Fault diagnosis approach of rolling bearing based on NA-MEMD and FRCMAC

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Abstract: This paper proposed a new method of fault diagnosis based on Noise Assisted Multivariate Empirical Mode Decomposition (NA-MEMD) and Fuzzy Recurrent Cerebellar Model Articulation Controller (FRCMAC) Neural Networks. Aiming at the problem that during the use of the NA-MEMD method, the white noise amplitude parameter needs to be selected by artificial experience, a method of using Genetic Algorithm (GA) to optimize its auxiliary white noise parameter is proposed, which facilitates the use of NA-MEMD. We proposed a novel FRCMAC structure which improved Learning efficiency and dynamic response speed than traditional CMAC structure. First, the GA-NA-MEMD method is applied to process the vibration signals of rolling bearings, and the signals are decomposed into a group of Intrinsic Mode Functions (IMFs). Then use energy moments of IMFs as fault feature vectors to train FRCMAC neural network, a neural network structure suitable for rolling bearing fault diagnosis is obtained. Finally, the data from bearing data center of Case Western Reserve University is used to prove that the fault diagnosis method proposed in this paper is superior to other methods in diagnosis time and precision, which can meet the training requirements more quickly with limited training samples and fault diagnosis results more accurate.

1 Introduction

It has become a popular research direction recently that sensors are placed on multiple parts of bearings to acquire more comprehensive information on mechanical movement. In this paper, a new fault diagnosis method based on noise-assisted multivariate empirical mode decomposition (NA-MEMD) and fuzzy recurrent cerebellar model articulation controller (FRCMAC) neural networks (NNs) is proposed to solve the problem of multisignal processing. NA-MEMD [1] can process multiple signals at the same time, avoiding the problem that the number and frequency of intrinsic mode functions (IMFs) obtained by separate processing are difficult to match, which makes the analysis and determination of the effective IMF difficult. It has strong adaptability and avoids the hassle of selecting wavelet bases in wavelet packet transform [2] and reduces the endpoint effect and modal aliasing effects in MEMD [3]. NA-MEMD has been applied in the fields of medicine [4] and noise elimination [5]. In NA-MEMD, there are some parameters that need to be selected by human experience in the process of use, such as the number of channels and amplitude of Gauss white noise, or the number of directional vectors. Gaussian white noise has a great influence on the decomposition result. Excessive or too small noise amplitude will have different degrees of influence on the decomposition result. Therefore, choosing appropriate auxiliary white noise amplitude is very beneficial and necessary to obtain accurate decomposition results. This paper presents a method to optimise the magnitude of Gaussian white noise amplitude in NA-MEMD using genetic algorithm (GA). This method solves the problem of parameter selection and improves the efficiency and accuracy of the algorithm.

Recently, many new types of intelligent fault diagnosis methods for rolling bearings have emerged [6]. Liu and Zio [7] proposed a fault detection method based on a k-nearest neighbours based fuzzy support vector machine, which solved the problem of too scattered data and slow computing speed. Wen et al. [8] used a convolution NN to extract the most primitive information in fault characteristics. Then, tested it on three famous datasets and proved that the proposed method has achieved significant improvements. In the paper by Karami and Wang [9], a new adaptive Gaussian mixture model method for fault diagnosis of non-linear systems is proposed, which can simultaneously detect multiple faults in the system. In the paper by Ciabattoni et al. [10], a new method of statistical spectrum analysis is proposed. This method can achieve a highly robust fault diagnosis under the condition of bad SNR and different working conditions. Zhu et al. [11] proposed a new composite fault diagnosis structure that combines fault feature extraction and probabilistic committee machine and another method to realise multisignal fault diagnosis of automobile engine. Zhao et al. [12] developed a variant of deep residual networks that is beneficial to the mining of fault features and has a wide range of application prospects. Fadda and Moussaoui [13] proposed an effective solution to the fault diagnosis of rolling bearing unknown signals. First, the SOM-PCA method is used to analyse the residual signal of the unknown signal. Then, the SOM model is used to classify the faults of the four working conditions to realise the fault diagnosis of the rolling bearing. Aiming at the shortcomings of noise interference in rolling bearing fault feature extraction and slow training speed, Ma et al. [14] proposed a fault diagnosis method based on the scattering transform and the least squares recursive projection twin support vector machine. Compared with other approximation methods, the proposed method is more effective. The CMAC [15], in a table look-up fashion, produced a vector output in response to a state vector input. The output is obtained through a series of mappings, including quantisation, initial address, hash address and sum of memory address weights. In this paper, FRCMAC is proposed and used as rolling bearing fault classifier, which avoids the slow convergence and local minimum in the NN such as back propagation (BP) NN, which not only meets the real-time requirements of fault diagnosis but also guarantees the accuracy of fault diagnosis.

