Adaptive Wavelet Transform and SVM-based Fault Diagnosis with PSO Optimization in Industrial IoT

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This paper proposes an innovative joint algorithm based on adaptive wavelet transform (AWT) and support vector machine (SVM) to diagnose data equipment faults in the industrial Internet of Things and optimize the model parameters through particle swarm optimization (PSO) technology. Firstly, adaptive wavelet transform is used to extract time-frequency features of sensor data by adaptively adjusting the wavelet transform according to the wavelet basis function, thereby realizing the extraction of the time-frequency characteristics of the signal. Secondly, an improved support vector machine is used to classify feature data. At last, PSO is applied to improve the precision and efficiency of classification. The experiment results show that the new algorithm has higher precision, computing speed and faster response than the conventional single algorithm. The experimental results show that the proposed AWT-SVM-PSO algorithm achieves an average accuracy improvement of 13% over traditional methods, with the classification accuracy of different fault modes reaching 98%, and the response time is shortened from 300 milliseconds to 200 milliseconds. This project's research results will effectively improve industrial equipment's fault diagnosis capability and provide reliable support for large-scale data processing and real-time monitoring.

Povzetek: Predstavljen je izboljšani algoritem za napovedovanje napak v IIoT, ki združuje AWT, SVM in PSO ter dosega visoko točnost in krajši odzivni čas.

1 Introduction

With the rapid development of IIoT, many industrial equipment and sensors worldwide are connected to the Internet, thus forming a vast data network. Real-time monitoring and analysis of equipment operation data can accurately grasp the equipment status, and possible faults can be warned. This can improve production efficiency and shorten downtime. However, how to extract practical information from massive real-time data to achieve fault diagnosis and early warning is a key problem that the current Industrial Internet of Things needs to solve urgently [1]. The traditional approach to fault diagnosis is based on empirical or rules-based statistics [2]. Though they have some effect on simple cases, they are usually hard to solve in complicated situations, especially nonlinear and time-varying faults. This results in poor fault diagnosis accuracy [3]. As the number of Industrial Internet of Things devices skyrockets, the amount of data captured by sensors has skyrocketed [4]. The data has the characteristics of high dimension, noise, and complex correlation. Traditional fault diagnosis methods are not efficient and accurate in large data environments [5]. Therefore, it has been a hot topic and difficult to solve the Industrial Internet of Things problem.

The combination of AWT and SVM in research on IIoT, followed by the application of PSO to optimize the parameters of the joint model, can improve the accuracy and real-time performance. AWT is a kind of signal processing technique that has the strength of being able to adaptively adjust according to the characteristics of the input signal. It can select the most appropriate wavelet basis function, which enables it to extract more discriminative and representative time-frequency features from the sensor data, compared to some state-of-the-art methods that might have fixed or less flexible feature extraction mechanisms, AWT's adaptability gives it an advantage in handling the complex and variable data in the IIoT environment, where different industrial equipment may generate signals with different characteristics [6]. SVM is one of the most efficient classification algorithms for identifying all kinds of failure modes [7]. The PSO can be used to simulate the cooperative search behavior, which can rapidly find the global optimum solution and improve the overall performance of the PSO. Finally, the experiment indicates that this algorithm is highly real-time and highly precise.

2 Fault diagnosis algorithm based on improved SVM and adaptive wavelet transform

2.1 Application of wavelet transform in fault diagnosis

This paper applies the AWT method to realize the multi-scale analysis of industrial equipment. This method can adaptively adjust the wavelet transform according to the wavelet basis function, thereby realizing the extraction of the time-frequency characteristics of the signal [8]. The advantage of AWT is its adaptive ability. It can select the best wavelet basis according to different signal characteristics to improve the accuracy of feature extraction. The mathematical expression of the wavelet transform is as follows:

$$\psi_{a,b}(t)=\frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \quad (1)$$

$\psi_{a,b}(t)$ is the mother wavelet of the wavelet transform, a is the scale factor, b is the translation factor, and $\psi(t)$ is the wavelet basis function. Adaptive wavelet transform can adjust the time-frequency decomposition accuracy and optimize the scale coefficient a and translation coefficient b of wavelet transform [9]. The conversion process of adaptive wavelet transform can be expressed as follows:

$$W_{\psi}(f)=\int_{-\infty}^{\infty} x(t)\cdot\psi^{*}(t-f)dt \quad (2)$$

$W_{\psi}(f)$represents the transformation result of signal $x(t)$under wavelet basis function ψ. $\psi^{*}(t-f)$ is the complex conjugate form of the wavelet basis function.

