Diagnosis of ball-bearing faults using support vector machine based on the artificial fish-swarm algorithm

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Abstract
Ball bearings are important parts of all modern rotating machines. Their function is to reduce friction, support rotating shafts and spindles, and bear loads. Bearing damage can result in abnormal vibrations, cause machine malfunction, and even be dangerous. In this study, analysis of four different ball-bearing conditions was carried out: normal bearings and bearings with inner ring, rolling body, and outer ring malfunction. This was based on electromechanical vibration signals produced on a fault diagnosis simulation platform. The objective was to use a series of signal processing analytical methods to build a set of identification models used to forecast malfunction. Wavelet packet transform technology was first used to process the vibration signal. The signals were pre-processed and analyzed before eigenvalue calculation was done to analyze the signal changes which allowed determination of the nature of the bearing malfunction to be made. The extracted eigenvalues and ball-bearing status categories were input to the support vector machine for model training and testing. Finally, the constructed model parameters were integrated with particle swarm optimization, and the artificial fish-swarm algorithm was used to obtain the optimal parameters for the classifier, and this improved the accuracy of malfunction classification.

Keywords
Artificial fish-swarm, ball bearing, particle swarm optimization, support vector machine

Introduction
As modern technology continues to improve, the production standards of industries all around the world have improved significantly. Production equipment development is moving toward being bigger, more automated, more precise, and smarter. Machine malfunction can be caused by many different unavoidable incidents and this can result in financial loss. There is a distinct commercial advantage in being able to accurately determine operating status and to diagnose malfunction in crucial machine parts, in this case ball bearings, and to discover abnormality and its location, as well as its cause.

The development of ball-bearing fault diagnostic technology began in the early 1960s. Research into ball-bearing operating status, inspection, and fault diagnosis resulted in rapid development of ball-bearing fault diagnostic technology.¹⁻³ In 1962, Guatafsson and Tallian¹ proposed comparing peak signal vibration values
and standard signals and used the difference to detect localized surface damage. Cooley and Tukey\(^5\) proposed using fast Fourier transform (FFT) spectrum analysis for diagnostics.

The rapid development of computer technology has allowed computer-based fault diagnostic systems to become an internationally popular research area.\(^6\)–\(^8\) For example, the REBAM system developed by the American Bently company has been applied to the monitoring and diagnostics of rotor vibration.\(^9\) The COMPASS system developed by B&K in Denmark has been applied to equipment malfunction segmentation and analytical research.\(^10\)

Artificial neural network (ANN) technology has been shown to have advantages over traditional methods in pattern recognition and categorization. For example, ANN can implement parallel distributed processing, can learn, and is robust as well as fault tolerant. Amongst identification algorithms, the neural network (NN),\(^11\) the support vector machine (SVM),\(^12\) and learning vector quantization\(^13\) are among the more well-known smart classifiers. However, NN requires a lot of sample data for training and application. In practice, it is difficult to obtain large amounts of malfunction data from actual large-scale operating machinery. Inadequate malfunction samples are a bottleneck that restricts practical application of the technology. SVM is a new smart application recently developed to solve machine-learning problems using a small number of samples. It can handle practical non-linear problems with small data sample sizes and high dimensionality and can be applied to medical information of a small sample size.\(^14\),\(^15\) These advantages have made SVM a leader in smart malfunction identification theory. Vapnik and Cortes\(^16\) proposed a new universal learning method based on VC statistical learning theory and the minimum structural risk principle. It can better solve non-linear practical problems with small samples, high dimensionality, and local minimum. This machine seeks the optimal compromise in model complexity and learning ability based on existing sample messages to obtain the best generalization.

