Fault Diagnosis of Rolling Bearing Based on EEMD and MMTS

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Abstract. Aiming at the non-stability of vibration signals and the inaccuracy of signal extraction of motor bearings, a fault diagnosis method based on the ensemble empirical modal decomposition (EEMD) and Multiclass Mahalanobis-Taguchi system (MMTS) is presented. Firstly, the original vibration signal is processed by EEMD and the processed signal is decomposed into a series of IMF with different characteristic time scales. Then select several IMF components in which the signal energy is concentrated to calculate the characteristic parameters of each order of IMF to construct fault eigenvector. Secondly, the fault eigenvector is used as input to construct the MMTS for fault identification. Finally, the accuracy of the method is verified by the bearing data set collected by the Electrical Engineering Laboratory of Case Western Reserve University (CWRU). The results show that the method can diagnose rolling bearing faults quickly and accurately.

1. Introduction
Rolling bearings are indispensable parts in modern machinery and equipment, providing guarantees for their safe and stable operation. The complex internal structure of the mechanical system makes the rolling bearing have a high-frequency working state, which makes the occurrence of failures unpredictable, which limits the use of mechanical equipment to a certain extent [1]. Deteriorating bearing failure status will cause abnormalities in mechanical equipment, and even casualties in severe cases. Therefore, it is necessary to accurately identify the fault state of rolling bearings.

The vibration signal of rolling bearing presents non-linear and non-stationary characteristics. Therefore, in order to ensure accurate fault state recognition, it is necessary to extract characteristic information of the signal. At present, the commonly used signal analysis methods include short-time Fourier transform [2], wavelet transform [3] and Wigner-Ville distribution [4], which are non-adaptive analysis methods. EMD is adaptive and avoids the uncertainty of wavelet basis selection. However, severe end effects and modal aliasing directly affect the correctness of the decomposition results [5]. To solve this problem, Wu and Huang proposed Ensemble Empirical Mode Decomposition (EEMD). This method automatically and effectively eliminates or reduces the end effect by adding white noise to the original signal and improves the accuracy of the decomposition [6]. EEMD has great advantages in nonlinear and non-stationary signal time-frequency analysis, and is very suitable for vibration signal processing.
MTS was developed by Dr. Taguchi as a diagnosis and forecasting technique using multivariate data. MTS combines the Mahalanobis distance with Taguchi’s robust engineering and is used for optimizing the multidimensional systems [7]. MTS is different from classical multivariate methods in the following ways. First, the methods used in MTS are data analytic instead of probability-based inference. This means that MTS does not require any assumptions on the distribution of input variables. Second, the Mahalanobis distance in MTS is suitably scaled and used as a measure of severity of various conditions. MTS can be used not only to classify observations into two different groups (i.e., normal and abnormal) but also to measure the degree of abnormality of an observation. Third, every example outside the normal space (i.e., abnormal example) is regarded as unique and does not constitute a separate population. Woodall introduced MTS and put forward the problems of MTS in concept, technology and operation [8]. Jugulum and Taguchi explained the problems raised by statisticians in different degrees, which made the theory of Martian system more perfect [9]. Although the theory of MTS is not perfect, its application has achieved remarkable results. MTS is widely used because of its significant advantages in system diagnosis and prediction using data sets and related features [10]. However, MTS was originally designed for binary classification problems, when it is applied to rolling bearing fault diagnosis, most of the problems are multiclass classification problems, so it is necessary to develop binary classification MTS into multiclass Mahalanobis-Taguchi system (MMTS) [11].

To be able to surmount the restriction on the suitability of using MTS against multiclass problems, the MMTS was proposed according to the framework of MTS. MMTS breaks the limitation of MTS in which only one Mahalanobis space is constructed for one problem. In contrast, MMTS establishes an individual Mahalanobis space for each class. Therefore, this paper selects EEMD to decompose the signals of the collected bearings, and extracts the time-domain and frequency-domain features from each order of IMF as the fault eigenvalues. The fault eigenvector is used as input to construct the MMTS for fault identification. And the correctness of the method is verified by the bearing data set collected by the Electrical Engineering Laboratory of Case Western Reserve University (CWRU).