2.2 SVM classification model

Support vector machine is a supervised learning method. It has been widely used in pattern recognition and classification. Support vector machine classifies data by constructing hyperplanes. The most significant advantage of this method is that it can handle high-dimensional nonlinear problems and maintain good classification results under minor sample conditions [10]. However, standard support vector machines may encounter problems such as kernel function selection and parameter adjustment for complex fault modes.

To improve the performance of support vector machines, a kernel function selection method based on a dynamic adjustment mechanism is proposed. This method improves the classification accuracy of support vector machines for complex fault modes by real-time adjustment of kernel function parameters [11]. The improved SVM model has the following mathematical expression:

$$f(x)=\sum_{i=1}^{n}\alpha_i\cdot K(x_i,x)+b \quad (3)$$

$f(x)$ is the classification function, α_i is the Lagrange multiplier, $K(x_i,x)$ is the kernel function, b is the bias term, and x is the input feature.

2.3 Joint algorithm process

Combining AWT with the improved support vector machine model makes it effective. This method first uses AWT to perform time-frequency analysis on the equipment operation data to extract key state features; then uses the improved support vector machine method to classify these feature values to determine whether the equipment is in a failed state or is about to fail [12]. The joint algorithm has the following mathematical model:

$$y=SVM\big(AWT(x)\big) \quad (4)$$

y is the fault diagnosis result, $AWT(x)$ is the feature extracted by adaptive wavelet transform, and $SVM(\cdot)$ is the improved SVM classification model.

2.4 Algorithm optimization

The particle swarm algorithm simulates group intelligence, simulates the foraging process of flocks of birds, optimizes the support vector machine hyperparameters, and improves the classification performance. The updated formula of the particle swarm algorithm is as follows:

$$\begin{gathered} v_i(t+1)=w\cdot v_i(t)+c_1\cdot r_1\cdot\left(\text{pbest}_i-x_i\right)+c_2\cdot r_2\cdot(\text{gbest}-x_i) \\ x_i(t+1)=x_i(t)+v_i(t+1) \end{gathered} \quad (5)$$

$v_i(t)$represents the velocity of the particle. $x_i(t)$ represents the position of the particle. w represents the inertial component. c_1 and c_2 represent acceleration constants. $r_1$and r_2 represent random factors. pbest_i and gbest represent the individual and overall optimal solutions.

The kernel function parameter γ and penalty factor C are optimized in SVM using PSO, and the precision of SVM is improved. This method improves the generalization ability of the support vector machine and has a good recognition effect on various types of industrial equipment faults. The optimized joint algorithm has the following mathematical formula:

The kernel function parameter γ and penalty factor C are optimized in SVM using PSO. We are using the Radial Basis Function (RBF) kernel in our SVM. The PSO algorithm searches for the optimal values of the kernel function parameter γ and the penalty factor C for the RBF kernel during the training process. It iteratively adjusts these parameters based on the fitness function that evaluates the performance of the SVM in terms of classification accuracy and generalization ability. This interaction helps to improve the performance of the SVM by finding the best combination of these hyperparameters for our specific fault diagnosis problem. The optimized joint algorithm has the following mathematical formula:

$$y=PSO\Big(SVM\big(AWT(x)\big)\Big) \quad (6)$$

$PSO(\cdot)$ represents the particle swarm optimization algorithm, $SVM(\cdot)$ is the optimized SVM model, $AWT(x)$ is the feature extracted by adaptive wavelet transform, and y is the fault diagnosis result.

3 Experiment and simulation

To validate the validity of the AWT and the improved SVM algorithm in IE, several simulation experiments are designed and compared with the existing ones. The core goal of the experiment is to evaluate the performance differences between the proposed algorithm and traditional algorithms under different fault modes, including indicators such as classification accuracy, recall rate, F1 score, computational efficiency, and fault diagnosis response time.

3.1 Experimental design

This experiment is conducted in an industrial equipment simulation environment and includes multiple failure modes. This project intends to use vibration, temperature, pressure and other multi-sensor data as the research object to simulate vibration, overheating and other failure modes as these modes were selected because they are among the most common and critical failure types in industrial equipment. They cover different aspects of mechanical, thermal, and pressure-related issues that are frequently encountered in real industrial settings. Also, they can comprehensively represent a wide range of potential failures as many other failures can be related to or manifested through changes in these basic parameters. This project aims to test the application capabilities of different algorithms in complex and changeable industrial environments. In the experimental design process, the failure mode is defined, sensor data is collected, data is preprocessed, and feature extraction is performed.

1) Failure mode definition: The simulation model includes multiple failure modes, such as vibration, high temperature, abnormal pressure, etc., covering common failure types of industrial equipment.