Particle swarm optimization (PSO) simulates the social behavior of animal groups to realize interaction effects and promote development of the whole group. PSO is used extensively in function optimization, signal processing, decision making, control engineering, and mode categorization as well as in NN training.\(^16\)–\(^19\) Samanta and Nataraj\(^20\) used PSO to optimize SVM parameters and improve bearing fault detection and identification. Janssens et al.\(^21\) used a convolutional neural network (CNN) to convert original time domain vibration signals into frequency domain in gear box bearing and gear fault diagnosis. CNN was then directly trained to realize fault diagnostics. This process improved the fault diagnosis rate of conventional algorithms by 6%.\(^21\) Luo et al.\(^22\) also used PSO and the genetic algorithm for optimization.

Ball-bearing vibration signals contain a large amount of information about bearing status. An accurate identification of bearing condition can be realized from an analysis of vibrations, and the nature of a malfunction and its frequency can be determined. This vibration analysis method involves the collection of vibration signals, feature information extraction, malfunction mode identification, and diagnostics. Extraction of malfunction features and how to accurately find the malfunction feature frequency from complex original vibration data is one of the key problems in the diagnosis of ball-bearing faults. Time domain analysis was the first method used in machine fault diagnostics, and although malfunctions can be detected, its type and location cannot be accurately determined. The frequency domain analysis method uses FFT to obtain the frequency domain distribution of vibration signals. However, FFT is focused on the global transforms of the signal and cannot accurately describe its local features. FFT is suitable for processing linear, stable, vibration signals. Time frequency analysis was used for simultaneous observation of time domain and frequency domain information. FFT has very wide scientific and technological application that includes: image analysis, EEG signal processing, optics, investment portfolio risk management, and engineering applications that include the detection of local malfunction in rotating machines.\(^23\)–\(^25\) Other commonly seen time-frequency analysis applications include short-time Fourier transform,\(^26\),\(^27\) Wigner–Ville distribution,\(^28\) and wavelet transform.\(^29\) Time-frequency analysis is used to extract the features, after which the malfunction category, cause, and location must be identified. Pattern recognition is one of the core problems in ball-bearing fault diagnosis research.

In this study, wavelet packet transformation was first used to find the eigenvalues of ball-bearing malfunction. After this, SVM was used to conduct model training and categorize the bearing malfunctions based on the training. In addition, a combination of PSO with AFSA was proposed to improve the rate of identification accuracy of the SVM model.

**Materials and methods**

The ball bearing is a mechanical component that changes sliding friction motion between the shaft and shaft support base into rolling friction. Ball bearings are used in machines that have rotating shafts or spindles because
they run true with high precision, have a low friction coefficient, and are economical and highly standardized. Under working conditions, the structure of the bearing can fail in time. This may be caused by material defect, or sometimes even faulty installation which can result in many types of malfunction. During the operating process, a bearing will be subjected to mechanical stress, friction, and other physical actions which will change the bearing operating status. This study was started with a description of the environment where the malfunction signals were collected, as detailed in the following section. “Fibration frequency analysis” section describes the vibration frequency analysis and “Feature extraction for the wavelet packet energy spectrum” section describes the extraction of wavelet packet energy spectrum features, while “Using the support vector machine for fault diagnostics” section explains fault diagnosis using SVM. PSO and artificial fish-swarm (AFS) optimization were used to adjust to the optimal SVM parameters.

The malfunction signal environment

The data from the Case Western Reserve University Bearing Data Center has become the most widely employed standard reference used to test these algorithms.30,31 The simulation platform used is shown in Figure 1, and it has four main components: the drive unit, a signal collection device, the torque-loading unit, and the bearing test seat. The drive-end bearing model number is 6205-2RS JEM SKF, and the bearing structure parameters are shown in Table 1.31 Samples were taken at a frequency of 12 kHz, and the bearing malfunction size was 0.1778 mm, the load power was 0, and the rotation speed used was 1797 r/min.

