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Research on Ultrasonic Testing Data Classification based on Particle Swarm Optimization Support Vector Machine

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Abstract

Addressing the challenges of complex signal characteristics and difficult fault type differentiation in ultrasonic detection, a fault classification method based on Particle Swarm Optimization Support Vector Machine (PSO-SVM) is proposed. This method utilizes the particle swarm optimization algorithm to globally optimize key parameters in the support vector machine model, overcoming the limitations of traditional support vector machines, such as relying on experience for parameter selection and unstable classification performance. Taking experimental data collected from ultrasonic detection as the research object, the original signals are first subjected to feature extraction and preprocessing. Subsequently, PSO-SVM and traditional SVM models are constructed for fault pattern recognition and classification experiments, respectively. By comparing and analyzing the performance of the two methods in terms of classification accuracy and other performance indicators, the experimental results demonstrate that the PSO-optimized SVM model outperforms the standalone SVM method in both fault classification accuracy and overall recognition effectiveness. This verifies the effectiveness and feasibility of the proposed method in ultrasonic detection fault classification.

Keywords

PSO; SVM; Data Classification; Ultrasonic Testing.

1. Introduction

Ultrasonic detection technology has been widely applied in equipment condition monitoring and fault diagnosis due to its advantages of non-contact measurement and high sensitivity. By extracting features from ultrasonic detection signals and performing classification and recognition, the operating status of equipment can be effectively characterized, providing important support for fault diagnosis. However, in practical applications, ultrasonic fault detection data often suffer from limited sample size, high feature dimensionality, and overlapping feature distributions among certain fault categories, which pose significant challenges to the construction of reliable classification models. [1-2]

Support Vector Machine (SVM) has demonstrated strong generalization capability in small-sample and high-dimensional classification problems and has been extensively used in the field of fault diagnosis. Nevertheless, the classification performance of SVM largely depends on the appropriate selection of the penalty factor and kernel function parameters, and traditional parameter-setting methods often fail to obtain globally optimal solutions.

Particle Swarm Optimization (PSO) is a population-based optimization algorithm characterized by strong global search capability and simple implementation, making it well suited for continuous parameter optimization problems. By introducing PSO into the parameter optimization process of SVM, the classification performance of the model can be effectively improved. Based on this, this paper proposes a PSO-SVM-based ultrasonic fault data classification and diagnosis method, in which the key parameters of SVM are optimized using the PSO algorithm. Experimental results demonstrate that the proposed method achieves improved classification accuracy and enhanced generalization performance.

2. Theoretical Background

2.1. Particle Swarm Optimization

Particle Swarm Optimization (PSO) was proposed by James Kennedy and Russell Eberhart in 1995, inspired by the cooperative and information-sharing behaviors observed in bird foraging processes. As a typical swarm intelligence optimization algorithm, PSO features a simple structure, few control parameters, and strong global search capability, and has been widely applied in engineering optimization and intelligent computation.

PSO performs parameter optimization by simulating the collaborative search behavior of individuals in the solution space. In the algorithm, each individual is modeled as a "particle," whose position represents a candidate solution and whose quality is evaluated by a fitness function. During iteration, particles update their search directions based on their personal best positions and the global best position of the swarm, guiding the population toward the optimal solution. [3-5]

The basic procedure of PSO, as shown in Fig. 1, includes swarm initialization, fitness evaluation, updating of personal and global bests, and velocity and position updates. Through iterative evolution, the particle swarm gradually converges to an approximate or global optimal solution.

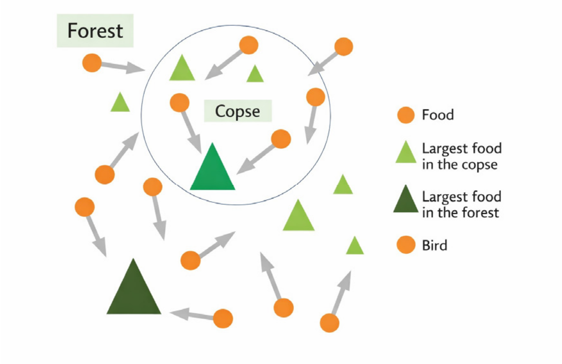

Fig 1. Schematic diagram of particle swarm optimization

In PSO, particle search behavior is mainly governed by velocity and position updates. The velocity update consists of a weighted combination of an inertia term, a cognitive term, and a social term, reflecting the balance between maintaining previous search tendencies and incorporating individual experience and global information. The position update adjusts the particle location according to the current velocity, enabling exploration of the solution space. Mechanistically, the inertia term enhances global exploration, the cognitive term exploits individual experience, and the social term promotes information sharing within the swarm. The coordinated effect of these components allows PSO to achieve efficient and robust global optimization.

