A novel scheme for intelligent fault diagnosis of marine diesel engine using the multi-information fusion technology

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Abstract. Various parameters in the process of diesel engine operation contain a lot of information. Through data mining, the inherent information of these parameters can be mined out to solve the problems of inaccurate diagnosis and time-consuming. In this paper, a fault diagnosis scheme for the diesel engine is proposed based on the K-means analysis and the back propagation (BP) neural network. K-means is used to cluster the data and BP neural network is designed to diagnose the running state of diesel engine. Then, the fault diagnosis scheme is optimized by principal component analysis (PCA) to simplify the raw data, which are clustered by K-means and set as the input of the BP neural network to establish the fault classification model. Through the analysis and comparison of the results of the two diagnosis algorithms, it shows that the optimized algorithm can extract data features more effectively, improve the diagnosis accuracy, and reduce the diagnosis time.

1. Introduction
The diesel engine plays a significant important role in the operation of the ship. Its performance directly affects the safety and efficiency of the ship operation. The working environment of diesel engine is very bad and the failure rate is relatively high. And the diesel engine structure is complex, when there is a fault, the maintenance is difficult and the maintenance time is long. Once the maintenance is wrong, it is likely to cause serious accidents, resulting in marine pollution and economic loss of goods, even endangering the lives of seafarers [1, 2]. Therefore, it is very important to predict the failure and potential danger of diesel engines. But with the continuous development of diesel engine technology, the traditional fault diagnosis method has been difficult to meet the current requirements. The integrated diagnosis technology based on fusion has become a new direction in the field of modern ship fault diagnosis. With the development of modern information technology, the ship industry has enough data accumulation, and it is feasible to realize the intelligent fault diagnosis of diesel engine [3].

At present, the intelligent diagnosis technology of diesel engine is not mature enough. Most of them use supervised learning which BP neural network is. Through the study of fault examples and diagnosis experience, fault identification can be realized, such as literature [4]. However, the learning time of neural network is too long, and when the raw data is complex, it is easy to fall into a local minimum, which affects the diagnosis results. This is difficult to meet in engineering practice. Some other
literatures use unsupervised learning, that is, classification algorithm to classify the data under the same working condition, such as literature [5-7]. However, diesel engine faults are complex and diverse, most of the classification methods are only limited to two classifications, and the prediction deviation is large when the sample data is unbalanced. In reference [8], a method of multi-technology fusion is adopted to diagnose diesel engine faults, and gratifying results are obtained. PCA is an effective multivariate statistical process monitoring based on second-order statistics. Each feature extracted by PCA is irrelevant. Harmouche et al. [9] used the PCA framework to isolate the fault and get the severity level of the detected abnormality based on a probability distribution. Perera et al. [10] designed a fault detection system combining data acquisition and PCA, where PCA was applied to identify the hidden structure of dataset. In this paper, the method of unsupervised learning and supervised learning is used to diagnose the fault of diesel engine. Using k-means clustering analysis and BP neural network to diagnose the running state of diesel engine, and on this basis, the PCA is used to extract the eigenvalue of the data, which can effectively reduce the dimension of the sample parameters, and combine K-means clustering analysis and BP neural network to establish the diesel engine fault diagnosis model. The information obtained is processed to realize the intelligent diagnosis of diesel engine fault.

2. Fault diagnosis based on Data Mining Technology

Methods in the field of fault diagnosis can be roughly divided into three categories: model-based, qualitative empirical knowledge-based, and data-based methods.

The model-based method is suitable for systems with sufficient information and can be modeled. The establishment of mathematical modelling must understand the mechanism of the whole process and the model must be accurate. The qualitative empirical knowledge-based method is suitable for the system which is not easy to establish a mechanism model and information is not sufficient. However, the qualitative empirical–based method needs the complicated and profound professional knowledge and long-term accumulated experience, which is beyond the scope of the engineers, so it is difficult to realize [11-14].

The data-based method is a kind of automatic diagnosis method. The intelligent fault monitoring scheme based on data-driven method can obtain and deal with such a large volume of information more effectively and accurately in a short time according to the operating parameters of a diesel engine, solving the drawbacks of insufficient and incorrect diagnosis in the traditional fault diagnosis method.

3. The principle of fault diagnosis based on data mining technology

Data mining technology is used to carry out a series of fault diagnosis for the equipment. Its principle is to extract the hidden potential valuable information from the data recorded by the sensor of the equipment. A large number of data are extracted, analyzed, and finally modeled to predict the trend of its operation and classify its operating state, which is embodied in data classification. Data mining can be divided into supervised learning and unsupervised learning.