Vibration frequency analysis

To explore the existing vibration frequency of a ball bearing, it is first necessary to understand the source of vibration. Ball bearings have a basic structure that includes inner and outer rings, a rolling body, and a cage. In actual use, the outer ring of the bearing is fixed in the bearing seat while the transmission shaft rotates the inner ring. All vibrations are affected by the ball-bearing load and movement, and vibrations in the system are caused by marginal errors in the component installation, local-bearing defects, and the interactions between the transmission shaft and components. A sensor, usually located on the bearing seat, is used to collect the rolling bearing vibration signals. However, the vibration signals collected by the sensor are produced by many different factors all acting on the bearing system. This means that the vibration signals that are caused by bearing malfunction must first be extracted from this combined vibration signal. This is the key to bearing fault diagnosis and is followed by detailed exploration of the source of the existing vibration frequency of the ball bearing. Structural malfunction and processing errors can cause random vibration during normal ball-bearing operation. Such vibration generally occurs at low frequency. However, these vibrations are generally small and of low amplitude and not strong enough for the diagnosis of early stage-bearing malfunction. This makes a determination and exploration of the frequency of normal existing vibrations from each part of the ball bearing necessary. The equations used for this
are: (1) the rolling body vibration frequency equation, (2) the inner/outer ring vibration frequency equation, and (3) the steel inner/outer ring vibration frequency equation

\[ f_b = \frac{0.424}{r} \sqrt{\frac{E}{2P}} \]  

where \( r \) is the rolling body radius (m), \( P \) the material density (kg/m\(^3\)), and \( E \) the elastic modulus of the rolling body material (N/m\(^2\))

\[ f_n = \frac{n(n^2 - 1)}{2\pi(D/2)^2 \sqrt{n^2 + 1}} \sqrt{\frac{E \times I}{M}} \]  

where \( n \) is the number of points, \( E \) is the material elastic modulus (N/m\(^3\)), \( I \) is the moment of inertia for the ferrule cross-section around the neutral axis (m\(^4\)), \( M \) is the ferrule length mass (kg/m), and \( D \) is the ferrule cross-section neutral axis diameter (m)

\[ f_n = 9.40 \times \frac{h \ n(n^2 - 1)}{D^2 \sqrt{n^2 + 1}} \]  

where \( n \) is the number of points, \( E \) is the material elastic modulus (N/m\(^3\)), \( D \) is the ferrule cross-section neutral axis diameter (m), and \( h \) is the ring thickness (m).

The above description shows that bearing failure is generally related to wear on the surface of the inner ring, outer ring, rolling body, or cage and fixing problems. Failure causes vibration, an increase in noise, and overheating which may become severe. These are all closely related to the bearing vibration signal characteristics. When problems arise during normal bearing operation, faults which develop in different components will give rise to different vibration signals of different frequency. However, the malfunction frequency is based on the geometric structure and size equations of the bearing. It is taken that the equations used are based on pure rolling action, that the geometric size is fixed and unchanging, that the outer ring of the bearing is fixed and unmoving, and that the bearing inner ring rotates with the shaft. When all these conditions are met, the malfunction feature frequency equations as shown as in equations (4) to (7) are valid

\[ f_i = \frac{N}{2} \left(1 + \frac{d_b}{D \cos \alpha}\right) f_r \]  

(4)

\[ f_o = \frac{N}{2} \left(1 - \frac{d_b}{D \cos \alpha}\right) f_r \]  

(5)

\[ f_b = \frac{D}{d_b} \left(1 - \left(\frac{d_b}{D \cos \alpha}\right)^2\right) f_r \]  

(6)

\[ f_d = \frac{1}{2} \left(1 - \frac{d_b}{D \cos \alpha}\right) f_r \]  

(7)

| Table 1. 6205-2RS JEM SKF-bearing structure parameters.\(^{31}\) |
|-----------------------------|------------------|
| Inner ring diameter         | 25 mm            |
| Outer ring diameter         | 52 mm            |
| Thickness                   | 15 mm            |
| Rolling body diameter       | 8 mm             |
| Bearing section diameter    | 39 mm            |
| Contact angle               | 0°               |
| The number of rolling bodies| 9                |

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Equation (4) is the inner ring malfunction feature frequency, equation (5) is the ring malfunction feature frequency, equation (6) is the rolling body malfunction feature frequency, and equation (7) is the cage malfunction feature frequency. \( N \) is the number of rolling bodies, \( d_b \) is the rolling body diameter, \( D \) is the bearing section diameter, \( \alpha \) is the contact angle, and \( f_r \) is the bearing rotation frequency. The unit is rotation speed/minute. By referencing the parameter specifications in “The malfunction signal environment” section and using equations (4) to (7), we can obtain the bearing malfunction feature frequency, which is 162.42 Hz for an inner ring malfunction, 107.12 Hz for an outer ring malfunction, and 139.86 Hz for a rolling body malfunction.

