Research on gear fault degree recognition method based on multi sensor fusion

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Abstract. The fatal fault of gear will inevitably experience the evolution of different fault degrees, and the accurate recognition of the fault degree of gear has more practical significance for predictive maintenance and efficient operation. A gear fault degree recognition method based on multi sensor fusion is proposed. Ensemble local mean decomposition (ELMD) is used to decompose the vibration signal of gear, which can eliminate the aliasing effect of LMD. Then, the fault feature is extracted by using envelope spectrum information entropy and time-domain kurtosis. Based on the initial recognition of the sub evidence formed by a signal sensor based on wavelet neural network (WNN), the basic belief function assignment and fusion methods of Dempster-Shafer (D-S) evidence theory are determined, and the accurate recognition based on multi sensor fusion for different fault degree of gear is realized, which is verified by experiments.

1. Introduction
With the rapid development of science and technology, electromechanical equipment tends to be complex, precise and reliable. Gear system is the most important part of electromechanical equipment, which realizes the movement and power transmission of electromechanical equipment [1]. However, some electromechanical equipment often work in bad working conditions, resulting in gear fault, so the accurate diagnosis of gear fault is very important to improve the performance of electromechanical equipment. However, the occurrence of fatal faults of gears will inevitably go through a series of degradation processes, that is, the fault degree will change from small to large. Therefore, it is of more practical significance for the predictive maintenance and efficient operation of electromechanical equipment to realize the accurate recognition of different fault degrees of gear.

Gear fault degree recognition is still a problem of pattern recognition, and the process of feature extraction is necessary. In the aspect of state feature extraction, traditional fault feature includes time-domain features and frequency-domain features, but they have no instantaneous characteristics, which only have global statistical significance [2]. The resolution of the signal is the same in time domain to frequency domain, which can not adapt to the non-stationary features of the vibration signal. Compared with the analysis in time-domain and frequency-domain, time-frequency analysis has more advantages. Dhamandea [3] combines continuous wavelet transform and discrete wavelet transform to decompose vibration signals, and the quantitative expression is carried out from time domain and frequency domain, respectively. Hu [4] realized the fault diagnosis by the combining of empirical modal decomposition and neural network. Zhang [5] used the improved LMD to decompose the vibration signal of rolling bearing, and the square envelope is combined to identify the feature
frequency. Li [6] also successfully applied the LMD and fractal dimension to the fault feature extraction of rolling bearing. It can be found that LMD has a wide range of applications in the field of fault diagnosis, but there are still some defects, and the main disadvantage is modal aliasing. Therefore, in order to solve the problem of modal aliasing in LMD, ELMD is applied more effectively by the way of EEMD, which eliminates modal aliasing by the combining of adding Gaussian white noise and ensemble average. It is the key to recognize the fault degree based on the feature extraction, and neural network has been applied in this field. WNN is an improvement of back propagation (BP) neural network, which uses the wavelet basis to replace the function of hidden layer in BP neural network, so that it has better learning ability and faster convergence speed [7, 8].

In addition, from the reliability perspective of diagnostics, the uncertainty of gear fault degree recognition by using a single sensor is large, which leads to the reduction of recognition accuracy and recognition trust. This problem can be effectively solved by multi-sensor fusion. In the aspect of multi-sensor fusion, the decision level fusion has higher flexibility. When one or more sensors make mistakes, correct results also can be obtained through appropriate fusion [9]. Therefore, it has the advantages of good fault tolerance, small communication and strong anti-interference ability. D-S evidence theory has been proved to be an effective method. Xu [10] proposed a turbine fault diagnosis method integrating neural network and D-S evidence theory. The diagnosis results can be obtained by D-S evidence theory on the basis of preliminary diagnosis by BP neural network and RBF neural network and the results show that the method has a good application prospect. Qtman [11] used D-S evidence theory to fuse vibration, sound and pressure signals of engine, and an engine fault diagnosis system based on multi-sensor fusion is established. However, in the applied process of D-S evidence theory, two key problems must be solved: the assignment of basic belief function and the influence of evidence conflict.