Based on the principle of data mining, this paper proposes a novel scheme of diesel engine fault diagnosis based on unsupervised and supervised learning. Unsupervised learning adopts K-means clustering analysis, supervised learning adopts BP neural network, and adopts PCA to further optimize the algorithm. Two algorithms are used to process a group of data, and the experimental results are analysed. The accuracy and efficiency of the algorithm optimized by statistics are better. The diagnosis process of the algorithm is shown in Fig. 1.
3.1. Unsupervised learning
Unsupervised learning directly classifies the data without training samples’ label in advance. The clustering algorithm is typical unsupervised learning.

In this paper, we choose a classical clustering algorithm which is K-means algorithm. Previous methods such as regression, naive Bayes and SVM must have specific categories, while K-means algorithm is a distance-based clustering algorithm. The principle of K-means is to find the number of categories, cluster the data points through the mean value, and put the characteristics of the same category together. Set the initial centroid of each category in advance, divide the similar data points, and finally obtain the optimal clustering results through the mean value iteration after the division.

Algorithm steps:
(1) Randomly select n clustering points, \( k_1, k_2, \ldots, k_n \in \mathbb{R}^n \).
(2) Repeat the following procedure until convergence:
For each example \( i \), calculate the class it should belong to:

\[
c^{(i)} = \arg \min_j \| x^{(i)} - k^{(j)} \|^2
\]

(1)

Where \( c^{(i)} \) represents the closest class between the \( i \) sample and \( n \) classes, with a value of 1 ton classes.

For each class \( j \), recalculate its centroid:

\[
k_j = \frac{\sum_{i=1}^{m} \left\{ c^{(i)} = j \right\} x^{(i)}}{\sum_{i=1}^{m} \left\{ c^{(i)} = j \right\}}
\]

(2)

(3) Define a distortion function to describe the convergence of calculation:
The $J$ function represents the sum of the squares of the distance from each sample point to its center of mass. Because $J$ function is a nonconvex function, it may fall into local optimization, which means that the minimum value cannot be guaranteed to be the global minimum value. In order to solve this problem, this paper adopts the idea of EM. The idea of EM is to determine the implicit class variable $C$ in step e, and update the parameter $K$ in step m to minimize the $J$ function.

$$J(c, k) = \sum_{i=1}^{m} \left\| x^{(i)} - k^{(c^{(i)})} \right\|^2$$ \hspace{1cm} (3)

Specify a $c^{(i)}$, in order to minimize the $J$-function, adjust the value of $k_j$ continuously to reduce $J$, it is found that if there is a better $c^{(i)}$ (category that minimizes the distance between the center of mass and the sample $x^{(i)}$) Assign to $x^{(i)}$, then $c^{(i)}$ can be readjusted, The above process is repeated until there is no better $c^{(i)}$ designation.

3.2. Supervised learning
Supervised learning must have training samples’ labels. Through training samples, a mathematical model is built to classify unknown data. BP neural network is a typical supervised learning, which is widely used in information processing.

The training algorithm of BP neural network is back propagation algorithm. Mean square error (MSE) is regarded as a function of all weights and all offsets. The smaller distance between all output vectors and target vectors can make the value of MSE smaller. When the MSE is the smallest, the training process of network has been finished.

3.3. Algorithm optimization
In the fault diagnosis of diesel engines, there are often multiple operating parameters to indicate a fault condition. When the number of parameter variables is large, it will increase the complexity of the fault diagnosis. Because some information is even redundant, we can use the main analytic hierarchy process. PCA is a statistical method, which is a dimension reduction method. The PCA adopts a mathematical dimension reduction method, which recombines many original symptom variables with certain correlation into a new set of unrelated comprehensive variables to replace the original variables, and synthesizes many variables into a few representative variables, so that these variables can represent the vast majority of information of the original variables and are not related to each other, which will reduce the amount of data and significantly reduce the workload.

The steps of PCA are as follows:

1. Standardize the original data;

$$x_{ij} = \frac{x_{ij} - \overline{x_j}}{\sqrt{\text{var}(x_j)}}, i = 1,...,n; j = 1,...,p \hspace{1cm} (4)$$

Where, \( x = \frac{1}{n} \sum_{i=1}^{n} x_{ij}, \text{var}(x_j) = \frac{1}{(n-1)} \sum_{i=1}^{n} (x_{ij} - \overline{x_j})^2 \).