**Feature extraction for the wavelet packet energy spectrum**

In bearing fault diagnosis, the bearing vibration signal is affected by the work load and can produce some fast-decaying impact pulses. Thus, the bearing itself can vibrate during operation. The frequency of the existing vibration is at a higher frequency and generally can be viewed as a carrier wave of the vibration signal. The rapidly decaying impact pulse appears irregularly, making the modulated signal not only complex but they can also affect a wide range of frequencies. All the signals are mixed together, and the source cannot be found intuitively, nor is it possible to identify the fault directly from feature frequency using spectrum analysis. However, the wavelet packet energy spectrum signal can be used to analyze the vibration signal and separate the low frequency vibration signal from the high frequency band, which adds more resolution to the signal analysis. The wavelet packet analysis method, developed by Coifman and Wickerhauser, was used to process different frequency segments at different levels and resolution. This made the malfunction features clearer within the frequency band. This method has better time frequency localization features than the wavelet transform. In addition, Muhaseena and Lekshmi proposed using wavelet packet transform for mixed signals, by dividing the signal into multiple channels, computing the spectrum for each channel, and summing the spectrum functions.

To find the source of malfunction in the signal, it was first demodulated to obtain a demodulation envelope curve, and the curve was then processed to obtain the envelope spectra. These envelope spectra often contain feature information about the bearing malfunction and will generally indicate the type of malfunction. The extreme value is most commonly used for envelope demodulation. Although this method is more basic and practical, it is not appropriate for complex bearing signals. Therefore, in this study, Hilbert demodulation was used for processing. The transform was defined as in equation (8): the original signal \( x(t) \) goes through the Hilbert transform to obtain the imaginary number \( ^\sim x(t) \) of \( x(t) \) and to obtain the envelope of the original signal, as shown in Equation (9). Next, analysis was done on the envelope signal to obtain the \( x(t) \) envelope demodulation signal. Signals that had undergone Hilbert demodulation were used as analysis data

\[
H[x(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} \, d\tau
\]

\[
p(t) = \sqrt{x^2(t) + ^\sim x^2(t)}
\]

**Using the SVM for fault diagnostics**

In this study, the SVM was used for fault diagnostic categorization. The principle is derived from the optimized hyperplane in linear separability. For example, \( H \) is a category hyperplane. With assuming two categories for classification, \( H_1 \) and \( H_2 \) are the samples that pass closest to the hyperplane of each category. These are hyperplanes that are parallel to the category hyperplane. The distance between them is called the category margin. The optimal category hyperplane requires the category hyperplane to not only separate the two sample categories correctly, but also must have the largest category margin.

For hyperplanes \( H_1 : w \cdot x + b = 1 \) and \( H_2 : w \cdot x + b = -1 \), the hyperplanes \( H : w \cdot x + b = 0 \) has the largest category margin of \( 2/\|w\|^2 \). Thus, solving the largest margin can be replaced by solving the smallest \( \frac{1}{2}\|w\|^2 \). If the condition is met, then see equation (10)

\[
y_i((w \cdot x_i) + b) \geq 1, \quad i = 1, 2, \ldots, n
\]
If the Lagrange method \( w = a_1 y_1 x_1 + a_2 y_2 x_2 + \ldots + a_n y_n x_n \) is used to optimize the category hyperplane, then the problem between the two SVM categories can be expressed as equation (11)

\[
\begin{align*}
\min & \quad \frac{1}{2} w^2 \\
\text{subject to} & \quad y_i [(w \cdot x_i + b)] - 1 \geq 0 (i = 1, 2, \ldots, t) \\
& \quad w_j = a_1 y_1 x_1 + a_2 y_2 x_2 + \ldots + a_n y_n x_n
\end{align*}
\]

