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The Study of Feature Extraction Method Based on Multi-scale Morphological Spectrum Entropy

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Multi-scale morphological decomposition is a decomposition method being proposed based on the basic theory of multi-scale morphology. Using from small to large scale of structural elements to deal with different “Scale domain” , thus the original signal is decomposed into a complete set of orthogonal In multi-scale mathematical morphology operation is the essence of it. This article combines multi-scale decomposition with the information entropy theory, put forward a kind of feature extraction method based on multi-scale morphological spectrum entropy, with multi-scale morphological spectrum entropy (multi-scale morphological spectrum entropy, multi-scale morphological singular spectrum entropy) as a feature vector can effectively distinguish between different running state of rolling bearings, and through the simulation and experiment validation.

1. Decomposition of multi-scale mathematical morphology

Feature extraction is the foundation of implement fault diagnosis, directly affect the accuracy of fault diagnosis and credibility, the feature extraction of the focus is on feature index to the distinguish ability of different failure modes. Rolling bearing vibration signals as the typical nonstationary and nonlinear characteristics (Angelo M, 1989), how to extract from vibration signal full and accurate is very important to reflect the characteristics of the bearing fault in the running state of the more commonly used methods include domain feature extraction method, the frequency domain feature extraction method and time-frequency domain feature extraction method(Wheeler, 1968), etc. With the deepening of the research, the EMD decomposition, morphological information entropy fractal theory was introduced to the field, such as some ideal results have been achieved (Eugene and Ware, 2000).
Anglicizing from the nature of signal changes, vibration signal of rolling bearing under different fault condition, its internal random component proportion is also different. As a starting point, using the method of complexity measure can synthetically to measure the complexity of the signal, and then to different bearing fault status is described. The information entropy is one of the most typical methods in the complexity of the measurement.
Multi-scale morphological opening and closing is multi-scale two basic operations of mathematical morphology, its computational expressions are as follows:

$$\begin{aligned} f \circ ng &= f \Theta ng \oplus ng \\ f \bullet ng &= f \oplus ng \Theta ng \end{aligned} \tag{1}$$

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$$ng = \underbrace{g \oplus g \oplus \ldots \oplus g}_{(n-1)times} \tag{2}$$

Multi-scale morphological decomposition based on the multi-scale basic operation, is set to the known signal, n for decomposition layers, namely the scale size. The multi-scale decomposition form defined as [8]:

$$\begin{cases} d_1(x) = f(x) - h_1 \\ d_{i+1}(x) = h_i - h_{i+1} (i = 1, 2, ..., n-2) \\ d_n = h_{n-1} \end{cases} \tag{3}$$

$$h_i = 0.5 \times ((f \circ ig \bullet ig)(x) + (f \bullet ig \circ ig)(x)) \tag{4}$$

Among them, di(x)(1 I n - 2 or less) or less on behalf of f (x) on the scale I decomposed signal on the form. By definition, you can see that the hi under different scale structure elements for the on - off and closed - combination morphology filter, and di (x) is the scale filter by filter hi signal on the I. From the hi defined and analyzed the effect of the filter, the effect is closely associated with structural elements, only match with the size and shape of the structural elements of primitive signal can be retained(Ronald, 1983). So, multi-scale morphological decomposition is essentially form combination filter results in different scales, the decomposition effects related to analysis scale, shape decomposition signal di (x) reflect the signal details in small scales, reflect signal contour under the large scale, because of the scale and frequency, so the multi-scale morphological decomposition signal in its essence on the coarse frequency of multi-scale.

2. Feature extraction based on multi-scale morphological spectrum entropy

Multi-scale decomposition form under the original signal in different scales and frequency division, but also realizes the distribution of signal energy in different scales.

2.1 MMSE, Multi-scale Morphological Spectrum Entropy is proposed

Proposed multi-scale Morphological Spectrum Entropy and multi-scale singular Spectrum Entropy of two concepts, because of its theoretical basis is the same, so collectively referred to as “MMSE, Multi - scale Morphological Spectrum Entropy". The definition, respectively, as follows:

(1) The multi-scale morphological MMESE spectral entropy

The calculation method of MMESE, Multi - scale Morphological Energy Spectrum Entropy is as follows: first of all to multi-scale Morphological decomposition of the original signal, get different decomposition scales signal component, we calculate the Energy value of the scale, to get the original signal multi-scale Morphological Spectrum, establish the original signal in the time-frequency domain, a division, in the end, to type (5) the calculation of the normalized MMESE multi-scale Morphological Spectrum Entropy.