2. Calculation of correlation coefficient matrix;
Find out the eigenvalue of correlation matrix (λ₁, λ₂, ..., λₚ) and eigenvectors;

\[ a_i = (a_{i1}, a_{i2}, ..., a_{ip}), i = 1, 2, ..., p \]  

(4) According to the eigenvalue of the correlation matrix, select the important principal components according to formula (7):

\[ \text{Contribution rate} = \frac{\lambda_i}{\sum_{i=1}^{p} \lambda_i} \]  

(5) According to formula (8), the principal component is calculated, and then the problem is further analysed and modelled according to the data of principal component score; la (8), the principal component is calculated, and then the problem is further analysed and modele

\[ F_{ij} = a_{j1}x_{1i} + ... + a_{jp}x_{pi} (i = 1, ... n; j = 1, ... k) \]  

Among them, \(a_{j1}, a_{j2}, ..., a_{jp}\) is the eigenvector in Eq.(6), \(x_{1i}, x_{2i}, ..., x_{pi}\) is the standardized data in Eq.(4).

In this paper, the data under the same operating parameters are clustered to simplify the parameters and show some regularity. The first algorithm uses the data after clustering as the input of neural network to identify the working condition of diesel engine and analyse the experiment. The second algorithm is to reduce the dimension of the data through PCA before clustering, which greatly simplifies many symptoms of the original data. Then, the data processed by PCA is processed by clustering, and the data processed by the two algorithms are finally used as the input of neural network to identify the working condition of diesel engine. Finally, the accuracy and efficiency of the two methods are compared.

4. Experimental verification
This paper takes MAN B&W 10L90MC marine diesel engine as the research object. Under 90% load of diesel engine, the data measured under five common working conditions (normal, carbon deposition of the injector nozzle, air leakage of the exhaust valve, wear of the high-pressure oil pump and damage of the piston ring) are six groups of data in each working condition. Among them {S1, S2, S3, S4, S5, S6, S7, S8} are operating parameters, which are mean effective pressure, exhaust manifold temperature, exhaust pressure, scavenging pressure, compression pressure, maximum burst pressure, rotation speed and oil consumption rate.
4.1. Data preprocessing

In this paper, K-means algorithm is used to cluster the sample data. The selection of K value is based on the calculation of J function. The clustering method can simplify the original sample data and show certain regularity. The classification results and centers are shown in Table 1.

| Parameters | K | Clustering center |
|------------|---|------------------|
| S1         | 3 | 188.53, 182.22, 174.47 |
| S2         | 3 | 82.63, 79.82, 77.92 |
| S3         | 3 | 13.86, 12.94, 12.23 |
| S4         | 3 | 12.16, 11.30, 10.28 |
| S5         | 2 | 0.23, 0.21 |
| S6         | 3 | 0.20, 0.18, 0.13 |
| S7         | 3 | 426.51, 412.90, 389.50 |
| S8         | 3 | 1.79, 1.71, 1.59 |

Due to limited space, only two sample data of each working condition after k-means algorithm clustering are listed in the Table 2. Among them, I is the normal working condition, II is the carbon deposition of injector nozzle, III is the air leakage of exhaust valve, IV is the wear of high-pressure oil pump, and V is the damage of piston ring.

| Fault type | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 |
|------------|----|----|----|----|----|----|----|----|
| I          | 2  | 2  | 1  | 2  | 3  | 2  | 3  | 1  |
| I          | 2  | 1  | 1  | 1  | 2  | 2  | 3  | 1  |
| II         | 1  | 2  | 3  | 2  | 2  | 3  | 2  | 3  |
| II         | 1  | 2  | 2  | 3  | 3  | 3  | 2  | 3  |
| III        | 3  | 3  | 2  | 2  | 3  | 2  | 2  | 2  |
| III        | 3  | 3  | 2  | 2  | 2  | 2  | 2  | 2  |
| IV         | 2  | 2  | 2  | 3  | 3  | 2  | 2  | 1  |
| IV         | 2  | 2  | 2  | 3  | 3  | 2  | 2  | 2  |
| V          | 2  | 2  | 2  | 2  | 2  | 1  | 1  | 1  |
| V          | 1  | 2  | 2  | 2  | 2  | 1  | 1  | 2  |

4.2. Neural network fault diagnosis

The sample data are processed by K-means, and Matlab software is used to establish neural network, taking 8 kinds of symptoms after clustering analysis as the input, and the output matrix of working mode as the target vector. After continuous testing, the network layer and structure are finally determined as: 8-9-5. The output matrix is represented by [1,0,0,0,0] as normal working condition, [0,1,0,0,0] as wear of high pressure oil pump, [0,0,1,0,0] as carbon deposition of nozzle nozzle, [0,0,0,1,0] as piston ring damage, [0,0,0,0,1] as air leakage of exhaust valve Five groups of data of each working condition are tested by the method of "training test". Select the network with the best training, and the network training error curve is shown in Fig. 2.
Figure 2. Network training error curve

It can be seen from Fig. 2 that when the calculation reaches step 8, the training error meets the requirements of the target error. Take the last group of data of each working condition as the test sample to test the trained network, and the test results are shown in Table 3 below.

