An improved bearing fault detection strategy based on artificial bee colony algorithm

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Abstract: The operating state of bearing directly affects the performance of rotating machinery and how to accurately and decisively extract features from the original vibration signal and recognize the faulty parts as early as possible is very critical. In this study, the one-dimensional ternary model which has been proved to be an effective statistical method in feature selection is introduced and shapelets transformation is proposed to calculate the parameter of it which is also the standard deviation of the transformed shaplets that is usually selected by trial and error. Moreover, XGBoost is used to recognize the faults from the obtained features, and an improved artificial bee colony algorithm (ABC) where the evolution is guided by the importance indices of different search space is proposed to optimize the parameters of XGBoost. Here the value of importance index is related to the probability of optimal solutions in certain space, thus the problem of easily falling into local optimality in traditional ABC could be avoided. The experimental results based on the failure vibration signal samples show that the average accuracy of fault signal recognition can reach 97% which is much higher than the ones corresponding to other extraction strategies, thus the ability of extraction could be improved. And with the improved artificial bee colony algorithm which is used to optimize the parameters of XGBoost, the classification accuracy could be improved from 97.02% to about 98.60% compared with the traditional classification strategy.

Keywords: fault diagnosis, feature extraction, improved one-dimensional ternary pattern method, improved artificial bee colony algorithm

1. Introduction

Rolling element bearings, as high-precision components that allow the rotating machine to run at extremely high speed, have been widely used in various precision instruments [1]. But due to the influence of overheating or overloading as well as the friction between different parts of the mechanical bearing, different types of failures often occur which eventually cause motor failures, lead to high maintenance costs, serious economic losses and safety hidden dangers [2]. Therefore, the diagnosis of bearing fault types and the prediction of the effective life of the machine are of great significance [3-4]. Since the accurate bearing fault diagnostics has been approached by developing a physical model of bearing faults, and understanding the relationship between bearing faults and measurable signals which can be captured by a variety of sensors and analyzed with signal
processing techniques, and feature extraction should be executed firstly for identifying
the most discriminating characteristics in signals. Actually, several traditional time-
domain or frequency-domain or time-frequency domain analysis methods such as
spectral analysis [5,6], cyclostationary approach [7], fast Fourier transform [8-9], wavelet
transform [10] and so on are used to extract useful features from signals but various
questions exist unavoidably as the complex working environment and signal formats.
Melih Kuncan et al. proposed a new vibration signal feature extraction method named
One-dimensional ternary pattern (1D-TP) [11] which could transform from the idea of
image feature extraction. The method could fully describe the oscillation as well as the
flat parts in all obtained signals and it can be extracted effectively in real time if the fault
frequency of the signal changes. However, the establishment of ternary pattern requires
selecting the parameters of center point \( P \) and threshold \( \beta \) which are often determined by
trial and error due to the influence of the abnormal value of the signal itself. In this paper,
with the help of shaplets transform [12-13] which is a method of extracting similar
subsequences, \( P \) and \( \beta \) are calculated as the center of the shapelets and the standard
deviation of shapelets repectively. As the shaplets transform has the strong ability of
denoising, the accuracy of feature extraction could be also improved.

Based on the extracted features, an effective classification strategy needs to be
introduced such as XGBoost constructed with boosting trees, which has proven their
superiority in many classification applications [14-15]. But the selection of parameters of
the XGBoost, such as the learning rate and the number of weak classifiers, always relied
on experiences, and the performance of the classifier can’t achieve the optimization. In
order to improve its performance, more and more optimization algorithms are introduced.
Chen et al. proposed a combined prediction method based on LSTM and XGBoost [16],
Zhang et al. proposed the Genetic Algorithm_XGBoost model, which used the
optimization ability of genetic algorithm to perform multiple searches on the parameter
combination of XGBoost to obtain a near-optimal solution [17], the improved Particle
Swarm Optimization algorithm is used to optimize the XGBoost parameters, and
established a machine learning model to predict the tensile strength and plasticity of
steel [18]. In this paper, we concentrate on artificial bee colony algorithm, developed by
Karaboga [19] based on simulating the foraging behavior of honey bee swarm, where the
numerical comparisons demonstrated that the performance of ABC algorithm is
competitive to other population-based algorithms with an advantage of employing fewer
control parameters [20–22]. But up to now, there isn’t any reference about the application
of ABC for optimizing XGBoost or other ensemble learning algorithm. What is more, ABC
algorithm can easily get trapped in the local optima when solving complex multimodal
problems [22]. Thus in this paper ABC algorithm is creatively introduced to optimize
XGBoost classifier, and aiming to escape from local optimal, an improved bee colony
algorithm where the search is guided with the importance indices of sub-region of solution
space is proposed.

