Research on Marine Diesel Engine Fault Diagnosis Based on the Manifold Learning and ELM

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Abstract. As the core equipment of marine power system, the operation state of marine diesel engine has a direct impact on the safe navigation of the whole ship. In order to extract fault features from vibration signals of diesel engine more comprehensively, a new fault diagnosis method is proposed based on the advantages of feature fusion and manifold learning algorithm in dealing with nonlinear data. The manifold learning method is used for feature extraction. Through this method, the vibration signal of diesel engine is extracted, and the feasibility and superiority of this method are verified from the perspective of three-dimensional visualization. The extracted features are input into the elm model to identify the working condition of marine diesel engine. Experimental results show that the proposed method can achieve real-time fault diagnosis with high classification accuracy.

1. Introduction

As the heart of a ship, the importance of marine diesel engine is self-evident. The intelligent condition monitoring and fault diagnosis of marine diesel engine is an important part of the realization of intelligent engine room. The complex structure, bad working environment, harsh operating conditions and strong time-varying characteristics of marine diesel engine increase the probability of equipment failure. In addition, due to the complexity of fault forms of marine diesel engine, the relationship between fault symptoms and fault sources is not simple, the traditional fault diagnosis method based on Expert knowledge and experience cannot meet the requirements. "In the era of intelligent ship, as a potential killer of safe and reliable operation of ship, the fault diagnosis of ship diesel engine needs the protection of intelligent fault diagnosis and other methods and theories.

Fault diagnosis is to judge and predict the ability of the equipment to complete the specified function without disassembling the equipment. It can be divided into four steps: signal detection, feature extraction, state recognition and prediction decision. At present, the commonly used fault diagnosis methods of marine diesel engine mainly include ferrography, thermal parameter analysis, vibration signal diagnosis, instantaneous speed analysis, mathematical statistics, fuzzy clustering analysis, artificial neural network, intelligent expert diagnosis system and grey theory.

In foreign countries, Japan, the United Kingdom, the United States, Denmark and other countries have made a breakthrough in the fault diagnosis of marine main engine. For example, the deuce
evaluation system developed by MIT uses modern signal processing and analysis technology to obtain the correlation between the gas pressure information in the cylinder of the diesel engine and the vibration signal of the fuselage [1]. The French SEMT PIELSTICK has developed the intelligent diagnosis system for the turbocharging system of the marine diesel engine. D. T. hountalas et al. [2] used thermal parameter method to monitor the working state of marine low-speed diesel engine. Roger johnsson et al. [3] used vibration signal, instantaneous speed and RBF neural network to reconstruct the pressure of diesel engine vibration signal. Charles P et al. [4] used neural network to study the fault diagnosis of diesel engine based on crank angle. Zhang B [5] et al. Used the artificial neural network algorithm to identify the fault pattern of the fuel injection system of diesel engine. Yuan K [6] extracted the characteristics of the pressure wave signal of the marine diesel engine fuel system, and uses the neural network to identify the fault. Sharkey a J C [7] extracted the cylinder pressure, vibration signal and other features for fault identification. Liu G [8] uses the neural network optimized by genetic algorithm and D-S evidence theory to study the fault diagnosis of diesel engine fuel system.

With the rapid development of signal acquisition and sensor technology, the acquisition of data information has become more and more diversified. Fault diagnosis method based on data-driven has gradually become a research hotspot in various fields. In the face of many data information, how to fully mine fault feature information is the key point of data-driven fault diagnosis. Based on the theory of system learning manifold learning and Extreme Learning Machine (ELM), in order to obtain comprehensive, low dimensional and sensitive fault feature information, manifold learning is used for feature extraction, aiming at the shortcomings of the original elm algorithm, and the improved algorithm is used for fault diagnosis of marine diesel engine, so as to provide a new method for intelligent fault diagnosis of marine diesel engine.