Table 3. Fault prediction results of diesel engine

| Condition number | Fault name                  | Prediction results                   | Actual results |
|------------------|-----------------------------|--------------------------------------|----------------|
| I                | Normal working condition    | [0.9992, 0.0002, 0.0002, 0.0002, 0.0018] | [1,0,0,0,0]    |
| II               | High pressure oil pump worn | [0.0008, 0.9967, 0.0021, 0.0002, 0.0091] | [0,1,0,0,0]    |
| III              | Carburization of nozzle     | [0.0020, 0.0000, 0.5814, 0.0357, 0.0009] | [0,0,1,0,0]    |
| IV               | Damaged piston rings        | [0.0011, 0.0000, 0.0004, 0.7927, 0.1988] | [0,0,0,1,0]    |
| V                | Air leakage of exhaust valve| [0.0000, 0.0007, 0.0017, 0.0100, 0.9998] | [0,0,0,0,1]    |

As shown in the Table 3, this neural network has a high diagnosis accuracy under normal working conditions and high pressure oil pump wear exhaust valve leakage conditions. Under the condition of nozzle carbon deposition and piston ring damage, although the diagnostic accuracy is 0.5814 and 0.7927, respectively, which are significantly small, and the diagnosis accuracy needs to be further improved.

4.3. Algorithm optimization

A condition is represented by multiple operating parameters, which greatly increases the training time of neural network, and significantly increases the complexity of the fault diagnosis model, so the monitoring accuracy of neural network will be weakened.

In fact, there is a certain correlation between these operating parameters, so we can use the PCA method to reduce the dimension of the original data, and recombine the original symptom data with a
certain correlation into a new set of unrelated comprehensive variables. PCA is used to reduce the dimension of data. The non-linear correlation data will lose some information of the original data after dimensionality reduction, however, due to the correlation between the symptoms of diesel engine, we can calculate the contribution rate of each component. The larger the contribution rate of parameter can contain more information is contained. Through the calculation of the cumulative contribution rate, the parameters with less dimensions are selected to represent most of the information of the original data, which can reduce the complexity of the learning algorithm.

After the data is standardized, the eigenvalues and component contribution rate of the data are calculated, and the eigenvalues obtained are arranged in the Table 4.

| Number | Characteristic value | Contribution rate | Cumulative contribution rate |
|--------|----------------------|-------------------|-----------------------------|
| 1      | 3.2329               | 0.4041            | 0.4041                      |
| 2      | 1.7094               | 0.2137            | 0.6178                      |
| 3      | 1.4903               | 0.1863            | 0.8041                      |
| 4      | 1.0442               | 0.1305            | 0.9346                      |
| 5      | 0.2281               | 0.0285            | 0.9631                      |
| 6      | 0.1513               | 0.0189            | 0.9820                      |
| 7      | 0.0975               | 0.0122            | 0.9942                      |
| 8      | 0.0463               | 0.0058            | 1.0000                      |

The number of principal components is determined by the cumulative contribution rate of principal components, and the contribution rate is determined by the proportion of eigenvalues in all eigenvalues. Generally, the cumulative contribution rate is required to be more than 85%, so that the calculated variables can include most of the information of the original variables. It can be seen from Table 4 that the contribution rate of the first four eigenvalues has exceeded 85% and reached 93%. That is to say, the first four comprehensive variables calculated can include 93% information of eight variables in the original data. Then calculate the main component values of the first, the second, the third and the fourth.