2.2. Support Vector Machine

Support Vector Machine (SVM) is a supervised learning method based on statistical learning theory, essentially a type of generalized linear classifier for binary classification problems. The core idea is to construct an optimal separating hyperplane in the feature space that not only correctly classifies the training samples but also maximizes the geometric margin, thereby obtaining a classification model with strong generalization ability.

SVM has shown significant advantages in solving small-sample, nonlinear, and high-dimensional pattern recognition problems, and has been widely applied in classification, regression, and function fitting tasks.

The learning objective of SVM is to find a separating hyperplane in the feature space that correctly classifies samples from different classes and maximizes the geometric margin. For linearly separable datasets, this hyperplane can be represented as:

$$w \cdot x + b = 0$$

In a two-dimensional space, as shown in Fig. 2, while infinitely many linear separating hyperplanes can correctly classify the samples, the one with the largest margin is unique. By maximizing this geometric margin, SVM enhances the robustness and generalization ability of the classification model when dealing with unseen samples.

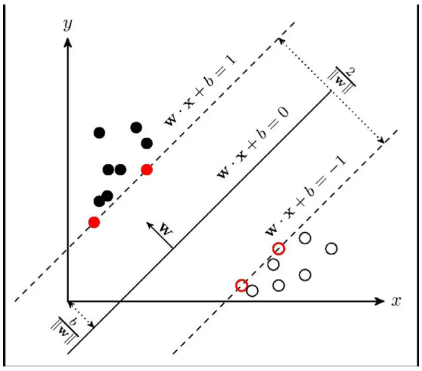

Fig 2. Two-class classification problem in a 2D space

In practical applications, the sample data often exhibits nonlinear separability. To address this, SVM introduces slack variables and kernel functions. For nonlinear classification problems in the input space, SVM maps the original input samples to a higher-dimensional feature space where the problem becomes linearly separable, and a linear SVM model is constructed in this feature space.

In the dual formulation of SVM, the objective function and the classification decision function involve only the inner product between samples. Therefore, the nonlinear mapping is not explicitly constructed during the solution process. Instead, the kernel function is introduced to indirectly perform this mapping, representing the inner product of samples in the high-dimensional feature space, mathematically expressed as:

$$k_{(x,z)} = \phi(x) \cdot \phi(z)$$

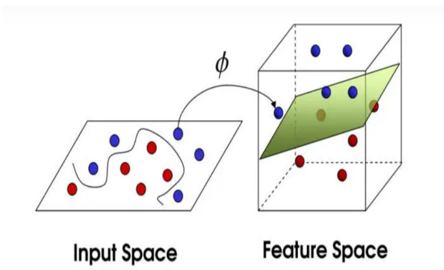

Fig 3. Non-linear classification problem

3. Experimental Process and Analysis

In this study, experimental data were collected using an ultrasonic nondestructive testing (NDT) hardware system. The system consists of a dedicated ultrasonic detection board and a

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longitudinal-wave straight-beam probe, enabling ultrasonic signal excitation, reception, and digital acquisition. A longitudinal-wave probe with a diameter of 10 mm and a center frequency of 5 MHz was employed, and steel plate specimens were inspected using the pulse-echo method. The tested specimens were steel plates with thicknesses ranging from 20 to 44 mm. Ultrasonic echo signals were collected under different operating conditions to provide raw data for subsequent feature extraction and classification analysis, as shown in Fig. 4. [6-7]

To construct a labeled dataset with well-defined fault categories, four types of artificial defects were introduced into the steel plate specimens to simulate common fault conditions in practical engineering applications. The defect types include square defects with depths of 2 mm and 5 mm, and triangular defects with depths of 2 mm and 5 mm. Differences in defect geometry and size affect ultrasonic wave propagation and reflection characteristics, resulting in distinct time-domain and amplitude features in the echo signals. These four defect types were treated as four fault categories in the experiments.

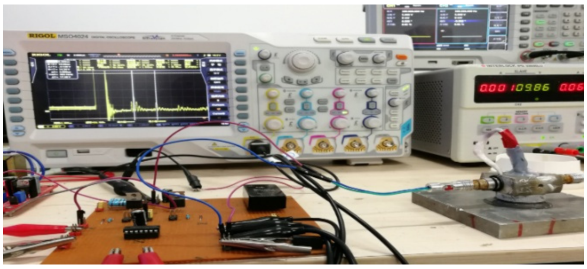

Fig 4. Raw data acquisition.