$$\begin{cases} MMESE = -\sum_{i=1}^{n} p_i . \ln(p_i) / \ln(n) \\ p_i = E_i / \sum_{i=1}^{n} E_i \\ \sum_{i=1}^{n} p_i = 1 \end{cases} \tag{5}$$

(2) MMSSE, Multi-scale Morphological Decomposition Singular-spectrum Entropy

The calculation method of MMSSE, Multi-scale Morphological Decomposition Singular-spectrum Entropy is as follows: First to multi-scale morphological decomposition of the original signal, get different scales of the signal component, the component of the initial eigenvector matrix, expressed as. Singular value decomposition of matrix, we get the initial feature vector matrix singular value, according to multiple scale singular spectrum, in the end, to type (6) calculate the normalized form of multi-scale singular spectrum entropy.

$$\begin{cases} MMSSE = -\sum_{i=1}^{n} p_i . \ln(p_i) / \ln(n) \\ p_i = \lambda_i / \sum_{i=1}^{n} \lambda_i \\ \sum_{i=1}^{n} p_i = 1 \end{cases} \tag{6}$$

2.2 Feature extraction method based on multi-scale morphological spectrum entropy

When rolling bearing operation state changes, a proportion of the random components in vibration signals are constantly changing. So the multi-scale morphological spectrum entropy MMSE can be characterized quantitatively different running state of rolling bearings. The calculation of rolling bearing feature extraction method based on MMSE process can be described as shown in figure 1.

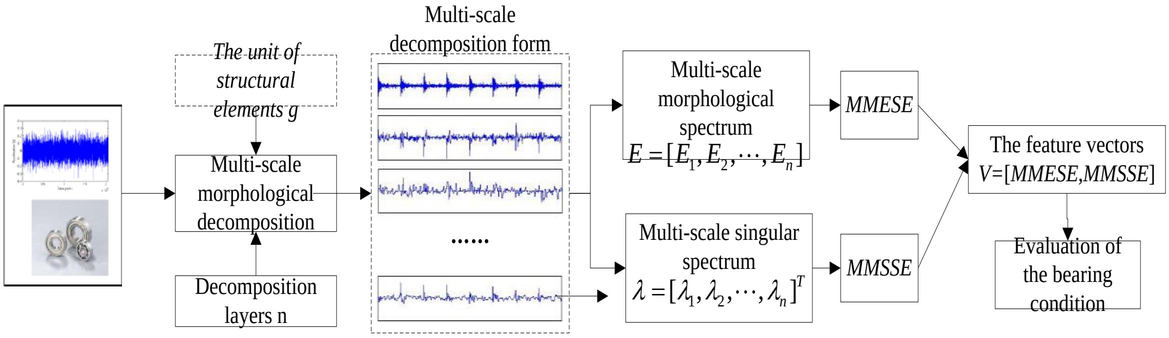


Figure 1: The process of feature extraction based on MMSE

3. Analysis of the simulation signal

The key to the feature extraction method is the selected characteristics can stability for different fault characteristics distinguishes ability(Wheele, 1968). This section chooses rolling bearing as the research object, analyzes the simulation signal, and verify the effectiveness of the proposed feature extraction method based on MMSE.

According to the principle of operation and fault of rolling bearing and rolling bearing simulation signal model is set up [13] for:

$$y(k)=e^{-\alpha t}\sin 2\pi f_c kT+n(t) \tag{7}$$

$$t=\mathrm{mod}(kT,\frac{1}{f_m}) \tag{8}$$

In the expression,α, fm, fc, Trespectively represent the Index of frequency, modulation frequency, carrier frequency and sampling interval of the rolling bearing. In this section of the simulation analysis,α=800, fc=5000Hz, T=1/20000s, Sampling time is 0.1 s, in order to make the simulation analysis results close to the reality, to join in the simulation signal noise intensity of 0.2 gaussian white noise, and the modulation frequency parameters were taken for 60 HZ and 120 HZ and 240 HZ, the understanding for the rolling bearing inner ring and outer ring, rolling body components on a failure frequency. Three different modulation frequencies of simulation time domain graph is shown in figure 2.