2 Fault feature extraction

2.1 NA-MEMD method

The meaning of the fault feature extraction is to remove the redundant and interfering signals in the fault signal through some signal processing methods and extract the information that can represent the fault features. This paper proposes using NA-MEMD method to preprocess the fault data and highlight the useful information in the data for fault diagnosis. NA-MEMD processes mixed signals consisting of multidimensional signals and Gauss white noise of independent
channels. In dealing with white noise, the characteristics of MEMD's binary filter banks are fully utilised to solve the modal aliasing phenomenon in MEMD. It can effectively separate the original signal and auxiliary white noise after decomposition. The NA-MEMD method decomposes the signal into IMF components with different characteristic time scales.

The detailed steps are as follows:

For an \( q \)-dimensional variable input signal \( s(t) = [x_1(t), x_2(t), \ldots, x_q(t)] \), the detailed steps of the NA-MEMD algorithm are as follows:

**Step 1:** Generate a \( p \)-channel irrelevant Gaussian white noise signal \( s(t) = [s_1(t), s_2(t), \ldots, s_p(t)] \), the length \( f \) of which is the same as the original signal \( s(t) \).

**Step 2:** Combine the \( p \)-channel Gauss white noise signal \( s(t) \) with the \( q \)-channel original signal \( x(t) \) to form the \( g \)-channel multivariate signal \( z(t) = [z_1(t), z_2(t), \ldots, z_g(t)] \), where \( g = q + p \).

**Step 3:** Hammersley sequence sampling method is used to obtain a proper direction vector of the \( n \)-dimensional space on the \((n - 1)\)-dimensional spherical surface.

**Step 4:** Calculate the projection \( p^k(t) \) of the signal \( z(t) \) along the \( k \)th direction vector \( X^k \), where \( l \) is the total number of direction vectors and \( k = 1, 2, \ldots, l \).

**Step 5:** Find the time \( t^k \) corresponding to the maximum and minimum values of the projection \( p^k(t) \).

**Step 6:** Multivariable spline interpolation is applied to the extreme point \([t^k, X^k]\) and the multivariate envelope \( E^k(t) \) is obtained.

**Step 7:** For the \( l \) direction vector of sphere space, the mean \( m(t) \) of envelope curve is calculated as

\[
m(t) = \frac{1}{l} \sum_{i=1}^{l} E^i(t) \tag{1}
\]

**Step 8:** Use \( D_i(t) = x(t) - m(t) \) to calculate the \( i \)th order IMF \( D_i(t) \). If \( D_i(t) \) satisfies the multivariate IMF criterion, \( D_i(t) \) is the \( i \)th multivariate IMF component, and the formula for calculating the residual function is \( r(t) = x(t) - D_i(t) \). Then, \( r(t) \) is taken as the new initial signal. The above steps are continued until the residual function \( r(t) \) becomes a monotonic function, and then, the sieving process is stopped. Otherwise, use \( D_i(t) \) instead of raw data to repeat step 4–7 until the stop criteria are met.