Therefore, a gear fault degree recognition method based on multi-sensor fusion is developed in this paper. For vibration signals of multi sensors, ELMD is used decomposed the vibration signal, and the envelope spectrum information entropy and kurtosis are applied feature quantification. The using of wavelet neural network to realize single sensor recognition to form a sub-evidence, integrating multi-sensor information, D-S evidence theory is used to fuse multiple sub-evidences to achieve the precise recognition of gear fault degree.

2. Relevant theoretical model

2.1. The fault feature extraction based on ELMD

ELMD is an improved algorithm for LMD. The mainly idea is to decompose the original signal after adding Gaussian white noise many times, and the influence of modal aliasing can be eliminated based on the idea of overall average. The algorithm process is as follows:

(1) Assuming that the original signal is \( x(t) \), the Gaussian white noise added to the original signal for the \( i \)-th time is \( s_i(t) \), and the number of times is \( I \), and the obtained signal is \( X_i(t) = x(t) + s_i(t) \).

(2) The LMD is carried out for \( X_i(t) \), and the specific process of LMD is as follows [12]: Firstly, the extreme values \( n_i \) is obtained, and the average value \( m_i \) and envelope value \( a_i \) of adjacent extreme values are obtained, and the corresponding average curve \( m_{i1}(t) \) and envelope curve \( a_{i1}(t) \) are obtained. Then, the difference between original signal and average curve can be demodulated, and that is \( s_{i1}(t) \). Repeat the above steps for the demodulated signal until the end condition of LMD is met.

Further, a series of PFs can be obtained, wherein the calculation formula of the \( j \)-th PF is

\[
P_{F_j}(t) = \prod_{q=1}^{\infty} a_{n_q}(t) y_{n_q}(t),
\]

and the decomposed signal can be expressed as follows:

\[
X(t) \approx \sum_{j=1}^{J} P_{F_j}(t)
\]  

(1)

(3) When the \( i \)-th Gaussian white noise is added, \( I \) groups of PFs can be obtained.
(4) Based on the idea of ensemble average, the final decomposition result of ELMD can be obtained by the averaging for each PF corresponding to \( I \) groups \([13]\), and it is expressed as follows:

\[
\overline{PF}(t) = \frac{1}{I} \sum_{i=1}^{I} PF_i(t), \quad X(t) \approx \sum_{j=1}^{J} \overline{PF}_j(t)
\]

The feature quantization of PF obtained above is carried out. And in this paper, the envelope spectrum information entropy and kurtosis are selected to quantify the non-stationary feature. For the signal \( x(t) = \{x_1, x_2, ..., x_N\} \), the corresponding calculation formulas are as follows:

\[
H_I = -\frac{1}{K} \sum_{k=1}^{K} \left( \sum_{m=1}^{M} A_k^m \log(A_k^m / A_{\text{om}}^m) \right) + \sum_{k=1}^{K} A_k^m \exp(-j \frac{2\pi n k}{N}), \quad A_{\text{om}} = \sum_{k=1}^{K} A_k^m
\]

where \( H_I \) is the envelope spectrum information entropy, and \( K \) is kurtosis.

2.2. Wavelet neural network (WNN)

WNN is an improvement of BP neural network, which uses the wavelet basis to replace the function of hidden layer. Assuming that WNN has 1 hidden layer, and the input feature is \( x = \{x_1, x_2, ..., x_m\} \), and the output of output layer is \( y = \{y_1, y_2, ..., y_l\} \). The output of hidden layer of WNN is \( \psi(j) = \psi_j((\sum_{i=1}^{n} w_i x_i b_i) / a_i) \), where \( a_i \) and \( b_i \) are the expansion factor and smoothing factor of wavelet basis function, and \( w_i \) is the weight. In this paper, Morlet wavelet is used as the basis function, and its expression is \( \psi(x) = e^{-x^2/2} \cos(1.75x) \) \([7, 14]\). The output of WNN can be obtained as follows:

\[
y(m) = g(\sum_{i=1}^{l} A_{\text{om}} w(t)), \quad g(x) = \frac{1}{1 + \exp(-x)}
\]

After the output of WNN is obtained, it is similar to BP neural network, and the output error \( e \) is calculated. The weight and wavelet basis function parameters of WNN are modified by gradient correction method, and the training of WNN can be completed by cyclic iteration.