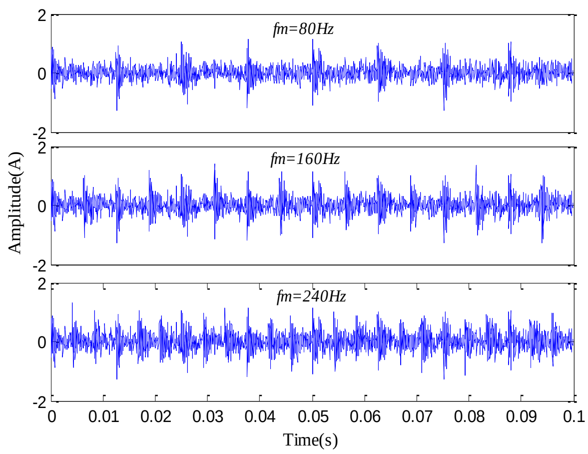


Figure 2: Time domain of simulation signal in different modulation frequency

Calculate the multi-scale morphological spectrum entropy of the simulation signal in each group separately, take the simulation signal of fm=80Hz for example. First of all, the group simulation signal multi-scale morphological decomposition, decomposition layers n = 5, unit structure element g = 0, 0, the decomposition result is shown in figure 3. It can be seen that due to the different scales of decomposed signal representing the scale morphology filter of signal filtering by the composition, therefore, different decomposition levels have different morphological characteristics, corresponding to the decomposition scale and frequency, the process of decomposition in essence is a kind "coarse frequency from low to high in the analysis process.

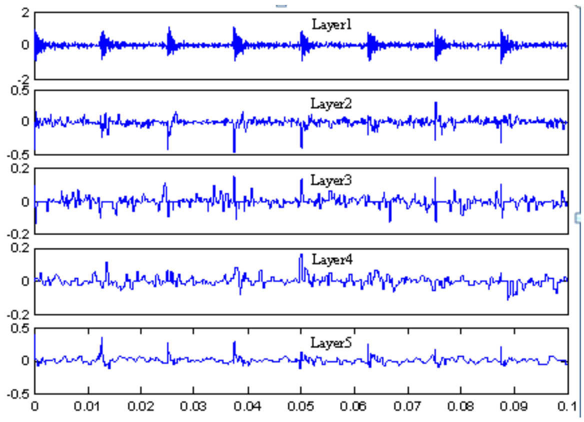


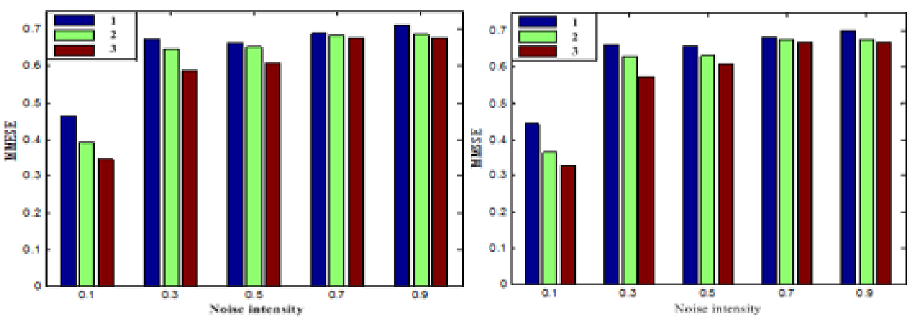
Figure 3: Diagram of multi-scale morphological decomposition

According to the calculation method of multi-scale morphological spectrum entropy of three groups of simulation signal spectrum entropy was calculated, and the calculation results as shown in table 1 and figure 1, which category 1-3 corresponding modulation frequency parameters of 60 Hz and 120 Hz and 240 Hz simulation signal. It can be seen that different groups of MMESE and MMSSE values has the obvious degree of differentiation, and the characteristic frequency, the greater the value is lower, that with the increase of characteristic frequency, its complexity is decreased gradually. Can be seen from the qualitative analysis on the two characteristic values for different fault simulation signal has the ability to distinguish.

Table 1: Spectral entropy value for three groups of simulation signals

Multi-scale morphological spectrum entropy	group 1	group 2	group 3
Multi-scale morphological spectrum entropyMMESE	0. 4373	0. 3823	0. 3356
Multi-scale morphological singular spectrum entropyMMSSE	0. 4164	0. 3544	0. 3159

In order to analyze the influence of different noise intensity of entropy values, respectively, in the noise intensity of 0.1, 0.3, 0.5, 0.7, 0.9, down to three groups of simulation signal to calculate. Through the analysis of figure4 shows the results it can be seen that under the same noise intensity, the size of the relationship between characteristic parameters and the degree of differentiation remain constant, show that the method has a certain stability. , with the increase of noise intensity MMESE MMSSE and the tendency of increase with the values on the whole, this is because the noise intensity, the greater the internal signal stochastic components will gradually increase, so the entropy will gradually increase.