2. Feature extraction based on EEMD

2.1. EEMD algorithm

EEMD is implemented on the basis of EMD. Its basic decomposition step is as follows:

1) Adding a Gaussian white noise signal N times (N>1) in the original signal \(x(t), n_i(t)\) (i=1~N), namely:

\[
x_i(t) = x(t) + n_i(t)
\]  

Among them, \(x(t)\) is original signal, \(n_i (t)\) is the added Gaussian white noise signal, the standard deviation of the amplitude is constant and the mean is zero, \(x_i (t)\) is the signal to be decomposed that is added to the white noise.

2) EMD decomposition of signals \(x_i(t)\) containing white noise:

\[
x_i(t) = \sum_{j=1}^{M} c_{ij}(t) + r_i(t)
\]

It can be obtained that the number of IMF components is M, which are recorded as \(c_{ij}(t)\) (j=1–M), and one remaining item is recorded as \(r_i (t)\). Among them, \(c_{ij}(t)\) represents the j component obtained after the white noise is added for the i time.

3) All the IMF components and remaining item obtained above are subjected to the population mean operation to eliminate the influence of Gaussian white noise on the data, and the final IMF component is obtained:
Among them, \( c_j(t) \) is the j-th IMF component decomposed by EEMD, and \( r(t) \) is the remaining item decomposed by EEMD.

2.2. Feature extraction based on IMF
In order to extract information fully, both time-domain and frequency-domain statistics features are utilized. The time-domain features for a signal shows its characteristic changing with time, such as root-mean-square (RMS) and kurtosis, which describe the overall trait of the signal. And frequency-domain is another aspect of description to a signal. Information that can hardly be extracted in time-domain can be revealed in frequency-domain. What's more, frequency-domain features such as root-mean-square frequency (RMSF) can extract the essence of the signal which is crucial to fault diagnosis. The feature parameters are as shown in Table 1.

| Feature | Formula |
|---------|---------|
| RMS     | \( \sqrt{\frac{1}{N_s} \sum_{n=1}^{N_s} (x(n))^2} \) |
| Range   | \( \max(x(n)) - \min(x(n)) \) |
| Kurt    | \( \frac{1}{N_s - 1} \sum_{n=1}^{N_s} \left( \frac{1}{N_s} \sum_{n=1}^{N_s} (x(n) - \bar{x}(n))^4 \right) \) |
| Peak    | \( \frac{\max|x(n)|}{RMS} \) |
| RMSF    | \( f_{bb} = \left[ \frac{\sum_{i=1}^{n/2} f_i^2 P(f_i)}{\sum_{i=1}^{n/2} P(f_i)} \right]^{1/2} \) |
| RVF     | \( f_{TV} = \left[ \frac{\int_0^\infty (f - f_{avg})^2 p(f)df}{\int_0^\infty p(f)df} \right]^{1/2} \) |

3. Fault diagnosis based on EEMD and MMTS
To implement MMTS, there are four main stages:

3.1. Stage 1: construction of a full model measurement scale with Mahalanobis space of each class as the reference.

In the first stage, after the problem and all related features are defined, the representative examples are collected and used to construct the individual Mahalanobis space for each class and establish the full model measurement scale.
3.2. Stage 2: validation of the full model measurement scale

Assume that there are k classes in a d-dimensional space. If the k-th class is used as Mahalanobis space, the other k-1 classes are regarded as abnormal sample to validate the Mahalanobis space. Use the mean and standard deviation of the normal sample to standardize the data of the abnormal sample, and then use the normal sample correlation coefficient matrix to calculate the abnormal Mahalanobis distance. If the normal sample Mahalanobis distance is around 1, and the abnormal sample Mahalanobis distance is far from the Mahalanobis distance of the normal sample indicates that the reference space construction is effective.