**Step 9:** After the above steps are completed, the \((q + p)\)-dimensional IMF component is decomposed. Among them, \( p \)-dimensional IMF components generated by the auxiliary noise channel decomposition are discarded, and finally the IMF component obtained by decomposing the \( q \)-dimensional channels from the original signal is obtained.

Different signals have the same number of IMFs after NA-MEMD, and the same frequency components in the different signal are existed in the same order IMF components, which provide great convenience for subsequent fault analysis.

### 2.2 Energy moment

When the bearing is in the normal state, its energy distribution of the vibration signal is relatively uniform. When the bearing breaks down and the local wear occurs, the frequency in the corresponding frequency band will change and its energy distribution will change. Therefore, when working with different faults, the energy of the vibration signal changes with the working condition of the bearing. We calculated the energy moment of the IMF to form fault feature vector [16]. This method considers the effect of time scale on energy entropy and can represent failure information more comprehensively.

The detailed calculation of the IMF energy moment is as follows:

**Step 1:** The \( q \)-dimensional vibration signal is decomposed by NA-MEMD, and the IMF component \( c_1, c_2, \ldots, c_q \) and residual function \( Res \) are obtained.

**Step 2:** The energy moment of \( c_1, c_2, \ldots, c_q \) is calculated as shown in (2). The energy moment \( E_R \) of the residual function \( Res \) is calculated by (3):

\[
E_n = \int |c_n(t)| dt \tag{2}
\]

\[
E_R = \int |Res(t)| dt \tag{3}
\]

where \( n = 1, 2, \ldots, N \). Then, all the IMF energy moments consist of the eigenvector \( T \):

\[
T = [E_1, E_2, \ldots, E_2, E_R] \tag{4}
\]

**Step 3:** Normalising the energy moment of IMF gives

\[
E = \left( \sum_{i=1}^{N} |E_i|^2 + |E_R|^2 \right)^{1/2} \tag{5}
\]

\[
T = [E_1, E_2, \ldots, E_n, E_R] \tag{6}
\]

Therefore, \( T \) is the extracted fault feature vector.

### 2.3 Genetic algorithms

GA is a parallel random search optimisation method, which was proposed by Professor Holland of the University of Michigan in 1962 to simulate the natural genetic mechanism and the theory of biological evolution. GA introduces the principle of biological evolution of survival of the fittest and survival of the fittest into the coding tandem group formed by optimisation parameters. After copying, crossing and mutation operations, fitness function was used to screen individuals, so that individuals with high fitness value could be retained to form new groups. The new group not only contains information from the previous generation but also outperforms the previous generation. This continues to iterate, and the individual fitness in the group continues to increase until certain conditions are met. The algorithm of the GA is simple and can be processed in parallel, and the global optimal solution can be obtained.

The general steps of the GA are as follows:

**Step 1:** Identify decision variables and various constraints, that is, determine the solution space of problem and individual phenotype \( X \).

**Step 2:** Establish an optimisation model. Determine the type of objective function and its mathematical description form or quantification method.

**Step 3:** Determine the specific operation methods of GA, such as selection operation, crossover operation and mutation operation to design genetic operators.

**Step 4:** Determine the parameters of the GA, such as group size, terminating evolution algebra, crossover probability \( P_c \) and mutation probability \( P_m \).

**Step 5:** Randomly initialised generation groups \( P(t) \).

**Step 6:** Calculate the fitness value \( f(X) \) of individuals in the population.

**Step 7:** According to genetic strategies, use selection, crossover and mutation operations to act on groups and form next generation groups.

**Step 8:** It is judged whether the group performance meets a certain index, or the number of predetermined iterations has been completed. If not, return to step 7, or modify the genetic strategy and return to step 7.
2.4 NA-MEMD optimisation method based on GA

The existence of endpoint effects and modal aliasing in the IMF can be used to judge whether the NA-MEMD decomposition is effective or not, and thus, the uniformity of the distribution of extreme points in the IMF can be used as the criterion. Based on this, this paper proposed a method of using GA to optimise the auxiliary white noise variance parameter in NA-MEMD. The standard deviation of the difference between the x-axis coordinate and the y-axis coordinate of the extreme point in the IMF is taken as an optimisation index of GA.