The rest of this paper is organized as follows. In Section 2, a brief introduction about
the bearing fault is provided. Then a new feature extraction method combined with 1D-TP
feature extraction method and shaplets transform is proposed in Section 3. In Section 4, in
order to improve the fault detection accuracy, an improved artificial bee colony algorithm is created and applied to the design of XGBoost classifier. Relative experiments are executed in Section 5 and the performance of the proposed feature extraction method and the improved ABC-XGboost are verified. Finally, the content of the paper is summarized and analyzed, and the future research directions is briefly described.

2. Bearing fault description

A rolling-element bearing consists of the outer race typically mounted on the motor cap, the inner race to hold the motor shaft, the balls or the rolling elements, and the cage for restraining the relative distances between adjacent rolling elements. As the most vulnerable component in motor drive system, four types of misalignments which are misalignment, shaft deflection, tilted outer race and tilted inner race are likely to cause the bearing failures.

As shown in Table 1, the data samples constructed for different defect sizes under different fault types (normal signal, inner ring fault, ball fault, outer ring fault) are listed. Single point faults are introduced to the bearings under test using electro-discharge machining with fault diameters of 7 mils, 14 mils, 21 mils, 28 mils and 40 mils, at the inner raceway, the rolling element and the outer raceway. Vibration data are collected for motor loads from 0 to 3 hp and motor speeds from 1,720 to 1,797 rpm using two accelerometers installed at both the drive end and fan end of the motor housing, and sampling frequency of 48 kHz were used.

Table 1. Establishment of sample data

| Bearing condition | Fault size | label | Training set | Test set |
|-------------------|------------|-------|--------------|---------|
| NS                | 0          | 0     | 450          | 150     |
| IRF               | 0.007 inch | 1     | 450          | 150     |
|                   | 0.014 inch | 2     | 450          | 150     |
|                   | 0.021 inch | 3     | 450          | 150     |
| BF                | 0.007 inch | 4     | 450          | 150     |
|                   | 0.014 inch | 5     | 450          | 150     |
|                   | 0.021 inch | 6     | 450          | 150     |
| ORF               | 0.007 inch | 7     | 450          | 150     |
|                   | 0.014 inch | 8     | 450          | 150     |
|                   | 0.021 inch | 9     | 450          | 150     |

3. Feature Extraction

3.1. One-dimensional ternary patterns

1D-TP is developed based on the local ternary pattern [23-24], which is generally used in image processing for texture analysis. Different from directly processing multi-dimensional matrices in local ternary mode, 1D-TP uses patterns obtained from the comparisons between two neighbors of the vibration signals. The procedure of algorithm could be described as follow:

After defining relative parameters, such as the center point in the transformed vector \( P_c \), the point \( P_i \) within a specific range around \( P_c \), as well as the range threshold \( \beta \) which
affects the encoding result, the value of the member within the threshold range \( \beta \) is
compared to neighbors in 1D-TP with Eq.1, and then ternary patterns code could be
generated.

\[
\text{binarycode} = \begin{cases} 
1 & P_c > P_i + \beta \\
0 & P_c \in (P_i + \beta, P_i - \beta) \\
-1 & P_i < P_c - \beta 
\end{cases}
\]  

Based on the encoding results, the positive and negative values are separated and
form two columns of binary codes, and converted to a decimal number who will replace
the center value with the generated one. Thus two different sets of feature vectors could
be obtained.