2. The manifold learning algorithm
Before the manifold learning method was put forward, the linear method represented by principal component analysis (PCA), linear discriminant analysis (LDA) and independent component analysis (ICA) was widely used in feature extraction. However, when the linear feature extraction method was applied to nonlinear data, it could not effectively find the hidden distribution law between data points, which made the result of feature extraction unsatisfactory. In view of this problem, some scholars have proposed some nonlinear feature extraction methods based on kernel transformation. Currently, the widely used kernel transformation methods include kernel function based principal component analysis (KPCA) and kernel Fisher discriminant analysis, etc. Manifold learning is a typical unsupervised learning algorithm, which has become a hot topic in recent years. Using manifold learning algorithm can effectively explore the internal structure of nonlinear high-dimensional data and retain the local structure features of data, which is very conducive to data analysis and feature extraction of high-dimensional data. In order to obtain better feature selection effect, the Isometric Mapping algorithm (Isomap), the local linear embedding algorithm (LLE) and t-distributed stochastic neighbor embedding algorithm (T-SNE) are selected for comparative analysis, and the algorithm with the best feature extraction effect for the vibration signal of marine diesel engine is selected.

2.1. Isometric Mapping
Isometric Mapping (Isomap) is a feature extraction algorithm based on multidimensional scale transformation proposed by Joshua B. The basic idea of Isomap algorithm is to use geodesic distance instead of Euclidean distance in multidimensional scale analysis algorithm, and on the basis of constructing global geodesic distance matrix, isometric mapping is established to establish the connection between high-dimensional input space and low-dimensional embedded space. Isomap is to obtain the corresponding representation of high-dimensional data set in low-dimensional structure through isometric mapping when the data has embedded manifold structure.

(1) Constructing neighborhood graph G
For any given sample point $x_i (i=1,2...N)$, if the Euclidean distance $d_x(i,j)$ between sample points $x_i$ and $x_j$ is less than a given threshold $\varepsilon$, they are $k$ neighbors of each other, then connect $i$ and $j$ with one edge. And set the edge length of this edge as the Euclidean distance $d_x(i,j)$ between the two points. According to this method, neighborhood graph $G$ including all sample points can be established.

(2) Estimating geodesic distance matrix $D_G$

Because the geodesic distance cannot be accurately obtained, Isomap maps the shortest path between two points on the nearest neighbor graph $G$ to the geodesic distance between two points in the manifold structure. Let the geodesic distance between $x_i$ and $x_j$ be $d_G(i,j)$. If there is an edge connection between $x_i$ and $x_j$, so $d_G(i,j)=d_G(i,j)$. According to the method, the whole sample space $L=x_1,x_2,...x_N$ is calculated by the following formula.

$$d_G(i,j) = \min\{d_G(i,j),d_G(i,L)+d_G(L,j)\}$$ (1)

$$D_G = \{d_G(i,j)\}$$ (2)

(3) Get low dimensional embedding

Applying MDS method to geodesic distance $D_G$, $r(D_G) = -\frac{HSH}{2}$, the $H$ is the centered matrix, and $S$ is the square matrix of distance. Then all eigenvalues and eigenvectors of the matrix are calculated, and they are arranged in the order of eigenvalues from large to small. Select the first $d$ eigenvalues $\lambda_1, \lambda_2,...\lambda_d$ and eigenvector to form the matrix $U=(u_1,u_2,...u_d)$, then the final $d$ dimension embedding result is as follows:

$$Y = diag(\lambda_1^2,\lambda_2^2,...\lambda_d^2)U^T$$ (3)

2.2. Local linear embedding

Local linear embedding (LLE) algorithm is a nonlinear data dimensionality reduction method based on manifold learning proposed by roweis and Saul in 2000. LLE and Isomap try to keep the manifold structure of high-dimensional space in the process of dimensionality reduction. The difference is that Isomap takes the geodesic distance between samples as the feature of manifold structure, while LLE thinks that the local relationship of samples describes the manifold structure. The calculation steps of LLE algorithm are as follows:

(1) Choose the neighbor

For any given data set $X=(x_1,x_2,...x_N),x_i \in R^D$. Find the neighbourhood points $k(k<N)$ of each sample point $x_i$ t, and use the following formula to calculate the Euclidean distance $d_{ij}$.

$$d_{ij} = \left[ \sum_{k=1}^{D} (x_{ik} - x_{jk})^2 \right]^{\frac{1}{2}}$$ (4)

(2) Linear reconstruction

The reconstruction weights of the neighborhood of sample points are calculated, the local reconstruction weight matrix is constructed, and an error function is defined.

$$\min \varepsilon(W) = \sum_{i=1}^{N} \left\| X_i - \sum_{j=1}^{N} w_{ij} x_j \right\|^2$$ (5)
Where, $w_{ij}$ is the weight between $x_i$ and $x_j$.

(3) Mapping to embedded coordinates
Minimize reconstruction errors and functions.

$$\min \Phi(Y) = \sum_{i=1}^{N} \left\| y_i - \sum_{j=1}^{N} w_{ij} y_j \right\|^2$$ \hspace{1cm} (6)

In order to avoid data set collapsing to coordinate origin in low dimensional space, the following formula is used to limit $Y$.

$$\sum_{i=1}^{W} y_i y_i^T = I$$ \hspace{1cm} (7)

Where $I$ represent N-dimensional unit matrix, the above optimization problems can be transformed into the following constrained problems.

$$\begin{cases}
\min \Phi(Y) = \sum_{i=1}^{N} \left\| Y I_j - YW_i \right\|^2 \\
= \sum_{i=1}^{N} \left\| Y (I_j - W_i) \right\|^2 \\
= \min \text{tr} YMY^T \\
st \quad Y Y^T = I
\end{cases}$$ \hspace{1cm} (8)

The low dimensional coordinate $Y$ can be obtained by Lagrange multiplier method. To sum up, the calculation process of LLE is as follows:

$$\{X_i\}_{i=1}^{N} \rightarrow \{W_i\} \rightarrow \{Y_i\}_{i=1}^{N}$$ \hspace{1cm} (9)

2.3. The t-distributed stochastic neighbor embedding algorithm
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The t-distributed stochastic neighbor embedding algorithm was proposed by Laurens Vander Matten in 2008. It is a manifold learning algorithm based on probability distribution. It has been widely used in machine learning in recent years. Different from the two nonlinear manifold learning methods mentioned above, the t-SNE method uses the form of probability distribution to model the original high-dimensional data and the low-dimensional data in the embedding space, and then uses the gradient descent method to optimize the objective function based on KL divergence, and then looks for the most suitable embedding point in the low-dimensional space in turn. The steps of T-SNE algorithm are as follows:

(1) Constructing probability distribution of high dimensional space
Given any set containing $n$ data points $X = \{x_1, x_2, ..., x_n\}$, Suppose that any two points $x_i$ and $x_j$, $x_i$ is centered on $x_j$. The conditional probability distribution similar to $x_i$ and $x_j$ is:
\[ P_{ij} = \frac{\exp(-\| x_i - x_j \|^2 / 2\delta^2)}{\sum_{k \neq i} \exp(-\| x_i - x_j \|^2 / 2\delta^2)} \] (10)

Where the similarity here is from the perspective of \( x_i \), the \( \delta_i \) is set according to the specified perp puzzle, it is determined by binary search method. The definition formula of puzzle degree is as follows:

\[ Perp(P_i) = 2^{H(P_i)} \] (11)

\[ H(P_i) = -\sum_j P_{ij} \log_2 P_{ij} \] (12)

The joint probability \( p_{ij} \) of similarity between data points \( x_i \) and \( x_j \) in all data sample points is defined as follows:

\[ p_{ij} = \frac{P_{ij} + P_{ji}}{2n} \] (13)