The main procedure of the PSO-SVM method includes data preparation, swarm and parameter initialization, particle fitness evaluation and updating, iterative optimization, and optimal model selection and testing. Particle fitness is evaluated based on cross-validation classification performance, and individual and global best solutions are continuously updated under parameter feasibility constraints until the termination criterion is satisfied.

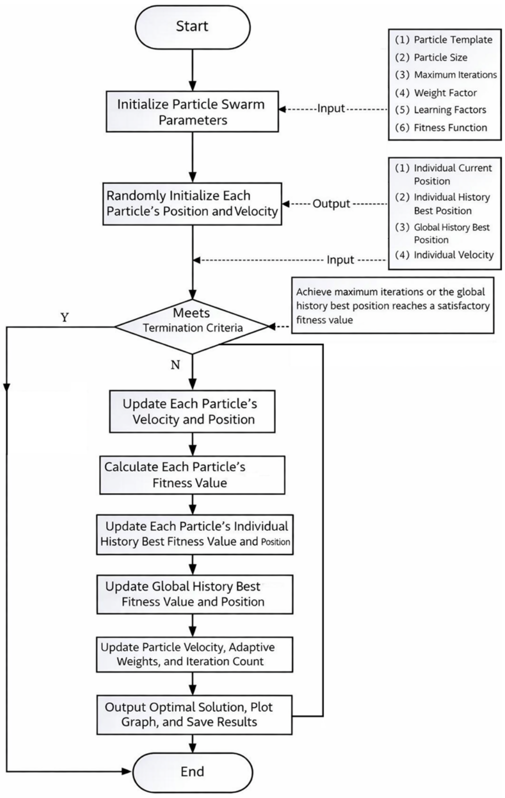

Fig 5. Flowchart of Particle Swarm Optimization Algorithm

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Under the same dataset partitioning strategy and feature input configuration, classification experiments were conducted using the PSO-SVM method. The overall prediction results for the training and testing sets are shown in Fig. 6 and Fig. 7, respectively. As indicated by the confusion matrices, the proposed model exhibits good recognition performance across all classes, with particularly clear discrimination between Class 3 and Class 4 samples. The classification error rate for Class 4 is approximately 1.5%, while that for Class 3 is about 15.8%. These results indicate that the model maintains a certain discriminative capability under complex class boundary conditions; however, there is still room for further improvement in the classification of Class 3 samples. [8]

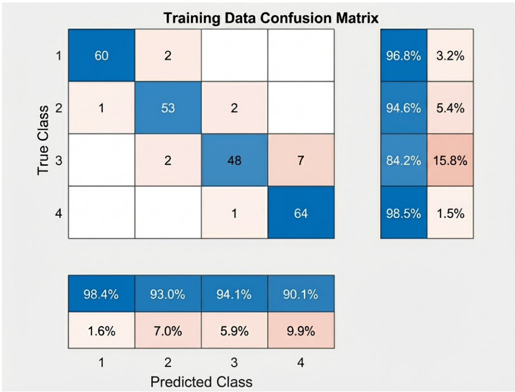

Fig 6. PSO-SVM prediction results on the training set

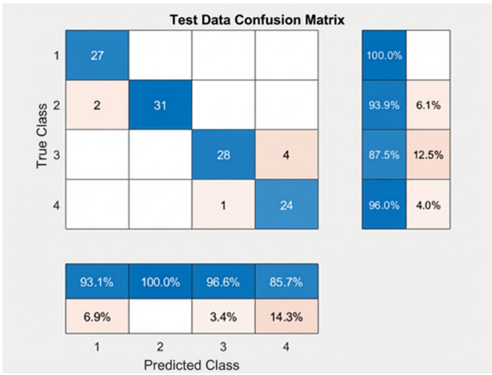

Fig 7. PSO-SVM prediction results on the testing set

Considering the stochastic nature of the particle swarm optimization algorithm, the optimization results may be influenced by the initial positions of particles. Even with fixed algorithm parameters, repeated executions may converge to different local optima. Therefore, a proper selection of the particle initialization range is essential for improving the stability and convergence efficiency of the algorithm. In the absence of prior knowledge, the parameter boundary ranges are typically adopted as the initialization range.