The 1D-TP method can fully describe the peak signal as well as the flat part in the
vibration signal which considers the integrity of the signal. Although it has been proved to
be effective in extracting features from raw data, there are still two problems: the first one
is how to choose the value of parameter \( \beta \) which is often obtained by trial and error to
guarantee the best extraction effect. The second one is how to overcome the influence of
outliers that exist in the original signal vector. For improving the performance of 1D-TP,
shapelets transform strategy is introduced.

3.2. Improved 1D-TP feature extraction with shapelets transform strategy

The shapelets transform [25] is a shape-based time series representation approach
which could identify the local or global similarity of shape and offer an intuitively
comprehensible way of understanding long time series. It could be executed with the
following steps as show in Figure 1.

First of all, assuming \( T_s \) is the original time series collection, and randomly divide it
to generate a set of shapelets candidates \( W = \{w_{min}, w_{min+1}, ..., w_{max}\} \) from the entire
sample set including the time series sample \( T_s = \{T_{s1}, T_{s2}, T_{s3}, ..., T_{sn}\} \) and corresponding
class labels.

Secondly, calculate the Euclidean distances which are the values between all
shapelets candidates \( w_i \) and the time series in \( T_s \) as Eq.2, and sort them in increasing order
to form the set \( D_s \)

\[
D_s(w_i, T_{s1}) = \sum_{i=1}^{T_{s1}} (w_i - T_{s1})^2
\]  

Next, information gain (IG) [24] defined as Eq.3 and 4 for each candidate in \( W \) is
calculated, thus their qualities could be assessed

\[
H(D_s) = -p(M) \log(p(M)) - p(N) \log(p(N))
\]  

\[
IG = H(D_s) - \frac{|D_{sm}|}{|D_s|} H(D_{sm}) + \frac{|D_{sn}|}{|D_s|} H(D_{sn})
\]  

\( p(M) \) and \( p(N) \) respectively represent the proportion of different fault categories \( M \)
and \( N \) in the sample set \( D_s \), \( D_{sm} \) and \( D_{sn} \) are two subsets in \( D_s \).

Finally, shapelets are extracted from the generated candidates by comparing their IG
values, and the data set \( W_{new} \) could be established, which is composed of the extracted
shapelet and arranged in descending order of IG value. The sequence after the shapelets transform is the sub-sequence with higher fault information.

Figure 1. diagram of shapelets transform

Through the aforementioned shaplets transform method, the information gain of the local subsequence relative to the original signal is compared, thus the extracted shapelets contain the main information of the original fault signal, and the outliers with little fault information content can be removed.

Thus for the original data, the influence of outliers could be eliminated with shapelets transform, and extract similar local subsequences. Then with the help of ID-TP, the features of the local sub-sequences could be extracted. During the procedure, the standard deviation of the local subsequence after the shapelets transform, which is calculated with Eq.5, is assigned to the parameter of $\beta$ in ID-TP, here $w_i$ represents the transformed shapelets, $n$ is the number of points in the sequence $W_{new}$:

$$\beta = \sqrt{\frac{\sum_{i=1}^{n}(w_i - \bar{w})^2}{n - 1}}$$

(5)

Thereby the effect of the one-dimensional ternary pattern feature extraction method could be improved. The detailed procedure could be described as Table 2.

Table 2. Overview of proposed method

| Feature extraction method with shapelets transform and 1D-TP |
|---|
| 01 Initialization, discovering shapelets |
| 02 Import series dataset |
| 03 $\text{min\_shapelet}$ (default = 3) |
| 04 $r$ (maximum number of shapelets to store, default = 10*size of TS) |
| 05 quality (predefined information gain threshold, default = 0.05) |
| 06 calculate the Euclidean distances between shapelets candidates by Eq2 |
| 05 calculate information gain by Eq3 and Eq4 |
| 06 Set shapelets candidates |
| 07 Calculate the standard deviation of parameter $\beta$ as shapelets candidates by Eq 6 |
| 08 switch $P_i$ |
| 09 case $P_i < P_i + \beta$ |
| bainarycode=1 |
| 10 case $P_i = (P_i + \beta, P_i - \beta)$ |
| bainarycode=0 |
| 12 case $P_i < P_i - \beta$ |
| bainarycode=-1 |
| 14 end |
| 15 Separation of positive and negative values; |
| 16 conversion binary values to decimal; |
| 17 end |

Obviously, the improved feature extraction method with 1D-TP and shapelets transform can not only quickly obtain the optimal parameters, but also can filter out
abnormal signals which affect fault recognition. With the extracted features obtained from the improved feature extraction strategy, classification methods will be introduced to detect the bearing faults.