When solving linear approximation separability problems, the non-negative relaxation variable \( \zeta \) concept and error penalty constant \( C \) can be introduced to change equation (11) to equation (12)

\[
\begin{align*}
\min & \quad \frac{1}{2} ||w||^2 + C \sum_i \zeta_i \\
\text{subject to} & \quad y_i [(w \cdot x_i + b)] - \zeta (i = 1, 2, \ldots, t) \\
& \quad w_j = a_1 y_1 x_1 + a_2 y_2 x_2 + \ldots + a_n y_n x_n
\end{align*}
\]

where \( \zeta > 0, \sum \zeta_i \) is the sum of all the training set error upper limits and \( C \) is the designated constant, which shows that the larger the value, the higher the weight of the penalty. For non-linear problems, the functional theory states that as long as one type of kernel function \( K(x,y) \) satisfies the Mercer conditions, then it can be used as the kernel function. Commonly seen kernel functions include the linear function, polynomial, radial basis (RBF), and sigmoid functions. Of these, the most widely used is the RBF radial kernel function which can be employed regardless of sample size and dimensionality. There also use RBF as kernel function to apply for vibration analysis. Therefore, we use an RBF as the kernel function, \( K(x_1, x_2) = \exp(-\gamma ||x_1 - x_2||^2) \) which is described as follows

\[
K(x_1, x_2) = \exp(-\gamma ||x_1 - x_2||^2)
\]

Because the parameter \( \gamma \) of the kernel RBF will affect the categorization efficiency of the SVM classifier, it is often not easy to select the error penalty constant \( C \) manually. Thus, PSO and AFSA were used to help find the optimal parameters \( C \) and \( \gamma \), and the optimization method was used to improve the identification rate of SVM. Compared to PSO, AFSA is a newer optimization method used in soft computing. In the next section, the AFSA algorithm will be introduced, and details of the use of PSO and AFSA to find the SVM parameter \( (C, \gamma) \) will be given, and a comparison of their advantages and disadvantages will also be made.

**The AFS algorithm used to search for optimal SVM parameters**

The support vectors are the critical elements of the training set and contain all the necessary information needed to determine the separating hyperplane and the parameters \( C \) and \( \gamma \) of the SVM classifier. This is difficult to do, but is essential for classification. Therefore, the PSO and artificial fish-swarm algorithm (AFSA) were used in an effort to find the optimal parameters \( (C, \gamma) \). Kennedy and Eberhart proposed an alternative solution to the complex nonlinear optimization problem by emulating the collective behavior of particles, fish flocks and bird flocks.

![Figure 2. Vision concept of artificial fish.](image)
and called the PSO. The AFSA was inspired by the social behavior of a shoal of fish and its various collective schooling movement. The AFSA is one of several intelligent swarm algorithms, and it follows a series of instinctive behaviors of fish. Fish maintain the integrity of the shoal as they search for food, immigrate, or deal with dangers. The interaction of all fish when schooling is dictated by social form. The AF realizes external perception by its vision as shown in Figure 2.

Let \( X \) be the current state of an AF, the variable visual is the visual distance, and \( X_v \) is the visual position at some moment. The AF will go forward a step in this direction if the state at the visual position is better than the current state. If the AF moves to a better position, then \( X_{next} \) is the next state after the movement; otherwise, the AF continues an inspection tour in the vision. As the number of inspection tours increases, the AF gains more knowledge about the overall state of the vision.