2.3. D-S evidence theory

2.3.1. The basic belief function assignment based on error distance. In this paper, the basic belief function assignment is realized by the output value of wavelet neural network corresponding to a single sensor. Combining with section 2.2, if the expected network output for a gear fault degree is 1, the error distance of each output neuron for wavelet neural network is \( d_j = ||\xi_j - \Omega_j|| \), and is the value of the \( j \)-th output neuron of the \( i \)-th network. Furthermore, Gaussian membership function is used to map the error distance into the trust function \([15]\), and the specific formula is as follows:

\[
f_j(j) = e^{-\frac{||\xi_j - \Omega_j||^2}{2\sigma^2}}
\]

Meanwhile, in order to satisfy the condition that the sum of all basic belief functions is 1, and the final basic belief function generated by \( j \)-th output neuron of \( i \)-th network is assigned as follows:

\[
m_i(j) = f_j(j) \sum_{j=1}^{J} f_j(j)
\]

2.3.2. Fusion methods based on evidence conflict detection. For the problem of evidence conflict, if the degree of evidence conflict is low, the basic fusion rules are adopted. If the degree of evidence conflict is high, the basic belief functions of each evidence body are modified and fused. Suppose that any two evidence bodies and their corresponding basic belief functions are: \( E_i = \{m_1(\xi_1), m_2(\xi_2), ..., m_n(\xi_n)\} \) and \( E_j = \{m_1(\xi_1), m_2(\xi_2), ..., m_n(\xi_n)\} \). The Euclidean distance of two evidence bodies is defined as evidence similarity, and its calculation formula is as follows:
Then, the supporting degree \( S(E_i) \) of all evidences to \( E_i \) is defined and normalized:

\[
S(E_i) = \frac{1}{N} \sum_{i=1}^{N} D_{ij} \quad \tilde{S}(E_i) = \frac{S(E_i)}{\sum_{i=1}^{N} S(E_i)}
\]  

(8)

Then, the belief weight \( \beta_i \) of evidence \( E_i \) can be obtained, and the mapping relationship between \( \tilde{S}(E_i) \) and \( \beta_i \) is as follows [10, 16]:

\[
\beta_i = (1 - \tilde{S}(E_i))e^{\tilde{S}(E_i)}
\]  

(9)

The belief weight of all evidences can be obtained based on above formula, and the basic belief functions can be modified, and the modified basic belief function of evidence \( E_i \) can be expressed as:

\[
\begin{align*}
    m_i(x_i) &= \beta_i \cdot m_i(x_i), \quad x_i \neq \emptyset \\
    m_i(\emptyset) &= 1 - \sum_{i=1}^{N} \beta_i \cdot m_i(x_i), \quad x_i = \emptyset
\end{align*}
\]  

(10)

### 3. Experimental introduction

In this paper, the vibration signals of different fault degrees of gears are collected in DDS fault simulation test bench, and the proposed method is verified based on this. The vibration signal acquisition experiment is shown in Figure 1, and the simulated gear fault degree is shown in Figure 2. Several vibration sensors are used to collect the vibration signals of different gear fault degree, and the motor speed in set to 45 Hz in this experiment.

**Figure 1.** The vibration signal acquisition experiment.

**Figure 2.** The simulated fault degree of gears.

### 4. Experimental analysis

During the experiment, for each vibration sensor, 80 samples were obtained for each gear fault degree, of which 60 samples are training samples, and there are 300 training samples in total. The remaining 20 samples are testing samples, and 100 testing samples in total. In this paper, the vibration signals of 3 vibration sensors are used, but due to space limitations, the vibration sensor 2 on the top of gearbox is taken as an example in the following. The obtained vibration signals of different fault degree of the
vibration sensor 2 are shown in Figure 3. It can be found that all signals are irregular and there is no rule to follow.