According to the standardized original data and Eq. (5), the new data of each sample under the first four principal components can be obtained. The score of the principal component is shown in Table 5.

| Sample number | First principal component | Second principal component | Third principal component | Fourth principal component |
|---------------|---------------------------|-----------------------------|---------------------------|----------------------------|
| 1             | 2.077                     | -0.323                      | -1.341                    | -0.570                     |
| 2             | 3.795                     | -2.071                      | 1.400                     | 0.689                      |
| 3             | 3.508                     | -1.818                      | 0.599                     | 0.124                      |
| 4             | 2.271                     | -0.367                      | -0.921                    | -0.746                     |
| 29            | -0.465                    | 0.314                       | 1.478                     | 0.931                      |
| 30            | -0.438                    | 1.073                       | 1.681                     | 1.653                      |

K-means is used to classify the sample data calculated by principal component analysis, and the complex data is replaced by simple numbers. The specific classification is k-value clustering analysis according to different data. Using EM idea, the value of K is determined according to the requirements of obvious distinction between classes and more categories. The classification results and centers are shown in Table 6.
Table 6. Clustering results of principal components

| Principal component number | K  | Clustering center     |
|----------------------------|----|-----------------------|
| 1                          | 3  | 2.911, -0.067, -2.331 |
| 2                          | 4  | 1.130, 0.422, -0.686, -1.851 |
| 3                          | 3  | 1.54, -0.116, -1.384 |
| 4                          | 4  | 0.985, 0.255, -0.4627, -1.64 |

According to the clustering center in the above table, the values of each principal component are classified, and the classification results of each principal component are shown in Table 7 below.

Table 7. Classification results of principal components

| Sample number | First principal component | Second principal component | Third principal component | Fourth principal component |
|---------------|---------------------------|-----------------------------|---------------------------|---------------------------|
| 1             | 1                         | 3                           | 2                         | 2                         |
| 2             | 1                         | 4                           | 1                         | 1                         |
| 3             | 1                         | 4                           | 1                         | 2                         |
| 4             | 1                         | 3                           | 2                         | 3                         |
| 29            | 2                         | 2                           | 1                         | 1                         |
| 30            | 2                         | 1                           | 1                         | 1                         |

After PCA and K-means algorithm simplify the original data, the new data are tested by the same method with neural network. The network structure is: 4-7-5. Select the network with the best training through multiple experiments, and the network training error curve is shown in Fig. 3.

![Network training error curve](image)

**Figure 3.** Network training error curve

It can be seen from the figure that when the calculation reaches step 7, the training error meets the requirements of the target error. Take the last group of data of each working condition as the test sample to test the trained network, and the test results are shown in Table 8 below.
Table 8. Fault prediction results of diesel engine

| Condition number | Fault name                        | Prediction results                      | Expected results |
|------------------|-----------------------------------|-----------------------------------------|------------------|
| I                | Normal working condition          | [1.000, 0.0012, 0.0012, 0.0001, 0.0003] | [1,0,0,0,0]      |
| II               | High pressure oil pump worn       | [0.0005, 0.9958, 0.0004, 0.0003, 0.0035]| [0,1,0,0,0]      |
| III              | Carburization of nozzle           | [0.0010, 0.0013, 0.9983, 0.0012, 0.0005]| [0,0,1,0,0]      |
| IV               | Damaged piston rings              | [0.0010, 0.0057, 0.0002, 0.9951, 0.0026]| [0,0,0,1,0]      |
| V                | Air leakage of exhaust valve      | [0.0008, 0.0000, 0.0006, 0.0043, 0.9988]| [0,0,0,0,1]      |

Through the analysis of the results in Table 8, the data processed by PCA and K-means are obtained. The accuracy of neural network diagnosis is very high. And the optimized algorithm can identify the two kinds of faults, which are carbon deposition in nozzle and piston ring damage.

4.4. Analysis of experimental results
The results of the two experiments are compared, as shown in Table 9 below.

Table 9. Comparison of experimental results

| Diagnostic algorithm characteristics | Clustering analysis neural network | Cluster analysis PCA neural network |
|--------------------------------------|-----------------------------------|------------------------------------|
| Number of input nodes                | 8                                 | 4                                  |
| Hidden layer                         | 9                                 | 7                                  |
| Iteration times                      | 8                                 | 7                                  |

As shown in the above table, the results show that the neural network algorithm optimized by PCA clustering analysis can not only maintain a high diagnosis rate, but also greatly reduce the number of input nodes and hidden layers of the neural network, simplify the network structure, reduce the sum of squares and iterations of the average error, and improve the diagnosis speed.

5. Conclusion
According to the understanding of data mining, this paper proposes a diesel engine fault diagnosis scheme based on the combination of unsupervised learning and supervised learning, which uses PCA method to reduce the dimension of the original data, K-means to simplify the operating parameters and BP neural network to classify fault. The experimental results show that the proposed scheme is reliable and effective. This algorithm can greatly improve the efficiency of diesel engine fault diagnosis, not only can identify the type of diesel engine fault, but also can simplify the monitoring data as much as possible, which greatly saves time for fault diagnosis.

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