The optimisation index calculation process is described as follows:

Step 1: The energy moment of the N-order IMF component of the q-dimensional input signal is obtained from the calculation method of the IMF energy moment in Section 2.2, denoted as $E = \{E_1, E_2, \ldots, E_N\}$, where $N = 1, 2, \ldots, q$. Then, the first three steps are found in which the energy moment is larger.

Step 2: In the nth IMF, find all its maximum and minimum points, where the coordinates of the maximum points are expressed as $(H_x, H_y)$, and minimum points are expressed as $(L_x, L_y)$.

Step 3: Calculate the difference value between $x$-axis coordinate and $y$-axis coordinate of the extreme points according to (7) and (8):

$$
\begin{align*}
D_{Hx}(k) &= H_x(k + 1) - H_x(k) \\
D_{Hy}(k) &= H_y(k + 1) - H_y(k) \\
D_{Lx}(k) &= L_x(k + 1) - L_x(k) \\
D_{Ly}(k) &= L_y(k + 1) - L_y(k)
\end{align*}
$$

Step 4: Calculate the standard deviation of $D_{Hx}(k)$, $D_{Hy}(k)$, $D_{Lx}(k)$ and $D_{Ly}(k)$ according to (9):

$$\sigma = \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2$$

where $\mu$ represents the average. The calculation results are expressed as $S_{Hx}$, $S_{Hy}$, $S_{Lx}$ and $S_{Ly}$, respectively.

Step 5: Calculate the optimisation index of the nth IMF of the nth signal as

$$S_n = \frac{S_{Hx} - S_{Lx} + S_{Hy} - S_{Ly}}{2}$$

Then, $S_n$ is the optimisation goal of the nth IMF. Similarly, the $S$ of another IMF in all the decomposition results is calculated, and the overall optimisation goal is obtained. It can be seen that the size of $S$ can reflect the distribution of IMF extreme points. The smaller the $S$, the more uniform the distribution of the extreme points. This shows that the frequency components contained in the IMF are single and the decomposition results are more reliable. The GA algorithm is used to find the minimum value of $S$, and is used to optimise the parameters of the white noise amplitude. Therefore, the decomposition results are relatively best.

3 Fault identification

The CMAC NN theory was proposed by Albus in the 1970s and is a neural structure that mimics the human memory model with rapid learning and response. CMAC is an adaptive NN that interrogates the form of complex non-linear functions. The network can change the contents of the form through learning algorithm, and has the function of information classification and storage. The basic idea of CMAC NN is described as follows: A state is given in the input space, an address corresponding to the state is found from the memory cell, and the contents of these memory cells are summed to obtain the output of the CMAC NN. This response value is compared with the expected output value and the contents of these activated memory cells are modified according to the learning algorithm.

A complete CMAC NN network includes an input layer, a middle layer and an output layer. Between the input layer and the middle layer, the middle layer and the output layer are composed of the input layer non-linear mapping and the output layer weight adaptive linear mapping, respectively. N-dimensional training samples entered and divided space by the input layer. In the middle layer, composed of M basis functions, there are c non-zero effective basis functions for any input, where $c \ll M$. The basis function of the middle layer is connected with the output layer through the connection weights, and the weight is adjusted by the gradient descent method to complete the training of the NN.

This paper proposed a FRCMAC NN for fault diagnosis. It has a clearer internal connection structure and a smaller storage space. In each Gaussian function of the association unit, an autoregressive unit was introduced to realise the dynamic mapping of the network. Learning efficiency and the dynamic response speed were greatly improved. The addition of fuzzy methods allows the network to more realistically respond to control objects. It is more general to describe the controlled object by fuzzy method.