4. The improved classification strategy

4.1 XGBoost classifier

XGBoost is highly efficient classification strategy based on Gradient Boosting Decision Tree (GBDT) which is widely used in biological sciences, and prediction of risks and financial etc[26-29]. Its basic idea is to combine multiple tree models with low classification accuracy to construct a more complex model with relatively high accuracy. The strategy executes iteratively, and in each iteration a new tree used to fit the residual of the previous tree will be generated. Compared with the traditional GBDT, the second derivative and regular term are introduced to make the loss function more accurate and avoid tree overfitting respectively.

In the classification strategy of ensemble learning, the selection of the parameter values of the classifier has an important effect on the performance of the classifier. Table 3 lists the parameters and ranges that can be optimized by the XGBoost classifier. In order to optimize the selection of classifier parameters in XGBoost classifier, this paper introduces artificial bee colony algorithm which has been proven to be more competitive with other population-based algorithms.

| Parameter           | Range  | Meaning                                      |
|---------------------|--------|----------------------------------------------|
| n_estimators        | [1,1000]| Number of trees                              |
| colsample_bytree    | [0,1.0]| subsampling of columns                       |
| learning_rate       | [0.001,0.9]| Step size shrinkage used in update to prevents overfitting |
| min_child_weight    | [1,100]| Minimum sum of instance weight (hessian) needed in a child |
| max_depth           | [1,15] | Maximum depth of a tree                      |

4.2 Improved artificial bee colony algorithm

ABC algorithm is an optimization algorithm based on the intelligent foraging behaviour of honey bee swarm which consists of three groups: employed bees, onlooker bees, and scout bees. The location of the food source represents the optimal solution to the problem, and its quality could be measured with the value of fitness function.

The traditional algorithm iteratively optimizes from the stage of employed bees, traverses each randomly generated solution vector and updates the solution with neighborhood search as Eq. 7. Then, according to the selection probability generated by
Eq. 8, the onlooker bee selects one of the generated solutions to execute the subsequent exploration.

\[ x_{ik}^* = x_{ik} + \text{rand}(V_{\text{min}}, V_{\text{max}})(x_{ik} - x_{jk}) \]  

(7)

\[ P_i = \frac{\text{fit}_i}{\sum_{i=1}^{N} \text{fit}_i} \]  

(8)

where \( x_{ik} \) represents the solution of the last iteration of the employed bee, \( x_{ik}^* \) represents new solution that updated based on \( x_{mk} \) as Eq.7, and \( i, j \) represent the indices of specific solution in the population, \( i \neq j \). \( k \) represents the dimension of the population, \( k \in \{1, 2, \ldots, D\} \). rand\((-1,1)\) is a random number between \([-1, 1]\). \( \text{fit}_i \) is the fitness value of the objective function, \( N \) is the number of food sources which is equal to the number of employed bees. \( P_i \) represents the selection probability of each solution vector.

As mentioned above, the randomly search or update are executed in the whole solution space and it is easy to fall into the local optimization. In order to overcome the shortage, an adaptive divergence control mechanism is introduced. As shown in Figure 2, the main steps of the improvements are described as follows:

Step 1: Initialize the parameters of ABC, set the number of bee colony, the maximum number of iterations and so on.

Step 2: Divide the whole solution space into \( v \) sub-regions who possess the same intervals.

And randomly assign weights to different sub-regions as \( \Phi(\theta_1, \theta_2, \ldots, \theta_v) \).

Step 3: The employee bee searches in each sub-region, generates a new solution \( x_{ik}^* \) according to Eq 7 and calculates the fitness value. According to the fitness value calculated after the sub-region search, the weight of the sub-region is scaled up or down generating a new set of weights.