(2) Constructing probability distribution in low dimensional space

Let \( Y = [y_1, y_2, \ldots, y_n] \) be a low-dimensional embedding coordinate of high-dimensional data set \( X = [x_1, x_2, \ldots, x_n] \). In the low dimensional space, if a data point is subject to the \( t \) distribution with a degree of freedom of 1, then the joint probability distribution of corresponding points \( y_i \) and \( y_j \) of data points \( x_i \) and \( x_j \) in the low dimensional data space is as follows:

\[ q_{ij} = \frac{(1+\| y_i - y_j \|^2)^{-1}}{\sum_{k \neq i} (1+\| y_k - y_i \|^2)^{-1}} \] (14)

(3) Compute low dimensional embedding

The similarity between high-dimensional spatial probability distribution \( P \) and low-dimensional spatial probability distribution \( q \) is measured by KL divergence:

\[ C = KL(P \| Q) = \sum_i \sum_j P_{ij} \log \frac{P_{ij}}{Q_{ij}} \] (15)

In order to obtain the low-dimensional embedding \( y_i \), the gradient descent method is used to minimize the KL divergence. The gradient values are as follows:

\[ \frac{\delta C}{\delta y_i} = 4 \sum_j (P_{ij} - Q_{ij})(y_i - y_j)(1+\| y_i - y_j \|^2)^{-1} \] (16)

2.4. The Extreme Learning Machine algorithm

Extreme Learning Machine is a new single hidden layer feedforward neural network proposed by Huang et al. The core idea of this algorithm is to randomly generate hidden layer weights and biases, to minimize the impact of artificial intervention, and directly get the output layer weights by solving the equations with the least square method, so as to complete the network training.

For any \( n \) different samples \((X_i, t_i)\), \( X_i = (x_{i1}, x_{i2}, \ldots, x_{in})^T \in \mathbb{R}^n \), and \( t_i = (t_{i1}, t_{i2}, \ldots, t_{im}) \in \mathbb{R}^m \), \( n \) represent the dimension of the input sample, \( m \) represent the dimension of the training sample. The single hidden layer ELM model with activation function \( g(x) \) and hidden layer node \( L \) is as follows:
\[
\sum_{i=1}^{L} \beta_i g(W_iX_j + b_i) = o_j, \ j = 1, 2, ..., N
\]  

Where \(W_i = [W_{i1}, W_{i2}, ..., W_{in}]^T\) is the input weight, \(b_i\) is the offset of the \(i^{th}\) hidden layer node, \(\beta_i\) is the output weight.

The learning goal of ELM is to minimize the output error, which can be expressed as follows:

\[
\sum_{j=1}^{N} \|o_j - t_j\| = 0
\]  

\[
\sum_{i=1}^{L} \beta_i g(W_iX_j + b_i) = t_j, \ j = 1, ..., N
\]  

\[\text{H} \beta = \text{T} \]  

Where \(H\) is the hidden layer node output, \(\beta\) is the weight output, and \(T\) is the expected output.

\[
H = \begin{bmatrix}
g(W_{11},X_{j1} + b_{11}) & \cdots & g(W_{1N},X_{j1} + b_{1N}) \\
\vdots & \ddots & \vdots \\
g(W_{L1},X_{N1} + b_{L1}) & \cdots & g(W_{LN},X_{N1} + b_{LN}) 
\end{bmatrix}_{N \times L}
\]  

\[
\beta = \begin{bmatrix}
\beta_{1}^T \\
\vdots \\
\beta_{L}^T 
\end{bmatrix}_{1 \times m}, \ T = \begin{bmatrix}
T_{1}^T \\
\vdots \\
T_{L}^T 
\end{bmatrix}_{L \times m}
\]  

In order to train the ELM, the \(\hat{W}_i, \hat{b}_i\) and \(\hat{\beta}_i\) can be obtained as follows:

\[
\|H(\hat{W}_i, \hat{b}_i) - T\| = \min_{W_i, b_i} \|H(W_i, b_i)\beta_i - T\|
\]  

Where \(i = 1, ..., L\), and minimum loss function is

\[
E = \sum_{j=1}^{N} \left(\sum_{i=1}^{L} \beta_i g(W_iX_j + b_i) - t_j\right)^2
\]  