FRCMAC NN specific construction process is as follows:

Step 1: Initialise FRCMAC NN parameters. Generalise parameters $c$, learning factor $\eta$, inertia factor $\alpha$ and expected error $e$, the number of FRCMAC layers $m$, the number of blocks contained in each layer $N$, etc.

Step 2: The input layer introduces the fault feature vector $\{x_1, x_2, \ldots, x_n\}$ into the network

$$O_i = x_i, \quad i = 1, 2, \ldots, n$$

Step 3: In the fuzzy layer, the Gaussian function is used as membership function, and the input feature vector is fuzzed

$$\begin{align*}
O_{ij} &= \exp(\text{net}_{ij}) \\
x_{ij}(t) &= x_{ij}(t) + \Delta O_{ij}(t-1)
\end{align*}$$

where $j$ is a block index that is activated by each component and $j = 1, 2, \ldots, N$, $x_{ij}$ represents the input after adding the autoregressive unit. $\lambda$ represents the autoregression gain coefficient and $\lambda > 0$. $O_{ij}$ is the associative degree function of each block in each level, and is also the output of the second layer.

Step 4: Calculate the activation strength of the input to the associative unit. The association function for each level is

$$O_k(t) = \prod_{i=1}^{m} O_{ij}$$

Step 5: The FRCMAC network output is

$$\dot{\theta}_r = \sum_{k=1}^{m} a_{rk} O_{kj}, \quad r = 1, 2, \ldots, N_{\text{out}}$$

where $N_{\text{out}}$ is the number of output layer nodes. $a_{rk}$ is the weight for each storage unit.

Step 6: The output is compared with the set target and the error is calculated by $e_r = \theta_r - \dot{\theta}_r$, where $\theta_r$ is the ideal output. Using $\delta$ learning rules to adjust the weights, weight adjustment indicator is

$$E = \frac{1}{2} \sum_{r=1}^{N_{\text{out}}} (\theta_r - \dot{\theta}_r)^2 = \frac{1}{2} \sum_{r=1}^{N_{\text{out}}} e_r$$

Step 7: Use the gradient descent method to adjust network weight $w_{kj}$

$$\Delta w_{kj}(t) = -\eta \frac{\partial E}{\partial w_{kj}} = -\eta \frac{\partial E}{\partial x_{kj}} \frac{\partial x_{kj}}{\partial w_{kj}} = \eta e_r O_k$$

Then, the weight learning algorithm is
\[ \omega_j(t) = \omega_j(t-1) + \Delta \omega_j(t) + \alpha(\omega_j(t-1) - \omega_j(t-2)) \quad (17) \]

where \( \alpha \) is a inertial factor.

**Step 8:** Learning algorithm of the weights \( a \) and \( b \) in the membership function is

\[ \Delta a_{ij} = -\sum_{t=1}^{N^a} e_i w_{0i}(x_i - a_{ij}) \]
\[ \Delta b_{ij} = -\sum_{t=1}^{N^b} e_i w_{0i}(x_i - b_{ij}) \]
\[ a_{ij} = a_{ij}(t-1) + \Delta a_{ij}(t) + \Delta a_{ij}(t-1) - a_{ij}(t-2) \]  
\[ b_{ij} = b_{ij}(t-1) + \Delta b_{ij}(t) + \Delta b_{ij}(t-1) - b_{ij}(t-2) \]

**Step 9:** The training process is continued until the actual error reaches the desired error. After training, the CMAC NN will remember the correct mapping of the special input states. Therefore, when the same or similar input status is input again, the network will make a corresponding output response based on similar input saved in the previous training process.