Let \( X = (x_1, x_2, \ldots, x_n) \) and \( X_v = (x_{v1}, x_{v2}, \ldots, x_{vn}) \), then the process of the AFSA can be expressed as follows:

\[
X_v = X + Visual \cdot Rand() \tag{14}
\]

\[
X_{next} = X + \frac{X_v - X}{||X_v - X||} \cdot \lambda \cdot Rand() \tag{15}
\]

where \( Rand() \) produces random numbers between 0 and 1, \( \lambda \) is the step length, \( xi \) is the optimizing variable, and \( n \) is the number of variables. The variables include: \( X \) which is the current position of the AF, and \( Visual \) which represents the visual distance. The AFSA include six kinds of behaviors: AF_Prey, AF_Swarm, AF_Follow, AF_Move, AF_Leap, and AF_Evaluate. The operation AF_Prey is a basic biological need/search for food. The AF perceives the concentration of food to determine the movement by vision or sense to choose the tendency. The different behaviors are described as follows:

1. **AF_Prey:** Let the current position of the AF be \( X_i \) and select a position \( X_j \) randomly in the AF’s vision. \( Y_i \) and \( Y_j \) are the objective function’s values (food concentration) with respect to \( X_i \) and \( X_j \)

\[
X_j = X_i + Visual \cdot Rand() \tag{16}
\]

If \( Y_j > Y_i \), then the AF goes forward a step \( \lambda \) in the direction. Otherwise, the AF will swim randomly and choose the optimal direction to seek food. If it cannot satisfy after a specified \( try\_number \) times, it moves a step randomly.

2. **AF_Swarm:** The AF assembles in groups naturally in the moving process in order to guarantee the existence of the colony and avoid dangers. The operation AF_Swarm causes a few fish confined to local extreme values to move in the direction tending toward a global extreme value. Let the current position of the AF be \( X_i \) and \( X_c \) be the center position. Consider the number of AF’s companions is \( n_f \) in the current neighborhood and the total fish number is \( n \). If \( Y_c > Y_i \) and \( \frac{n_f}{n} < \delta \) are satisfied, then it means that the companion center has the higher fitness function value, and the AF is not very crowded. The AF goes forward a step to the companion center and \( \delta \) is a parameter to be determined for the crowded status. Otherwise, the AF executes the preying behavior

\[
X_i(t + 1) = X_i(t) + \frac{X_c - X_i(t)}{||X_c - X_i(t)||} \cdot \lambda \cdot Rand() \tag{17}
\]

3. **AF_Follow:** This operation accelerates AF moving to better states and, at the same time, accelerates AF moving to the global extreme value field from the local extreme values.

4. **AF_Move:** Fish swim randomly in water to seek food or companions in larger ranges. The behavior AF_Move is as follows

\[
X_i(t + 1) = X_i(t) + Visual \cdot Rand() \tag{18}
\]

5. **AF_Leap:** This operation is used to avoid from falling into the local extreme. If the difference of the objective functions is smaller than a proportion during the given \( m-n \) iterations, then some fish are randomly chosen in the whole fish swarm and set parameters randomly to the selected AF.
6. AF_Evaluate: This operation is used to evaluate the objective function of the optimization and store the best parameters of the swarm searching.

**Results and discussion**

The experiment flowchart in this study is shown in Figure 3.

**Ball-bearing vibration signal analysis based on wavelet packet transform**

The bearing signal described in “The malfunction signal environment” section is used for the experiment, and the samples were taken at 12,000 Hz. The length of each sample was 2000 points. A sample was taken from bearings in four different conditions: normal bearings and bearings with inner ring, rolling body, and outer ring malfunction. Three layers of wavelet packet decomposition were conducted on the vibration signals, and db11 was used as the mother wavelet function to obtain a feature signal composed of eight frequency band coefficients in the third layer. The original vibration signals from bearings in these four conditions are shown in Figure 4.

Figure 4 shows the different vibration signals from the four types of fault categories. However, these signals are very complicated and need to be processed using wavelet packet decomposition. Wavelet decomposition was carried out in three layers, and the db11 wavelet was chosen in this study. After decomposition, the normal and malfunctional-bearing signals all yielded eight sub-frequency bands, and the energy value was calculated for each of them. Normalization was used to process the resulting energy values which were presented as an energy spectrum histogram, as shown in Figure 5.