Traditional neural networks and other algorithms are usually solved by gradient descent method, but gradient descent method needs to adjust all parameters in the iteration process, and gradient descent is easy to fall into local minimum. With the increase of network layer number, there will be gradient disappearance and gradient explosion. The biggest feature of elm is that it does not need to solve iteratively. The output matrix of hidden layer is uniquely determined with the random determination of input weight and hidden layer bias. The training of network can be completed by solving formula \(H\beta = T\), and the output weight \(\beta\) can also be solved by the following formula:

\[
\hat{\beta} = H^T
\]
\[
H^* = (H^T H)^{-1} H^T
\]  

(26)

Where \( H^* \) is the generalized inverse matrix of \( H \).

3. Experimental verification

In this paper, four stroke diesel engine (model: R6105AZLD) is taken as the research object, and the validity of the proposed method is verified by monitoring and diagnosing its health status. The test bench simulates five different working conditions of diesel engine, and the five working conditions simulation scheme is shown in Table 2. The vibration signal data are collected under the same diesel engine speed (1500rpm) under each working condition. The sampling frequency of the sensor is 40 kHz. Since the diesel engine is four stroke, 720° crankshaft rotation is a working cycle. So in this paper, we take 3200 data points as a sampling period. The vibration signals of each working condition are collected after reaching the stable working state at the speed set by the diesel engine. Because the fault condition of the simulated diesel engine has a great impact on the diesel engine system, the diesel engine can not run for a long time under the fault condition. So in each case, we sampled 200 sets of data, a total of 1000 sets. In the experiment, 80% of the samples were randomly selected for training and 20% for testing. Repeated training and testing to ensure the accuracy of the test results. The fault condition simulation scheme of R6105AZLD diesel engine is shown in Table 1.

| Number | Conditions                  | Methods                          |
|--------|-----------------------------|----------------------------------|
| G1     | Normal                      | Normal working condition         |
| G2     | Single cylinder fire        | Oil cut-off of left cylinder 1   |
| G3     | Combustion advance          | Fuel supply advance angle increased by 2.5 |
| G4     | Combustion lag              | Fuel supply advance angle reduced by 2.5 |
| G5     | Air filter blocked          | Air filter blocked               |

The following three classic manifold learning methods are used to extract the features of the data, and the results are as follows, only part of the data samples are shown in the Table 2.

| Number | Feature1  | Feature2  | Feature3  | Condition |
|--------|-----------|-----------|-----------|-----------|
| 1      | -0.2122   | 0.2914    | -0.1240   | G1        |
| 2      | -0.3036   | 0.4332    | -0.2202   | G1        |
| 3      | -0.8037   | -0.2825   | 0.2308    | G2        |
| 4      | -0.6731   | -0.3164   | -0.1556   | G2        |
| 5      | -1.4142   | -0.5818   | -0.0361   | G3        |
| 6      | -1.4858   | -0.7324   | -0.0579   | G3        |
| 7      | 1.6430    | 0.0186    | -0.2282   | G4        |
| 8      | 1.6229    | -0.1525   | -0.2730   | G4        |
| 9      | 0.9073    | 0.0810    | -0.2540   | G5        |
| 10     | 1.1524    | 0.1069    | -0.1618   | G5        |

In order to better display the feature extraction results, draw the feature extraction results into a three-dimensional visual image, as shown in the following Figure 1.
Figure 1. The influence of Isomap

It can be found from the observation of the above figure that the feature data after dimensionality reduction by Isomap has basically obtained satisfactory dimensionality reduction effect, all the sample points of G3 are scattered with other samples, G1 and G2 have a small amount of aliasing from the perspective of 3D visualization, and there are also a small amount of aliasing between G4 and G5. Five kinds of data points under different working conditions are basically grouped together, but some individual sample points deviate from their own groups. This is because the Isomap algorithm is too dependent on the stability of the original data topology space, which is more suitable for the calculation of geodesic distance in the case of large samples.

