been introduced into the field of fault diagnosis. The most widely used are neural networks and supporting vector machines. Support vector machine (SVM) overcomes the difficulty of determining neural network structure and converges to local minima, and solves the problems of high dimension and nonlinearity. The least squares support vector machine replaces the inductive loss function in the SVM with the quadratic loss function, and the quadratic optimization of the algorithm in the original SVM is changed to solve the linear equation, which reduces the computational complexity and has better noise immunity, and faster operation speed. However, the kernel function parameters and normalization parameters of LSSVM have a significant impact on the classification performance of LSSVM. Based on the improvement of particle swarm optimization algorithm, the structural parameters of LSSVM are optimized and optimized, so that the particles can be guaranteed in the parameter optimization process, to enhance the ability to jump out of local optimal value, to find the optimal kernel functions and regularization parameters, and then improve the classification performance of LSSVM, accurately identify whether there is fault.
Parameter Optimization of LSSVM Based on Improved Particle Swarm Optimization

The Basic Principle of LSSVM Numbers

The goal of classification problem is to solve the decision function \( y(x) = \text{sign}(f(x)) \). The function \( f(x) \) form is [2]:

\[
f(x) = \omega^T \phi(x) + b \tag{1}
\]

Where: \( \phi(\cdot) \) is the nonlinear mapping of the input space to the feature space; \( \omega \) and are the quantities to be determined. Then, construct a classification function in the mapping space as shown in equation (2):

\[
f(x) = \sum_{i=1}^{l} a_i K(x, x_i) + b
\]

Where: \( a_i \) is a Lagrangian multiplier; \( K(x, x_i) \) is a kernel function that satisfies the Mercer condition; \( b \) is the amount of deviation. The unknown can be solved by equation (3).

\[
\min_{\omega, b, e} Q(\omega, b, e) = \frac{1}{2} \| \omega \|^2 + \frac{1}{2} \sum_{i=1}^{l} e_i^2, \quad y_i(\omega^T \phi(x_i) + b) = 1 - e_i, \quad i = 1, 2, \ldots, l, \quad \text{Its Lagrangian function is}
\]

\[
L(\omega, b, e, a) = Q(\omega, b, e) - \sum_{i=1}^{l} a_i [y_i(\omega^T \phi(x_i) + b) - 1 + e_i]
\]

The KKT condition of equation (4) is:

\[
\begin{bmatrix}
I & 0 & 0 & -Z^T \\
0 & 0 & 0 & -y^T \\
0 & 0 & 0 & 0 \\
Z & y & I & -I
\end{bmatrix}
\begin{bmatrix}
\omega \\
b \\
e \\
a
\end{bmatrix}
= \begin{bmatrix}
0 \\
0 \\
0 \\
I
\end{bmatrix}
\]

Where: \( Z = [y_i \phi(x_i), y_i \phi(x_i), \ldots, y_i \phi(x_i)]^T \), \( y = [y_1, y_2, \ldots, y_l]^T \), \( I = [1, 1, \ldots, 1]^T \), \( e = [e_1, e_2, \ldots, e_l]^T \), \( a = [a_1, a_2, \ldots, a_l]^T \). Then eliminate the variables \( \omega, e \) and Mercer, and equation (5) becomes (6):

\[
\begin{bmatrix}
0 & -y^T \\
y & \Omega + \gamma^{-1}I
\end{bmatrix}
\begin{bmatrix}
b \\
a
\end{bmatrix}
= \begin{bmatrix}
0 \\
-\gamma I
\end{bmatrix}
\]

Where: \( \Omega_{ij} = y_i y_j K(x_i, x_j) \). Let \( A = \Omega + \gamma^{-1}I \), solve equation (6):

\[
b = y^T A^{-1}I, \quad a = A^{-1}(I-by)
\]

From equation (3), \( \omega = \sum_{i=1}^{l} a_i y_i \phi(x_i) \) is known, so the classification function can be (8)

\[
f(x) = \sum_{i=1}^{l} a_i y_i K(x, x_i) + b
\]