### 4 Experiment and analysis

This paper used the data from the Bearing Data Center of Case Western Reserve University [17] to verify the proposed fault diagnosis method. In this study, the fan end bearing fault data are used. We choose three kinds of faults of fan end bearing, namely, outer race fault, inner race fault and ball fault. The motor speed is 1730 r/min. The scale of each failure is 0.007 in diameter. The NA-MAEMD method is used to get the best decomposition result when the variance of auxiliary white noise is 0.1896. The value is taken as the NA-MAEMD parameter for fault feature extraction. The energy moment of the base, drive-end, and fan-end accelerometer data is calculated and the energy moment is normalised. Decomposition results and energy moment of the inner race fault data are shown in Figs. 1 and 2, respectively. Figs. 3 and 4 show the NA-MAEMD decomposition results and the energy moments of the outer race fault are shown, respectively. The Ball fault data are shown in Figs. 5 and 6. From the three kinds of fault energy moment diagrams, it can be seen that the energy moments contained in each fault signal are very different. Therefore, the energy moment can be used as the fault feature vector to identify different faults. The maximum first three orders of each energy moment of each group are used to form a fault feature vector. The above energy moments contain the main frequency components in the signal and are used to compose the fault feature vector, which not only can simplify the feature vector but also can ensure that the important information is not lost, thus ensuring the accuracy of fault diagnosis. A nine-dimensional fault eigenvector is constructed in this paper. We train the CMAC NN and FRCMAC using the training samples obtained above. The training process is shown in Fig. 7. CMAC achieved the best in the 52 generations, while FRCMAC achieved the best in the 22 generations. It is proved that the proposed FRCMAC structure has a faster convergence speed and higher accuracy. To illustrate the advantages of using FRCMAC as a classifier in this paper, different NNs are used to compare the fault diagnosis accuracy. Comparison of various aspects is presented in Table 1.

As can be seen from the data in Table 1, the FRCMAC converges much faster than the BP NN, radial basis function (RBF) NNs and CMAC. The FRCMAC requires far less training and testing time than the other two NNs to meet the real-time and error requirements of the fault diagnosis system. By comparison, the FRCMAC NN, characterised by faster speed and better recognition, can obtain better diagnosis results. BP and RBF are global approximation networks. For each input and output data, each weight of the network needs to be adjusted by the gradient descent method, resulting in slow training. However, the FRCMAC is a local approximation network; adjusting only the partial weight, there are no local minimum problems; there are obvious advantages in training time and accuracy. BP and RBF networks use non-linear functions as neurons, so even though the training samples are the same, the output results tend to be different. The FRCMAC is an adaptive NN based on interrogating form. We can guarantee the stability of the output with better generalisation ability as long as generalisation parameters are adjusted. Therefore, the method proposed in this paper can be effectively used for fault diagnosis of rolling bearings.

### 5 Conclusion

We introduced a new fault diagnosis method based on NA-MAEMD and FRCMAC NN for multisignal fault diagnosis of a rolling bearing in this paper. We proposed using the NA-MAEMD method...
to process the signals generated by multiple sensors during the collection of fault signals. The use of multiple sensors to collect signals has become a recent research hotspot. It can more comprehensively collect the signals of the collected objects. Then, we proposed the GA-NA-MEMD method to solve the need for manual selection of parameters in the NA-MEMD method to improve the efficiency and accuracy of the method. Finally, we proposed and used FRCMAC NN as a failure classifier. FRCMAC is much better than CMAC in terms of dynamic response and learning rate. We experimentally verify the proposed method using data from the Bearing Data Center of Case Western Reserve University and compared the results with those of the BP-, RBF- and CMAC-based classification methods. The experimental results show that the proposed fault diagnosis method is superior to other...
methods in diagnosis speed and diagnostic accuracy, and is more effective in practical applications.

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| Table 1 Comparison with BP and RBF using the Case Western Reserve University bearing data |
|---------------------------------|----------|-----------|----------|-----------|
| Diagnostic methods      | Number of training samples | Average training time, s | Number of testing samples | Average testing time, s | Average accuracy, % |
| BP                  | 160      | 56.715    | 80       | 0.097     | 93.75       |
| RBF                 | 160      | 31.642    | 80       | 0.051     | 95.00       |
| CMAC                | 160      | 3.591     | 80       | 0.025     | 95.00       |
| FR-CMAC            | 160      | 3.746     | 80       | 0.020     | 98.75       |

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