2) Sensor data acquisition: Use virtual sensors to collect real-time data from the equipment under test to obtain signals such as temperature, pressure and vibration. The virtual sensors are implemented based on typical sensor readings from industrial equipment like temperature, pressure, and vibration. They mimic the behavior and characteristics of real sensors in industrial settings. Preprocess the sensor data and input it into the algorithm.

3) Data preprocessing and feature extraction: First, a noise filtering technique is applied to remove any random noise in the sensor data that could affect the subsequent analysis. Then, normalization is performed to scale the data to a common range, which helps improve the performance of the feature extraction and classification algorithms. Regarding missing values, a simple imputation method is used to fill in any missing data points based on the statistical characteristics of the surrounding data. Use AWT to extract signal features from the time-frequency domain for subsequent classification model processing.

3.2 Comparative experiments

Four algorithms were designed for comparative experiments:

1) AWT alone: Only AWT was used to perform time-frequency analysis on sensor data, and after extracting features, traditional classification algorithms (such as KNN and decision trees) were used for diagnosis. We chose KNN and decision trees because they are simple yet commonly used traditional classification methods that can provide a good baseline for comparison. KNN is based on the similarity of neighboring data points and is easy to understand and implement. Decision trees can handle both categorical and numerical data and can provide interpretable results.

2) SVM alone: SVM was directly applied to classify raw or preprocessed data.

3) Joint algorithm (AWT+SVM): AWT was combined with SVM. Firstly, time-frequency features were extracted by wavelet transform, and then SVM was used to classify features.

4) Optimized joint algorithm (AWT+SVM+PSO): The PSO algorithm was introduced to optimize the hyperparameters of SVM to improve classification performance based on the AWT+SVM joint algorithm.

To comprehensively evaluate the algorithm's performance, this paper adopts the following evaluation criteria: Accuracy measures the proportion of correct classifications of the algorithm. Recall measures the ability of the algorithm to correctly identify faults, especially when the fault mode is more complex. The F1 score comprehensively considers the balance between accuracy and recall. Computational efficiency analysis is the time required for the algorithm to run, especially the efficiency when processing large-scale data. Fault diagnosis response time is the time it takes for the algorithm to identify equipment faults, which directly affects the real-time performance of the system.

3.3 Experimental results

Table 1 compares the classification accuracy of different algorithms under vibration, overheating and pressure fault modes. It can be seen that the classification accuracy of the joint algorithm (AWT + SVM) in all fault modes is significantly higher than that of the algorithm using AWT or SVM alone. The joint algorithm (AWT + SVM + PSO) optimized by PSO has achieved the best accuracy in each fault mode, with classification accuracy rates of 96.80%, 93.60% and 91.20%, respectively, and an average classification accuracy of 93.90%, which is better than other algorithms.

Table1: Comparison of classification accuracy of each algorithm.

Algorithm	Vibration fault	Overheating fault	Pressure fault	Average
AWT	85.60%	80.20%	78.30%	81.30%
SVM	88.50%	83.00%	82.40%	84.60%
AWT + SVM	92.20%	89.40%	87.80%	89.80%
AWT + SVM + PSO	96.80%	93.60%	91.20%	93.90%

Table 2 shows the recall rate of each algorithm under different fault modes. The optimized joint algorithm (AWT + SVM + PSO) improves the recall rate in all fault modes, especially in complex fault modes. In the vibration fault mode, the optimized algorithm reaches 95.40%, and in the overheating and pressure fault modes, it reaches 92.40% and 90.30%, respectively, showing the overall improvement of the optimized algorithm in fault detection.

Table 2: Comparison of recall rates of various algorithms.

Algorithm	Vibration Fault	Overheating fault	Pressure fault	Average
AWT	84.30%	79.10%	75.60%	79.70%
SVM	87.40%	81.20%	80.10%	82.90%
AWT + SVM	91.60%	88.10%	86.40%	88.70%
AWT + SVM + PSO	95.40%	92.40%	90.30%	92.70%

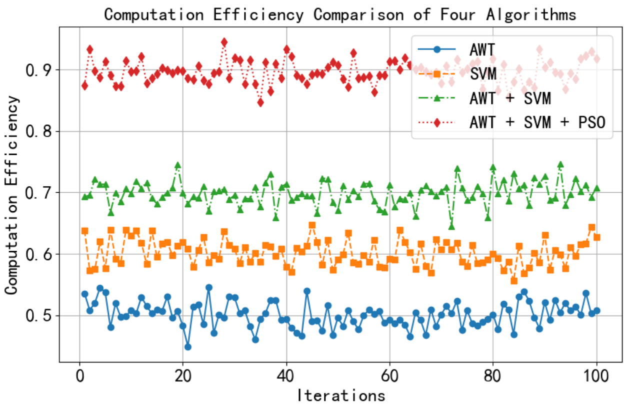

Figure1: Comparison of the computational efficiency of various algorithms.