Where: \( K(x, x_i) \) is the kernel function of LSSVM. Typical kernel functions include polynomial kernel functions, RBF kernel functions, and Sigmoid kernel functions [3]. Since the RBF kernel function has better performance in the classification problem, the radial basis kernel function is used as the kernel function of LSSVM, and its expression is \( K(x, x_i) = \exp(-\|x - x_i\|^2 / (2\sigma^2)) \). The parameters to be optimized are regularization parameter \( \gamma \) and kernel function parameter \( \sigma \).
Particle Swarm Optimization

The classical particle swarm optimization algorithm can be described as: suppose the velocity and position of the particle in the D-dimensional search space are represented as \( V_i = (v_{i1}, v_{i2}, \ldots, v_{id}) \) and \( X_i = (x_{i1}, x_{i2}, \ldots, x_{id}) \) respectively. The optimal position \( p_{id} = (p_{best_1}, p_{best_2}, \ldots, p_{best_d}) \) through which each particle passes at and the optimal position \( p_{gd} = (g_{best_1}, g_{best_2}, \ldots, g_{best_d}) \) found by the group are determined by evaluating the objective function of each particle. Then update the speed and position of each particle separately as shown below.

\[
v_{id}(t+1) = \omega v_{id}(t) + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \tag{9}
\]

\[
x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{10}
\]

In the formula: \( \omega \) is the inertia weight coefficient, which is used to control the influence of the front velocity on the current velocity; the learning factors \( c_1 \) and \( c_2 \) are non-negative constants as acceleration factors, \( rand \) are random numbers between 0 and 1, and in addition, By setting the velocity ranges of \( [v_{min}, v_{max}] \) and \( [x_{min}, x_{max}] \), the particle movement can be restricted appropriately.

Improvement of Particle Algorithm

The choice of the inertia weight coefficient \( \omega \) directly affects the convergence performance of the algorithm [4]. The larger \( \omega \) has a stronger global convergence ability, while the smaller \( \omega \) has a stronger local convergence ability. Therefore, the method of correctly selecting the inertia weight should be that as the number of iterations increases, the inertia weight should be reduced continuously, so that the particle swarm algorithm has strong global convergence ability in the early stage of evolution, and has strong local convergence ability in the late evolution. In this paper, the particle swarm optimization algorithm is improved by the method of adaptive inertia weight [5,6] and the value of inertia weight \( \omega \) is shown in equation (11).

\[
\omega = (\omega_{max} - \omega_{min}) \cdot \exp(-\lambda \cdot \left(\frac{t}{T_{max}}\right)^2) + \omega_{min} \tag{11}
\]

Where, \( t \) is the current evolutionary algebra, \( T_{max} \) is the maximum evolutionary algebra, the learning factor is \( c_1=1.5, c_2=1.5, v_{min}=0.9 \). At the same time, each particle is constantly updated during the optimization process [7]. In the later iteration process, any particle will converge to the global optimal particle \( p_{gd} \), that is \( x(t) \rightarrow p_{gd} \). In order to ensure the diversity of particle swarm and the diversity of rich particle species in the late iteration process, the Euclid distance is introduced into the particle swarm optimization process to determine the distance between the particles, and the particles in the particle swarm are randomly selected according to the distance, so that the particle swarm algorithm can find the real optimal value.

Optimization of LSSVM Based on Improved Particle Swarm Optimization

LSSVM parameters \( \gamma \) and \( \sigma \) have a great influence on the prediction accuracy. The parameter space exhaustion search method is usually used to optimize the parameters of LSSVM. Its disadvantage is that it is difficult to determine a reasonable range of parameters. Therefore, this paper uses PSO to optimize the diagnostic model of LSSVM parameters. The algorithm flow is shown in Figure 1. The overall optimization steps are as follows [8,9]:

1. Sample data selection. The representative sample data of the liquid rocket engine test phase is selected, and the selected sample data is normalized.