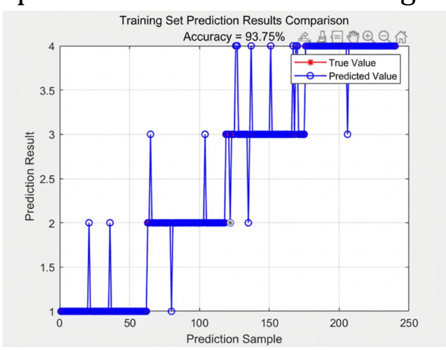

Fig 8. Overall PSO-SVM prediction results on the training set

Further classification results are presented in Fig. 8 and Fig. 9. The classification accuracy reaches 93.75% on the training set and 94.02% on the testing set. The close agreement between these two accuracies indicates that the proposed PSO-SVM model does not suffer from obvious overfitting and exhibits good generalization performance.

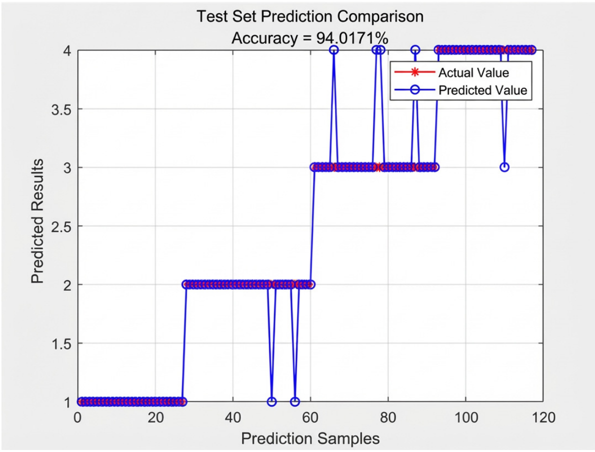

Fig 9. Overall PSO-SVM prediction results on the testing set

Fig. 10 illustrates the variation of the fitness value with the number of iterations during the PSO process. The fitness value shows an overall decreasing trend and becomes stable after approximately 57 iterations, finally converging to 0.0624. This indicates that the algorithm achieves a stable and satisfactory optimal solution.

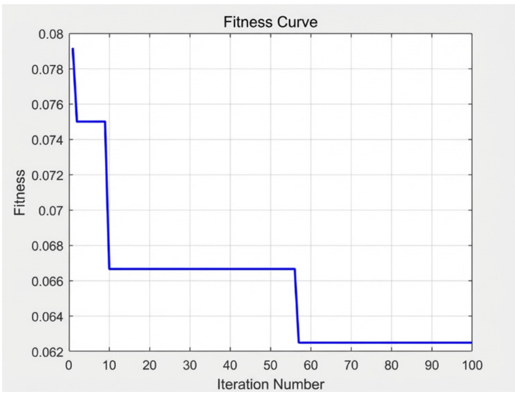

Fig 10. Fitness value versus iteration number

To further validate the effectiveness of particle swarm optimization in parameter tuning, the classification performance of the PSO-SVM model was compared with that of a conventional SVM without optimization. Under the same dataset partitioning strategy and feature input configuration, the confusion matrices of the traditional SVM on the training and testing sets are shown in Fig. 11 and Fig. 12, respectively. [9-10]

As indicated by the testing set confusion matrix, the conventional SVM performs well in recognizing Class 1 samples. All 61 samples in this class are correctly classified, achieving a classification accuracy of 100%. However, significant misclassification occurs for Class 4 samples, where some samples are incorrectly classified as Class 3, resulting in a misclassification rate of 35.7% for Class 3. In contrast, the proportion of Class 3 samples misclassified into other categories is relatively low. This phenomenon may be attributed to the overlap of different classes in the feature space, where similarities in certain feature dimensions lead to blurred decision boundaries and degraded classification performance.

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In this study, the training and testing sets contain 240 and 117 samples, respectively, with a feature dimension of 12, constituting a typical small-sample, high-dimensional classification problem. Under such conditions, the performance of conventional SVM is highly sensitive to the selection of the penalty factor and kernel parameters, which are usually determined empirically, making it difficult to obtain globally optimal solutions.