Step 4: Calculate the selection probability of each sub-region according to Eq 10

\[ P_j = \frac{\theta_j}{\sum_{a=1}^{n} \theta_a} \]  

(10)

Where \( j = 1, 2, \ldots, n \), \( P_j \) is the value of probability of selection, \( \theta_j \) is the weight value corresponding to the sub-region, and \( n \) is the number of all sub-regions.

Step 5: According to the selection probability of each sub-region, observe the bees first search for important sub-regions and select the nectar source according to the greedy strategy.

Step 6: The scout bee judges whether there is a nectar source that needs to be abandoned, and if it exists, it randomly generates a nectar source to replace it.

Step 7: Record the optimal solution until the iterative termination condition is met and output the optimal solution.

The improved artificial bee colony algorithm will search under the guidance of the weights of sub-region every time, and will increase the search effort for the sub-region
that may contain the optimal value. This method speeds up the search for the optimal solution, and at the same time helps to avoid the misjudgment of the local optimal.

Figure 2. Flow chart of adaptive divergence control mechanism

In order to verify the effectiveness of the improved artificial bee colony algorithm optimization ability, five benchmarks from CEC2017 as shown in Table 4 are introduced. The parameters in the bee colony are set as follows: the total number of bee colonies is 200, the maximum number of iterations is 1000, and the search range is the threshold range of the solution of each function.

Table 4. The benchmark functions

| Function expression | Search space | Maximum value | Modality |
|---------------------|--------------|---------------|----------|
| $f_1(x) = \left(20+\left(x^2-10\cos(2\pi x)\right)\left(y^2-10\cos(2\pi y)\right)\right)/\sqrt{2}$ | [-5.12,5.12] | 118 | Multimodal |
| $f_2(x) = \frac{\sin(x)}{x}/\frac{\sin(y)}{y}$ | [-10,10] | 1 | Unimodal |
| $f_3(x) = x^2 + y^2$ | [-10,10] | 0 | Unimodal |
\[ f_4(x) = \frac{\left( x \sin(4\pi x) - y \sin(4\pi y + \pi + 1) \right)}{2} \quad [-1, 2] \quad -1.5 \quad \text{Unimodal} \]

\[ f_5(x) = \frac{20 + \left( x^2 - 10 \cos(2\pi x) \right) + \left( y^2 - 10 \cos(2\pi y) \right)}{\sqrt{2}} \quad [-5, 12, 5, 12] \quad 0 \quad \text{Multimodal} \]

Figure 3 shows the fitness values with the traditional ABC and the improved algorithm corresponding to five benchmarks, and Table 5 is the statistics information of the results. It is clear that the improved ABC possesses better convergence performance than ABC for all the benchmark functions, especially for \( f_2(x) \) the convergence speed increases by 55.7%. The improved artificial bee colony algorithm can have fewer iterations and higher iteration accuracy. Meanwhile, for the optimization accuracy, the results corresponding to the improved algorithm possess better performance, where the fitness value obtained by improved algorithm is a 36.2% reduction with respect to ABC for \( f_3(x) \).

Thereby the effectiveness of the improved bee colony algorithm could be verified, and further application of the optimization of classifier parameters is possible.
Figure 3. Fitness values of five benchmark functions

**Table 5. Statistics information of different benchmark functions**

| functions | method  | Best-F  | iterations | Optimal solution               |
|-----------|---------|---------|------------|---------------------------------|
| $f_1(x)$  | ABC     | 117.9375| 932        | $(x=-4.83,y=4.96)$             |
|           | IABC    | 117.9402| 876        | $(x=-4.87,y=4.98)$             |
| $f_2(x)$  | ABC     | 1.0000  | 79         | $(x=0,y=0)$                     |
|           | IABC    | 1.0000  | 35         | $(x=0,y=0)$                     |
| $f_3(x)$  | ABC     | 1.35E-19| 53         | $(x=0.34,y=0.062)$             |
|           | IABC    | 0.86E-19| 37         | $(x=0.14,y=0.047)$             |
| $f_4(x)$  | ABC     | -1.4301 | 2983       | $(x=1.83,y=0.93)$              |
|           | IABC    | -1.4302 | 2924       | $(x=1.95,y=0.95)$              |
| $f_5(x)$  | ABC     | 6.77E-12| 992        | $(x=0.013,y=0.052)$            |
|           | IABC    | 0.0000  | 996        | $(x=0.0,y=0.0)$                |