2. Initialize various parameters of the PSO: population size, learning factor, maximum number of iterations, initial position and velocity of the particles, etc. A set of parameters, \( (\gamma, \sigma^2) \) was randomly generated as the initial position and velocity of the particle.
(3) Fitness function definition. Each particle vector is compared with the corresponding LSSVM learning sample to obtain the error of the current position value of each particle, which is regarded as the corresponding fitness value. The fault diagnosis prediction of the LSSVM is selected as the fitness function.

(4) Update the optimal particle. Comparing the fitness value of each particle’s own optimal position with the fitness value of the optimal position of the group. If it is better, the optimal position of the particle is taken as the optimal position of the group.

(5) Update particle swarm. The inertia weight is calculated according to equation (11), and the velocity and position of the particle are updated by equations (9) and (10).

(6) Initialize the particles. Arbitrarily select particles in the particle group, determine the similarity between the particles according to the Euclid distance, initialize the particles with similar similarity, and update the particles of the particle group.

(7) Termination particle swarm optimization. Check whether the optimization end condition (reach the preset maximum iteration number or preset precision), if satisfied, end the optimization and map the global optimal particle to \((\gamma, \sigma^2)\); otherwise, go to step (4) and continue a new round of search.

(8) Establish a LSSVM diagnostic model. The LSSVM is retrained with the obtained optimal parameters \((\gamma, \sigma^2)\) to establish an LSSVM fault diagnosis model, and then the samples are classified and tested.

![PSO-LSSVM modeling flow diagram.](image)

**Simulation Experiment and Result Analysis**

Since the training samples have a great influence on the performance of the model, it is necessary to select the test data that covers the most abundant information as the training sample. By analyzing and comparing the existing historical test data, 320 sets of data in the test data between 0~2s are randomly selected for simulation experiment verification, 90% of the data is selected as the model training sample, and the remaining data is used as the test sample set. Normalization of the data is conducive to improve the learning speed, and the relationship between the data is not weakened, the time series formed by these data generally have a strong nonlinearity.

The PSO-LSSVM predictive model is modeled using the steps in Section 2 of this paper. The obtained least squares support vector machine parameters are: \(\gamma = 3871.4333\), \(\sigma^2 = 0.63598\). The optimal fitness curve in the improved particle swarm optimization algorithm is shown in Figure 2.
Using the selected sample data, the detection data of PSO-LSSVM model, BP neural network prediction model and traditional support vector machine (SVM) prediction model are predicted respectively. The prediction results are shown in Figure 3, Figure 4 and Figure 5, respectively.

Figure 3. PSO-LSSVM liquid-propellant rocket engine fault prediction results.

Figure 4. SVM liquid-propellant rocket engine fault prediction results.
The estimated square root and predicted time of liquid-propellant rocket engine by the PSO-LSSVM optimization model SVM and BP models are shown in table 1. The predicted time of PSO-LSSVM optimization model, SVM model and BP model for fault detection sample of liquid-propellant rocket engine is respectively 17 s, 21 s and 12 s.

Table 1. The square mean root and the time taken for the prediction of LRE.

<table>
<thead>
<tr>
<th>Model type</th>
<th>PSO-LSSVM</th>
<th>SVM</th>
<th>BP neural network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Root mean square</td>
<td>0.0098344</td>
<td>0.01002343</td>
<td>0.01123214</td>
</tr>
<tr>
<td>Prediction time</td>
<td>17s</td>
<td>21s</td>
<td>12s</td>
</tr>
</tbody>
</table>

The simulation results show that compared with the SVM model, the PSO-LSSVM optimization model has the advantages of fast testing speed and high precision. Compared with the BP model, the prediction time of the PSO-LSSVM optimization model is slower than that of the BP model. But the accuracy of the prediction is more accurate.

Conclusion

This paper contains less samples of the liquid-propellant rocket engine in the test phrase, and the accuracy of fault detection is low. Combining the particle swarm optimization algorithm with the LSSVM method, a liquid-propellant rocket engine fault detection model based on PSO-LSSVM is constructed. At the same time, the PSO-LSSVM optimization model is more accurate than the SVM model and the BP neural network model. Therefore, the PSO-LSSVM optimization model is more effective in liquid-propellant rocket engine fault detection.

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