3.3. Stage 3: feature selection

In this stage, orthogonal arrays and SN ratio are used to identify the important features for multiclass classification. The orthogonal experiment is designed through the orthogonal array. Use orthogonal table to find different combinations of characteristic variables. In MTS, different Mahalanobis spaces can be constructed through a two-level orthogonal array, and each Mahalanobis space is used to calculate the Mahalanobis distance (MD) of the abnormal sample, and then the SN ratio under each test condition is calculated according to equation (5), so as to obtain each the main effect of each variable.

\[
\eta = -10\log_{10}\left[\frac{1}{q}\sum_{k=1}^{q} \frac{1}{MD_k^b}\right]
\]

(5)

After the SN ratio of every run is calculated, the set of useful features is obtained by evaluating the “effect gain.” For the \( l \)th feature, \( SNR_l^+ \) is used to represent the SN ratio of all runs including the feature, while \( SNR_l^- \) represents the SN ratio of all runs excluding the feature. Because of the usage of orthogonal array, it is allowable to independently evaluate the effect of each main factor. Thus, the effect gain of each feature can be directly calculated using the following equation:

\[
\Delta = SNR_l^+ - SNR_l^-
\]

(6)

If the effect gain corresponding to a feature is positive, the feature may be important and be considered as worth keeping. However, a variable with negative effect gain should be removed.

3.4. Stage 4: future prediction with important features.

Once the important features are identified in the third stage, we reconstruct the measurement scale using these useful features. Based on this reduced model, a classification can be achieved by simply classifying examples into the class with threshold value, and thus the classification accuracy can be acquired. The thresholds set in this article is calculated using the following equation:

\[
\lambda = \mu + 6\sigma
\]

(7)

Where \( \mu \) is the mean value of the Mahalanobis distance of the normal sample, and \( \sigma \) is the standard deviation of the Mahalanobis distance of the normal sample. When the Mahalanobis distance of the test set sample is less than the threshold, it is judged as a normal sample, otherwise it is an abnormal sample. The fault diagnosis flowchart of rolling bearing based on EEMD and MMTS is as shown in Figure 1.
4. The proposed method of bearing fault diagnosis

In order to verify the effectiveness of the proposed method, this paper uses the bearing data set collected by the Electrical Engineering Laboratory of Case Western Reserve University (CWRU) as the verification data. This article uses the SKF drive end bearing data, the fault point of the outer raceway is at 3 o'clock, and the speed is 1797 rpm. Digital data was collected at 12,000 samples per second. In addition to the normal state, the data set also contains 3 typical fault states, namely ball faults and inner race faults and outer race faults; faults are arranged by electro-discharge machining with fault diameters of 7 mils and a data sample length of 1024. In this article, 100 sets of samples corresponding to 4 different states are taken, totaling 400 sets of data. Choose 60 groups (60%) of the 100 groups of data in each of the 4 states as the training set, and the remaining 40 groups (40%) as the test set to verify the effectiveness of the algorithm. The vibration signal of the bearing in the 4 states are shown in the Figure 2.
First, 400 sets of samples in 4 states are decomposed by EEMD, and each sample is decomposed into more than 10 IMF components, which contain multi-scale fault information of rolling bearings. Taking the inner race fault sample as an example, after the vibration signal is decomposed by EEMD, the signal energy is mainly concentrated in the first few IMF components. As shown in Figure 3, the first 3 IMF components in are the most obvious, so this article selects the first 3 IMF components to calculate the eigenvalues.

This article chooses the first 3 IMF components to calculate the above 6 eigenvalues, from which a total of 18 fault eigenvectors are obtained. Take IMF1 as an example and the features extract from IMF1 is shown in Table 2.
Table 2. The features extract from IMF1.