4.3. XGBoost strategy with improved ABC

Based on the evaluation of improved ABC in the previous section, a new framework as shown in Figure 4 where the improved bee colony algorithm is applied to optimize the parameters of XGBoost classifier is proposed. The main process is described as Figure 4:

Step 1: Import and preprocess the bearing fault data.
Step 2: Initialize the relevant parameters of ABC and the optimized classifier parameters.
Step 3: Divide the solution spaces into different sub-regions.
Step 4: Execute the search with seperated groups in different sub-regions, and update the weight values of each subregions according to the fitness values of optimal solution searched in that region. Here the the solution is the paramters of XGBoost and the fitness value is the classification accuracy corresponding to each solution.
Step 5: Under the guidance of the weights, onlooker bees and scout bees perform the further exploration.
Step 6: After reaching the maximum number of iterations, output the optimized parameters.
Figure 4. Improved bee colony algorithm to optimize XGBoost

5. Experiments and Results

With the bearing fault data mentioned in Section 2, the effectiveness of the improved fault detection method is tested in this part.

5.1 Comparison of feature extraction method

In order to verify the performance of the improved feature extraction strategy, XGboost classifier whose parameters are selected by experience is introduced. The corresponding values of XGBoost are set as: n_estimators=100, learnrate=0.1. Figure 5 shows the confusion matrix with 1D-TP and 1D-TP-ShapeletTransform strategies. The red numbers in the white squares represent the probability of misjudgment of the label. The number of misjudged labels in Figure 5(a) is obviously more than that in Figure 5(b), which means that the improved feature extraction method has better performance. Figure 6 is a histogram of the comparison between the actual number of labels and the number of accurate predictions on the test data set. The number of correct predictions for label 2,
3 and 8 has increased by 10, 10 and 7 respectively, and the number of correct predictions for other labels has also significantly increased.

Figure 5 (a) is the confusion matrix with 1D-TP-XGBoost. (b) is the confusion matrix with 1D-TP-ShapeletTransform-XGBoost

Figure 6 (a) is the prediction of the test set with 1D-TP-ShapeletTransform method, (b) is the prediction of the test set with 1D-TP

Figure 7 presents the receiver operating characteristic curves (ROC) with two methods. It is clear that the area below ROC curve corresponding to the improved 1D-TP method is larger than the other one, explain that the improved feature extraction method makes the ROC curve of the classifier better.
Other feature extraction methods such as FFT are also introduced to compare with improved 1D-TP strategy, and the results are shown in Figure 8 and Table 6. As the 1D-TP method needs to establish ternary patterns over the entire time series, it takes longer computing time than improved 1D-TP. Compared with the traditional time-domain and frequency-domain feature extraction methods, the error rate was reduced by about 18.75%. The accuracy of the improved feature extraction method is about 97%, which is much higher than other methods.

**Table 6.** Accuracy under different feature extraction methods.

| Feature extraction method                  | Accuracy | Time |
|--------------------------------------------|----------|------|
| shapelets transform with 1D-TP             | 97.02%   | 36s  |
1D-TP
Time domain (Root mean square, pulse factor, etc.) 95.03% 90s
FFT (fast Fourier transform) 80.66% 15s
Wavelet packet transform 94.35% 32s

5.2 Comparison of XGBoost Parameter Optimization

From the experimental comparison in the previous section, it can be seen that the fault classification model established by Shaplets transform-1D-TP combined with XGBoost has the best performance. In order to further improve the classification model, the experiment in this section is based on the improved feature extraction method proposed, the improved artificial bee colony algorithm proposed in the previous chapter be applied to the optimization of XGBoost parameters in this paper. Table 7 lists the parameters that need to be automatically optimized. During the optimization process, the parameters in the bee colony are set as follows: the total number of bee colonies is 200, the maximum number of iterations is 1000, the range of n_estimators is [1,1000], and the optimization range of learning rate is [0.01,1].