Next, the ELMD is used to decompose the above vibration signal samples. In the decomposition process, the number of times of the added Gaussian white noise is set to 100, and the standard deviation of the added Gaussian white noise is set to 0.25. The gear sample of 25% breakage is taken as an example, and its decomposition result of ELMD is shown in Figure 4.

Figure 3. The vibration signals of different fault degree of gears.

Figure 4 shows the decomposition result of the vibration signal of 25% breakage by ELMD, and the vibration signal is decomposed to a total of 7 PFs, which are arranged from high frequency to low frequency. The modal aliasing of each PF is improved to some extent. By ELMD, the feature information in the vibration signal can be adaptively decomposed into different PFs. Next, the feature quantization is carried out for each PF. The indicators used in this paper are envelope spectrum information entropy and kurtosis. The feature quantization results of each PF are shown in Figure 5.

Figure 4. The decomposition result of ELMD.

Figure 5 shows the decomposition result of the vibration signal of 25% breakage by ELMD, and the vibration signal is decomposed to a total of 7 PFs, which are arranged from high frequency to low frequency. The modal aliasing of each PF is improved to some extent. By ELMD, the feature information in the vibration signal can be adaptively decomposed into different PFs. Next, the feature quantization is carried out for each PF. The indicators used in this paper are envelope spectrum information entropy and kurtosis. The feature quantization results of each PF are shown in Figure 5.

As can be seen from Figure 5, the feature quantization of each PF is realized from two aspects. In the aspect of envelope spectrum information entropy, the feature value of normal gear is small, and the envelope spectrum information entropy increases with the complexity of signal components caused by faults. It can be seen from the figure that the envelope spectral information entropy of some PFs has a great difference to some fault degree of gears, while the envelope spectral information entropy of some PFs has little difference. However, the envelope spectral information entropy of each PF of the
same fault degree samples fluctuates very little and has strong robustness by observing multiple samples in the experiment. In kurtosis, kurtosis reflects the impact components contained in the signal. From the figure, it can be seen that the kurtosis of PFs of normal gear is small, and with the occurrence of fault, kurtosis changes significantly, and the kurtosis of PFs with different fault degrees has a certain degree of differentiation.

![Figure 5](image1.png)

**Figure 5.** The feature quantization results of different fault degree of gears. (a) Envelope spectrum information entropy, (b) Kurtosis.

![Figure 6](image2.png)

**Figure 6.** The obtained initial recognition result of single sensor.

The extracted fault feature is defined as the input of WNN, and WNN is used to realize the initial recognition of gear fault degree. A sub evidence can be obtained from a single sensor, and the number of hidden layer nodes is set to 35, and the iteration times is set to 100. The training samples established in this paper are used to train WNN, and the testing samples are used to test the recognition rate of fault degree. Vibration sensor 2 is taken as an example, and the obtained initial recognition result of single sensor is shown in Figure 6. It can be found that the overall recognition rate is 89%, among which the recognition rate of 75% breakage is the highest, and it is 95%. The error recognition between 25% breakage and 50% breakage is more serious. Next, based on the D-S evidence theory, multi sensor fusion recognition of three sensors is carried out, and the obtained recognition rate is shown in Figure 7. From the Figure 7, it can be seen that the recognition rate after using multi sensor fusion has a great improvement, and the overall recognition rate is up to 94%, and for the normal and fault degree with 75% breakage, the recognition rates are up to 100%.
5. Conclusions
This paper proposed a gear fault degree recognition method based on multi sensor fusion. Combined with ELMD, envelope spectrum information entropy and kurtosis, the feature extraction of different gear fault degree can be realized in multiple signal components. On the basis of the advantages of WNN, gear fault degree recognition of a single sensor can be realized to form single sub evidence; Based on the multiple sub evidences generated by multiple sensors, the basic belief function assignment method based on error distance and the fusion method based on evidence conflict detection of D-S evidence theory are determined to achieve accurate recognition of gear fault degree. The experimental results show that the proposed method has an overall recognition rate of 94%, which is an effective recognition method.

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