Table 3. The extraction results of LLE

| Number | Feature1 | Feature2 | Feature3 | Condition |
|--------|----------|----------|----------|------------|
| 1      | 0.0219   | 0.0721   | 0.0349   | G1         |
| 2      | 0.0243   | 0.0005   | 0.0277   | G1         |
| 3      | 0.0288   | 0.0084   | 0.0012   | G2         |
| 4      | 0.0298   | 0.0128   | 0.0119   | G2         |
| 5      | 0.0313   | 0.0422   | 0.0389   | G3         |
| 6      | 0.0318   | 0.0314   | 0.0431   | G3         |
| 7      | 0.1211   | 0.0642   | 0.0252   | G4         |
| 8      | 0.1115   | 0.0293   | 0.0363   | G4         |
| 9      | 0.0219   | 0.0690   | 0.0713   | G5         |
| 10     | 0.0257   | 0.0396   | 0.0483   | G5         |
Figure 2. The influence of LLE

It is easy to find that LLE algorithm is much worse than Isomap algorithm in dimensionality reduction. It can be seen that after LLE dimensionality reduction, the distribution of some data sample points is very uneven, the dimensionality reduction effect is not very good, there is a large overlap between G4 and G5, the interval between G1, G2 and G3 is not large, and the distribution between the same kinds is relatively discrete. The reason for this kind of phenomenon may be that LLE describes manifold structure based on local neighborhood that is, assuming that each point can be reconstructed linearly by its neighborhood point, when its neighborhood cannot reconstruct the point well, there will be a large deviation.

Table 4. The extraction results of t-SNE

| Number | Feature1 | Feature2 | Feature3 | Condition |
|--------|----------|----------|----------|-----------|
| 1      | 6.0567   | 5.24976  | 2.4127   | G1        |
| 2      | 7.0303   | 3.8043   | 3.092    | G1        |
| 3      | 2.0152   | 2.3941   | 6.2404   | G2        |
| 4      | 1.8538   | 2.8682   | 2.9758   | G2        |
| 5      | -3.3387  | -8.4917  | 5.9848   | G3        |
| 6      | -2.3732  | -9.8454  | 7.9171   | G3        |
| 7      | -5.9493  | -1.8210  | -9.5992  | G4        |
| 8      | -4.2050  | -0.9427  | -7.2039  | G4        |
| 9      | -1.4304  | 0.84120  | -12.1639 | G5        |
| 10     | 0.2635   | 1.0981   | -9.6907  | G5        |
Figure 3. The influence of t-SNE

It can be seen from the observation above that the data classification of t-sne method after dimensionality reduction is clear, and the clustering effect of each working condition is obvious. Five different working conditions are far away from each other in low dimensional space, which has strong separability. Compared with the two manifold learning algorithms mentioned above, it is found that t-sne has great advantages in dimensionality reduction of high-dimensional data, especially in the visualization of high-dimensional data.

The extracted features are input into the ELM to realize the recognition of diesel engine working condition. The classification accuracy is shown in Table 5.

| Average accuracy (%) | ELM |
|----------------------|-----|
| LLE                  | 86.74 |
| ISOMAP               | 89.23 |
| TSNE                 | 90.11 |

The fault data of marine diesel engine extracted by three manifold learning feature extraction methods are classified by ELM model. The results show that t-sne and Isomap are both good at fault extraction, of which t-sne feature extraction is the best with classification accuracy of 90.011%.

4. Conclusion

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In this paper, the manifold learning algorithm is used to extract the secondary features of the fusion features, and the results of feature extraction are analyzed from the perspective of 3D visualization. The
results of feature extraction of t-SNE and Isomap manifold learning methods are very good, which verify the feasibility and superiority of the feature extraction method in this section. At the same time, the fault diagnosis of marine diesel engine is carried out by the ELM model, and the result shows that the classification accuracy of the algorithm in t-SNE data set is as high as 90%, which verifies the superiority of the feature extraction method proposed in this paper and the accuracy of the classifier model.

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