Table 7. The parameters of XGBoost

| parameters       | range       | Meaning                                           | Optimal parameter setting |
|------------------|-------------|---------------------------------------------------|---------------------------|
| n_estimators     | [1,1000]    | Number of trees                                   | 876                       |
| learning rate    | [0.01 1]    | Step size shrinkage used in update to prevent overfitting | 0.26                      |

In this experiment, the classification accuracy is used as the objective function, and the iterative optimization curve is compared as shown in Figure 9. Figure 9 and Table 8 show that the iterative optimization curve of the improved artificial bee colony algorithm finds the optimal value of accuracy faster and converges, and improves the accuracy to about 98.60%.
6. Conclusions

In this paper, for solving the problem of bearing fault detection, a novel feature extraction method is introduced based on the traditional 1D-TP. In order to obtain the optimal parameters which is usually selected by trial and error and overcome the influence of outliers in original signals, the shapelets transform method is proposed to optimize 1D-TP. Meanwhile, an improved ABC algorithm is created and introduced to optimize the performance of XGBoost classifier. The improved algorithms of feature extraction and classification are applied to the problem of bearing fault detection, and results show the effectiveness of the proposed strategies.

In future work, more advanced machine learning algorithms need be applied to improve detection accuracy, and multi-core parallel computing will be used to accelerate the speed of optimization procedure.

Supplementary Materials: The following are available online at www.mdpi.com/xxx/s1, Figure 1: diagram of shapelets transform, Figure 2: Flow chart of adaptive divergence control mechanism, Figure 3: Fitness values of five benchmark functions, Figure 4: Improved bee colony algorithm to optimize XGBoost, Figure 5: Confusion matrix comparison Figure 6: Comparison of sample classification results, Figure 7: Comparison of ROC between the feature extraction method, Figure 8: Comparison of fit time and error of different feature extraction strategies, Figure 9: Iterative optimization curve comparison, Table 1: Establishment of sample data, Table 2: Overview of proposed method, Table 3: XGBoost classifier related parameters and range, Table 4: The benchmark functions, Table 5: Statistics information of different benchmark functions, Table 6: Accuracy under different feature extraction methods, Table 7: The parameters of XGBoost, Table 8: Model results.