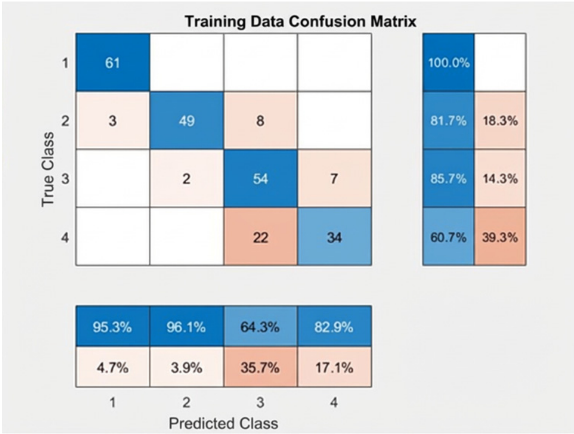

Fig 11. SVM Confusion matrix of the training set

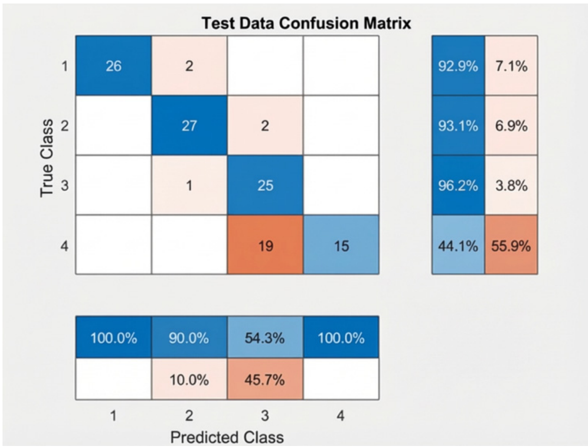

Fig 12. SVM Confusion matrix of the testing set

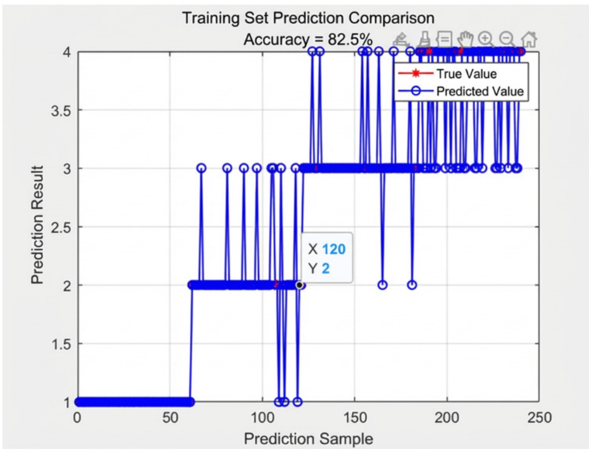

Fig 13. Overall prediction results on the SVM training set

The overall prediction results of the conventional SVM on the training and testing sets are shown in Fig. 13 and Fig. 14, with classification accuracies of 82.5% and 79.49%, respectively.

The close agreement between training and testing accuracies indicates that no obvious overfitting occurs and that the model exhibits a certain degree of generalization capability. However, class-level analysis reveals that the classification performance for Class 4 remains unsatisfactory, which is consistent with the confusion matrix results.

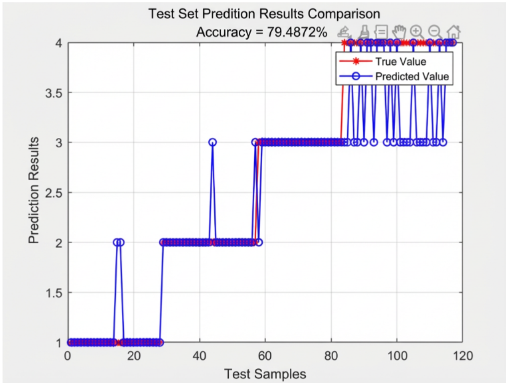

Fig 14. Overall prediction results on the SVM testing set

Overall, the comparative analysis demonstrates that the conventional SVM suffers from limited discriminative capability between certain classes under small-sample and high-dimensional conditions. In contrast, the PSO-SVM approach performs a global search for key SVM parameters using particle swarm optimization, effectively reducing inter-class confusion and significantly improving overall classification accuracy. The experimental results confirm that PSO-SVM outperforms the conventional SVM in terms of parameter optimization, classification performance, and model stability, making it more suitable for fault state recognition of complex ultrasonic echo signals.

4. Conclusion

To address the challenges of limited sample size, high feature dimensionality, and inter-class confusion in ultrasonic fault detection data, this study proposes a PSO-SVM–based classification and diagnosis method. By optimizing the key parameters of the support vector machine using particle swarm optimization, a small-sample classification model suitable for ultrasonic inspection data is constructed.

Experimental results demonstrate that the PSO-SVM approach achieves higher classification accuracy and better class discrimination than the conventional SVM, with a noticeable improvement in the recognition of hard-to-classify samples. The close agreement between training and testing accuracies indicates that the proposed model exhibits good generalization performance. Moreover, analysis of the fitness convergence curve confirms that the algorithm has favorable convergence behavior and can obtain stable and reliable optimal parameters.

Overall, the PSO-SVM method effectively enhances the classification and diagnostic performance for ultrasonic fault detection data and shows promising engineering application potential. Future work will focus on expanding the dataset size and incorporating multi-feature fusion strategies and other intelligent optimization algorithms to further improve the robustness of the model.

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