The initial modulated vibration signals needed to be demodulated using the Hilbert method. Envelope analysis was conducted on the reconstructed s3 and s7 signal wavelet packet coefficient because the energy of the three types of malfunctioning bearing was concentrated in the third (s3) and seventh frequency bands (s7). There were clear differences in energy concentration between the frequency bands of the normal bearing, and the malfunctioning bearings showed that the use of energy eigenvalues to categorize malfunction was effective.

The wavelet packet coefficient envelope spectrum could show the frequency spectrum peak values very clearly. Tables 2 and 3 can be used to compare the different types of bearing malfunction feature frequency. Because the initial vibration signals were modulated, the Hilbert method was used to demodulate the signals. And also because the energy from the three types of malfunctioning bearings was concentrated in the third and the seventh frequency bands, envelope analysis of the wavelet packet coefficient from the reconstructed third and seventh frequency bands had to be carried out. Figure 6 shows the signal envelope of a bearing inner ring malfunction node; Figure 7 shows that of a rolling body malfunction; and Figure 8 shows that of the outer ring malfunction.

**Figure 3.** Flowchart of the experiment setup.
The RBF radial and SVM sigmoid kernel functions were used to conduct the classifier categorization accuracy experiment. Forty sets of data, each from normal bearings and bearings with rolling body, inner ring, and outer ring malfunction were used to obtain the classifier categorization accuracy results in Table 2. The table shows the
diagram.

**Figure 4.** The original vibration signals of the four malfunction categories. (a) Normal bearing’s original malfunction vibration signal. (b) Rolling body bearing’s original malfunction vibration signal. (c) Inner bearing’s original malfunction vibration signal. (d) Outer bearing’s original malfunction vibration signal.

**Figure 5.** Energy spectrum histogram (normal bearing and bearings with rolling body, inner ring, and outer ring malfunction).

| Test | Classifier categories | Training sample: 160 | Test sample: 160 | Training sample: 80 | SVM (RBF) Categorization accuracy | SVM (Sigmoid) Categorization accuracy |
|------|-----------------------|----------------------|------------------|---------------------|----------------------------------|--------------------------------------|
|      | SVM (RBF)             | 100%                 | 76.875%          | 65%                 | Categorization accuracy          | Categorization accuracy              |
|      | SVM (Sigmoid)         | 25%                  | 25%              | 25%                 | Categorization accuracy          | Categorization accuracy              |

**SVM categorization results**

The RBF radial and SVM sigmoid kernel functions were used to conduct the classifier categorization accuracy experiment. Forty sets of data, each from normal bearings and bearings with rolling body, inner ring, and outer ring malfunction were used to obtain the classifier categorization accuracy results in Table 2. The table shows the
Table 3. The SVM categorization accuracy of penalty function C.

| C value | Total time (s) | Training sample number | Test sample number | Support vector number | Accuracy (%) |
|---------|----------------|------------------------|--------------------|-----------------------|--------------|
| 10      | 0.189731       | 20                     | 60                 | 19                    | 65           |
| 50      | 0.165808       | 20                     | 60                 | 19                    | 41.6         |
| 80      | 0.150982       | 20                     | 60                 | 20                    | 56.6         |
| 100     | 0.152489       | 20                     | 60                 | 20                    | 66.6         |
| 200     | 0.156657       | 20                     | 60                 | 20                    | 65           |
| 500     | 0.163515       | 20                     | 60                 | 20                    | 70           |

Figure 6. Inner ring malfunction signal node envelope (Left – s3 band; Right – s7 band).

Figure 7. Rolling body malfunction bearing signal node envelope; (Left – s3 band; Right – s7 band).