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References

1. Huang W, Sun H, Luo J, Wang W. Periodic feature-oriented adapted dictionary free OMP for rolling element bearing incipient fault diagnosis. Mech Syst Signal Process 2019; 126:137–60.
2. Zhang Z, Li S, Wang J, Xin Y, An Z. General normalized sparse filtering: A novel unsupervised learning method for rotating machinery fault diagnosis. Mech Syst Signal Process 2019; 124:596–612.
3. Sun RB, Yang ZB, Zhai Z, Chen XF. Sparse representation based on parametric impulsive dictionary design for bearing fault diagnosis. MechSyst Signal Process 2019; 122:737–53.
4. Ben Salem S, Bacha K, Chaari AK. Support vector machine based decision for mechanical fault condition monitoring in induction motor using an advanced Hilbert–Park transform. ISA Trans 2012; 51:566–72.
5. Frosini I, Bassi E. Stator current and motor efficiency as indicators for different types of bearing faults in induction motors. IEEE Trans. Ind. Electron. 2010; 57:244–51.
6. Mohanty S, Gupta KK, Raju KS. Burst based vibro-acoustic feature extraction of bearing using emd and vmd. Measurement 2018; 117:200–20.
7. Zhou Y, Chen J, Dong GM, Xiao WB, Wang ZY. Application of the horizontal slice of cyclic bispectrum in rolling element bearings diagnosis. Mech Syst Signal Process 2012; 26:229–43
8. Shang Rongyan,Peng Changqing,Shao Pengfei,Fang Ruiming. FFT-based equal-integral-bandwidth feature extraction of vibration signal of OLTC.[J]. Mechatronics, 2014.
9. Hayri Arabaci,Mohamed Ali Mohamed. A knowledge-based diagnosis algorithm for broken rotor bar fault classification using FFT, principal component analysis and support vector machines[J]. International Journal of Intelligent Engineering Informatics,2020,8(1).
10. Kedadouche M, Liu Z, Vu VH. A new approach based on om-empirical wavelet transforms for bearing fault diagnosis. Measurement 2016; 90:292–308.
11. Melih Kuncan,Kaplan Kaplan,Mehmet Recep Minaz,Yilmaz Kaya,H. Metin Ertuńç. A novel feature extraction method for bearing fault classification with one dimensional ternary patterns[J]. ISA Transactions,2020,100.
12. Zhang Jitao,Shen Weiming,Gao Liang,Li Xinyu,Wen Long,Versaci Mario. Time Series Classification by Shapelet Dictionary Learning with SVM-Based Ensemble Classifier[J].Computational Intelligence and Neuroscience,2020,8(1).
13. Hills J, Lines J, Baranauskas E, Mapp J, Bagnall A. Classification of time series by shapelet transformation. Data Min Knowl Disc 2014;28:851–81.
14. Koushik C,Shreyas Madhav A V,Singh Rabindra Kumar. An Efficient Approach to Microarray Data Classification using Elastic Net Feature Selection, SVM and RF[J]. Journal of Physics: Conference Series,2021,1911(1).
15. Karthikeyan V,Suja Priyadharsini S. A strong hybrid AdaBoost classification algorithm for speaker recognition[J]. Sadhanā,2021,46(3).
16. Li C, Chen Z , Liu J , et al. Power Load Forecasting Based on the Combined Model of LSTM and XGBoost[J]Power Syst Technology,2020(2):1–8.
17. ZHANG C F,WANG S,WU Y D,et al.Disavetes Risk Prediction Based on GA_Xgboost Model[J].Computer Engineering, 2020(3):315–320.
18. Song K , Yan F , Ding T , et al. A steel property optimization model based on the XGBoost algorithm and improved PSO[J]. Computational Materials Science, 2020, 174:109472.
19. D. Karaboga, An idea based on honey bee swarm for numerical optimization, Erciyes University, Technical Report-TR06, Kayseri, Turkey, 2005.
20. D. Karaboga, B. Basturk, A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm, Journal of Global Optimization 39 (2007) 459–471.
21. D. Karaboga, B. Basturk, On the performance of artificial bee colony (ABC) algorithm, Applied Soft Computing 8 (2008) 687–697
22. D. Karaboga, B. Basturk, A comparative study of artificial bee colony algorithm, Applied Mathematics and Computation 214 (2009) 108–132.
23. Ojala T, Pietikainen M, Maenpaa T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Transaction on Pattern Analysis and Machine Intelligence, 2002. 24(7), 971–987.
24. Bagnall A, Lines J, Bostrom A, Large J, Keogh E. The great time series classification bake off: a review and experimental evaluation of recent algorithmic advances. Data Min Knowl Disc 2017;31:606–60.
25. Ahmed ALDhanhani,Ernesto Damiani,Rabeb Mizouni,Di Wang. Framework for traffic event detection using Shapelet transform[J]. Engineering Applications of Artificial Intelligence,2019.82.
26. Huang H , Sun H. Network intrusion detection based on particle swarm optimization algorithm and information gain[J]. Journal of Computer Applications, 2014.
27. Sakhnovich A . On the GBDT Version of the Bäcklund-Darboux Transformation and its Applications to Linear and Nonlinear Equations and Weyl Theory[J]. Mathematical Modelling of Natural Phenomena, 2012, 5(4):340-389.
28. Zhou Z , Zhao L , Lin A , et al. Exploring the potential of deep factorization machine and various gradient boosting models in modeling daily reference evapotranspiration in China[J]. Arabian Journal of Geosciences, 2020, 13(24).
29. Chen Tao, Zhu Li. Mapping landslide susceptibility at the Three Gorges Reservoir, China, using gradient boosting decision tree, random forest and information value models [J]. Journal of Mountain Science, 2020, 17(03): 670-685.