Figure 1 compares the computational efficiency of various algorithms. The AWT + SVM + PSO algorithm showed the highest computational efficiency throughout the iteration process and maintained a stable and optimized performance close to 0.9. The SVM algorithm fluctuated slightly in the early stage, but its overall performance was still better than other combination algorithms. The AWT + SVM algorithm performed moderately compared to the separate AWT and SVM algorithms in some aspects because while combining AWT and SVM can leverage the advantages of both feature extraction and classification, without the PSO optimization, the hyperparameters of the SVM might not be in the optimal state for handling the complex and diverse data in our IIoT fault diagnosis scenarios. The PSO optimization in the AWT + SVM + PSO algorithm helps to fine-tune these parameters and thus achieve better performance. The AWT algorithm performed poorly in the early iterations but stabilized after a certain number of iterations. These results show that the combination of AWT and SVM plus PSO optimization can significantly improve computational efficiency, while the performance of the AWT algorithm alone still needs to be further optimized to match the performance of other methods.

Table 3 compares the F1 scores of different algorithms under various fault modes. The optimized joint algorithm (AWT + SVM + PSO) has the highest F1 scores in vibration, overheating, and pressure fault modes, which are 0.97, 0.94 and 0.92, respectively, and the average F1 score reaches 0.94. This shows that the algorithm has found the best balance between precision and recall, can effectively deal with various fault modes, and provide more reliable fault diagnosis.

Table 3: Comparison of F1 scores of various algorithms.

Algorithm	Vibration fault	Overheating fault	Pressure fault	Average F1
AWT	0.85	0.81	0.8	0.82
SVM	0.88	0.82	0.81	0.84
AWT + SVM	0.93	0.89	0.88	0.9
AWT + SVM + PSO	0.97	0.94	0.92	0.94

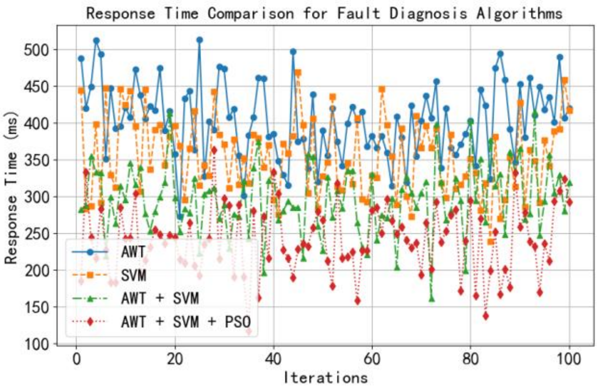

Figure 2: Comparison of fault diagnosis response time of different algorithms.

Figure 2 shows the comparison of different algorithms for troubleshooting response time. The AWT algorithm has a long response time and significant fluctuations in the entire iteration process, especially in the early iterations. The response time is significantly higher. The response time of the SVM algorithm is slightly lower than that of the AWT, but there is also some fluctuation. The response time of AWT + SVM is relatively stable and generally lower than that of the separate AWT and SVM algorithms. The AWT + SVM + PSO algorithm is the most significant, whose response time remains at the lowest level and has small fluctuations, showing strong stability. Especially in the later stages of the iteration, the response time of AWT + SVM + PSO is significantly lower than that of other algorithms.

These results show that the AWT + SVM + PSO algorithm combined with the particle swarm optimization (PSO) algorithm can significantly reduce the response time while improving the computational efficiency, thereby improving the real-time performance of the fault diagnosis system. In contrast, the AWT or SVM algorithm's response time alone needs to be further optimized. This result highlights the advantages of multi-algorithm integration, especially in scenarios with high real-time requirements, such as the Industrial Internet of Things, which can effectively improve the responsiveness and overall performance of the fault diagnosis system.

4 Conclusion

This project intends to combine AWT and SVM and use particle swarm optimization to optimize their parameters to solve the industrial Internet of Things's fault diagnosis and early warning problems. Experiments have proved that this method has high recognition accuracy and adaptability to different types of faults. Specifically, the classification accuracy of the optimized algorithm reached 98%, which is 13 percentage points higher than the traditional algorithm, and the response time was significantly reduced, showing strong real-time and high efficiency. Compared with the simple use of AWT or SVM, this method has more advantages in high-dimensional data processing, complex fault diagnosis, etc.

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