(a) Relationship between MMESE and noise intensity
(b) Relationship between MMSSE and noise intensity

Figure 4: MMSE value in different noise intensity

4. Analysis of The measured bearing signals

To analysis the feature extraction based on multi-scale morphological spectrum entropy effectiveness, taking the Case Western Reserve University bearing data for example. The test bench contains 0, 0.746, 1.492, 0.746 kW four kinds of normal load condition, failure of the inner ring and outer ring and roller fault 4 kinds of running state. 6205 test model for SKF bearing, and the research object of this article type is the same. The sampling frequency is 12000 Hz, failure is a 7 "diameter small pit. Choose the 0.746 kW load under four kinds of operation data analysis, each running status data collected 10 samples, sample, sampling points in each group is 1200, figure 6 depicts a typical four time domain in the running state of graphics.

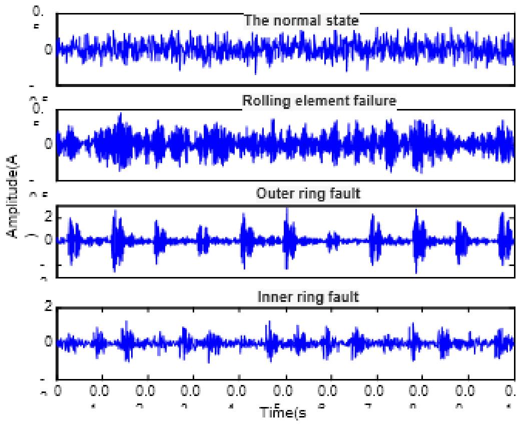


Figure 5: Running state signals for four kinds of rolling bearings

Analysing the measured samples using the feature extraction method based on multi-scale morphological spectrum entropy, choose g= [0, 0, 0] as unit structure elements, decomposition layer number n = 3. Figure 6 shows the four kinds of running state of multi-scale decomposition form contrast. As you can see, three layers have the characteristics of different shape decomposition of graphics.

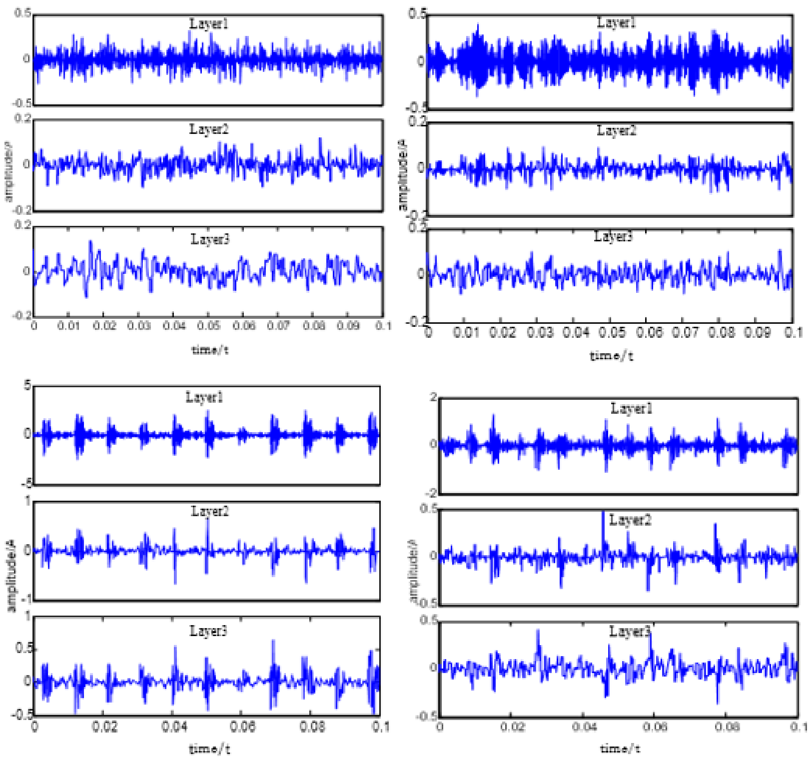


Figure 6: Three layers morphological decomposition diagram

Figure 6 shows the feature extraction of 40 groups of test sample, it can be seen that different running condition of bearing test sample has the obvious degree of differentiation; randomness is the strongest in normal state, so it is of the highest values, which verified the effectiveness of the method. General, in order not to lose in this way to CWRU bearing under other load and sampling frequency in the database data is analyzed, which can get similar effect, go here.

5. Conclusions

Feature extraction is the foundation of implement fault diagnosis, this paper analyses the feature extraction method, based on the theory of multi-scale mathematical morphology calculation, information entropy theory, proposes feature extraction method based on multi-scale mathematical spectrum entropy, through the simulation and real example shows that the spectral entropy based on multi-scale morphological decomposition and singular spectrum entropy can describe the complexity of the signals from different angles ,can quantitatively distinguish different bearing characteristic of the running state.

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