| component       | sample | class   | RMS    | Range | Peak   | Kurtosis | RMSF    | RVF     |
|-----------------|--------|---------|--------|-------|--------|----------|---------|---------|
|                 | 1      | Normal  | 0.0264 | 0.0957| 3.6272 | 6.4592   | 1.5498×10⁻⁶| 3.8784×10³|
|                 | 2      | Normal  | 0.0256 | 0.1157| 4.5163 | 10.8359  | 7.6897×10⁻⁶| 4.9993×10³|
|                 | ...    | ...     | ...    | ...   | ...    | ...      | ...     | ...     |
|                 | 100    | Normal  | 0.0250 | 0.0858| 3.4352 | 6.2545   | 7.4787×10⁻⁶| 4.9843×10³|
|                 | 101    | IR fault| 0.3236 | 1.1691| 3.6133 | 4.9636   | 1.8038×10⁻⁴| 5.2641×10³|
|                 | 102    | IR fault| 0.3041 | 1.1076| 3.6428 | 5.4712   | 3.9911×10⁻⁵| 6.2168×10³|
|                 | ...    | ...     | ...    | ...   | ...    | ...      | ...     | ...     |
|                 | 200    | IR fault| 0.3302 | 1.0756| 3.2581 | 5.0540   | 4.0504×10⁻⁵| 6.2267×10³|
|                 | 201    | OR fault| 0.9865 | 2.7673| 2.8065 | 4.5413   | 0.0021  | 4.7728×10³|
|                 | 202    | OR fault| 0.9250 | 2.4556| 2.6561 | 3.9110   | 2.3329×10⁻⁵| 6.3747×10³|
|                 | ...    | ...     | ...    | ...   | ...    | ...      | ...     | ...     |
|                 | 300    | OR fault| 0.9003 | 2.7245| 3.0270 | 4.2037   | 2.4493×10⁻⁵| 6.1917×10³|
|                 | 301    | Ball fault| 0.1690 | 0.4401| 2.6050 | 2.8256   | 5.3274×10⁻⁵| 5.2943×10³|
|                 | 302    | Ball fault| 0.1589 | 0.3825| 2.4084 | 2.6843   | 3.2807×10⁻⁶| 5.8828×10³|
|                 | ...    | ...     | ...    | ...   | ...    | ...      | ...     | ...     |
|                 | 400    | Ball fault| 0.1737 | 0.4454| 2.5651 | 3.0428   | 3.7534×10⁻⁶| 5.9678×10³|

Input the obtained features into the MMTS, and select important features using orthogonal array and SN ratio, and the result is as shown in Figure 4 to Figure 7. Finally, calculate the MD of the test data with selected features, then classify the test set according to the threshold and the result obtained is shown in the Figure 8 to Figure 11 below.

**Figure 4.** The effect gain based on Mahalanobis space of Normal status.

**Figure 5.** The effect gain based on Mahalanobis space of Inner race fault.
Figure 6. The effect gain based on Mahalanobis space of Outer race fault.

Figure 7. The effect gain based on Mahalanobis space of Ball fault.

Figure 8. The MD of test sets based on Mahalanobis space of Normal status.

Figure 9. The MD of test sets based on Mahalanobis space of Inner race fault.

Figure 10. The MD of test sets based on Mahalanobis space of Outer race fault.

Figure 11. The MD of test sets based on Mahalanobis space of Ball fault.
It can be seen from Figure 3 to Figure 6 that the MMTS in this paper can clearly distinguish the class in the test which is the same with the Mahalanobis space class. For 160 test sets, the MMTS fault diagnosis accuracy is 98.75% (158/160), among which the diagnosis result of the normal state is (40/40); the diagnosis result of the inner ring fault state is (40/40); the outer ring fault state the diagnosis result is (38/40); the diagnosis result of the rolling element failure state is (40/40), as shown in Table 3.

| Fault position    | Threshold | Accuracy |
|-------------------|-----------|----------|
| Normal            | 3.64      | 100%     |
| Inner race fault  | 5.44      | 100%     |
| Outer race fault  | 4.72      | 95%      |
| Ball fault        | 5.39      | 100%     |

5. Conclusions
In this research, we proposed a method based on EEMD processing and MMTS algorithms for rolling bearing fault diagnosis. This approach requires the ability of EEMD to decompose vibration signals with an adaptive noise in order to extract accurately the most significant IMFs that utilized afterward to calculate the fault features. Our MMTS-based method still maintains high performance for rolling bearing fault diagnosis and can achieve 98.75% of classification accuracy. The application of EEMD-MMTS method to CWRU bearing database validates the robustness and reliability of our approach where the classification accuracies attain 100%, 100%, 95% and 100% corresponding to healthy status, inner race fault, outer race fault and ball fault, respectively.

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