Figure 8. Outer ring malfunction bearing signal node envelope (Left – s3 band; Right – s7 band).
The effect of penalty function $C$ and radial kernel function gamma on identification rate. Twenty sets of malfunction energy feature each from bearings with rolling body, inner ring, and outer ring malfunction were selected as the training sample (a total of 60 sets were used). The RBF radial kernel function was used as well as the $\gamma$ value of 0.01. C values of 10, 50, 80, 100, 200, and 500 were selected in turn to obtain the penalty function C values, as shown in Table 3.

It can be seen in Table 3 that the optimal value of the penalty function C was 500. Analysis of the total training time shows that the difference in time taken for different C values was insignificant. When the C value increases, so does the support vector number, and analysis of the categorization accuracy showed that it was highest when the C value was 500. It was clear that the selection of the penalty function C value had a substantial impact on SVM performance.

With $C = 500$, $\gamma$ values of 0.01, 0.05, 0.1, 0.5, 1, and 2 were used to obtain the RBF radial kernel function $\gamma$ value. The results are shown in Table 4.

Table 4 shows that when the $\gamma$ value was 0.01, experimental parameters were optimal. Analysis of the total training time shows that as $\gamma$ became larger, the required time decreased. The support vector number portion shows that as the $\gamma$ value increased, the number of support vectors also increased. Analysis of categorization accuracy shows that a $\gamma$ value of 0.01 had the highest accuracy.

Both the penalty function C value and the RBF radial kernel function $\gamma$ value have a significant impact on the SVM classifier performance. Algorithms were therefore used to search for the optimal C and $\gamma$ values to improve the performance of the SVM classifier.

The identification rate of PSO–SVM and AFSA–SVM. In the previous section, the experiments show that the parameter setting of C and $\gamma$ has a certain impact on the identification rate. Therefore, in this section, the experiments show that PSO-SVM and AFSA-SVM are used to solve efficiency problems. To compare the advantages and disadvantages of using PSO and AFSA and to adjust for the optimal C and $\gamma$ values, we used 40 sets of data each from normal bearings and bearings with body, inner ring, and outer ring malfunction, a total of 160 sets was used. Of these, 80 were for training and 80 were test sample sets. Two hundred PSO parameter iterations were run, and learning factors were $c_1=1.5$, $c_2=1.5$. The particle swarm numbers used were 5, 10, 15, 20, and 30. The AFSA parameter with artificial fish perspective was 10, the artificial fish swarm number was 5, 10, 15, 20, 25, and 30, and the moving step length was 0.5. Table 5 shows the PSO experimental results, and the AFSA experiment results are shown in Table 6. It can be seen in Table 5 that as the number of particles in the swarm grew, so did the operation time. The support vector number also changed with the number of particles. In all external categorization accuracy experiments, a particle swarm number of 30 gave the highest accuracy, and the time taken was also shorter. The results in Table 6 show that in all the external categorization accuracy experiments, the greatest accuracy was achieved when the artificial fish number was between 10 and 20. When the support vector number had 20 artificial fish, the accuracy was the lowest. Comparison of all the external data shows that AFSA was better than PSO, and more accurate results could be obtained in a shorter calculation time with a smaller support vector number.
Conclusion

Smart ball-bearing malfunction diagnostics is data driven, and performance depends on the quality and quantity of the training samples. In practice, engineering is often affected by the data collection environment, and samples are often uneven and limited in number. A study of ball-bearing fault diagnostic methods is very important to ensure the operation accuracy and safety of machinery. In this study, the focus was on ball-bearing malfunction feature extraction and pattern recognition. The vibration principle of ball bearing was analyzed for inner ring, outer ring, and rolling body surface damage, and theories were proposed for malfunction in different ball-bearing locations as well as for feature frequency calculation methods. Extraction of wavelet packet energy spectrum features was used to process bearing vibration signals, not only to remove noise but also to decompose high frequency band malfunction vibration signals. This effectively extracted the malfunction-bearing signal features. In this study, SVMs were used to conduct malfunction categorization. Experimental observations, based on the RBF kernel function, were used to select parameters for the penalty function C and radial kernel function gamma. Identification experiments also showed AFSA–SVM to be superior to PSO–SVM.

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