Feature extraction method of cavitation acoustic emission signals of hydraulic turbines based on improved EMD

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Abstract. The cavitation of hydraulic turbine is one of the most difficult problems in the world. Empirical mode decomposition (EMD) is capable of decomposing the cavitation signals in an adaptive way. Because the traditional EMD has a special end effect, an improved EMD method was erected and applied to extract the features of cavitation acoustic emission (AE) signals of hydraulic turbines in this paper. Comparison of the mirror extension method and the average extremum extension method was carried out on the base of their ability to reduce the end effect, and the better mirror extension was adopted to deal with the cavitation AE signals. The measured AE signals generating from the cavitation were processed and the features were extracted by the improved EMD. Spectrogram can be drawn from cavitation inception to cavitation intensifies. In combination with the energy ratio of the intrinsic mode function (IMF) and the cavitation coefficient, it is found that the absolute energy ratio varies sharply under the cavitation conditions. The results show clearly that the improved EMD method can solve the defects of the end effect and is effective in the feature extraction of the cavitation acoustic emission signals of hydraulic turbines. The findings can be used as a technical basis for the identification of the cavitation conditions of Francis turbines.

1. Introduction

Hydraulic turbines are the key equipment in hydraulic power stations, and cavitation is one of the factors that affect the stability and the efficiency of hydraulic turbines. Cavitation signals are difficult to be observed directly [1,2]. At present, the acoustic emission (AE) signals of hydraulic turbines are widely used, which is an effective way to study cavitation [3,4]. AE signals refer to a kind of stress wave produced by the release of energy from the mechanical deformation. AE technology based on internal stress wave is a nondestructive testing method. It can detect the components or materials in the internal structure or detect the potential defects in the process of change. It is sensitive to dynamic defects, and the acoustic wave is from the defect itself rather than the external.

For traditional signals processing, the signals are usually assumed stable and periodic. The time-frequency method based on wavelet transform can extract the time and frequency features of the non-stationary signals, but the selection of wavelet base and the decomposition level should be done artificially. It doesn’t have the ability of adaptive decomposition, thus limits the wavelet analysis functions [5,6].

The empirical mode decomposition (EMD) method proposed by Huang provides a good idea for processing of instable or aperiodic signals [7]. The decomposition process is adaptive, fast and
effective. Due to its advantage of reflecting the local variation of the signals, it is widely used in the analysis of non-stationary signals. The high quality analysis of EMD method depends on the decomposition quality. However, the three spline interpolation and the sifting process adopted in the EMD algorithm have special end effects, seriously affecting the EMD process.

Therefore, this paper attempts to improve the EMD method to suppress the endpoint effect, and deal with the cavitation AE signals of the hydraulic turbine via the improved EMD method.

2. Empirical mode decomposition

2.1. EMD algorithm

The EMD decomposes the signals into a series of subsequences with different feature scales, which are called the intrinsic mode functions (IMF) [8-10]. An IMF is a function that satisfies the two conditions.

Condition 1: in the whole data set, the number of extrema and the number of zero-crossings must either be equal or differ at most by one.

Condition 2: at any point, the mean value of the envelope defined by local maxima, and the envelope defined by the local minima is zero. So the EMD is based on the average of extreme envelope of the signals.

The decomposition process is as follows:

Step1: The local extrema of the signal shall be identified, and then all the local maxima are connected by a cubic spline line as the upper envelope. Repeat the procedure for the local minima to obtain the lower envelope.

Step2: Compute the envelope mean of the upper and lower envelopes and designate the mean as \( m_i \) and designate the difference between the data and \( m_i \) as the first component.

\[
x(t) - m_i = h_i
\]  
(1)

Step3: It should be estimated whether \( h_i \) satisfies the above definition of IMF. If not, \( h_i \) is treated as the input data, and repeat the above two steps until \( h_{ik} \) is an IMF.

\[
h_i - m_{i+1} = h_{i+1}
\]  
(2)

\[
c_i = h_{ik}
\]  
(3)

Step4: \( SD \), the criterion by limiting the size of the standard deviation, is used to stop the sifting process.

\[
SD = \sum_{k=0}^{T} \left( \frac{(h_{ik-1}(t) - h_{ik}(t))^2}{h_{ik-1}(t)^2} \right)
\]  
(4)

Step5: The signals are obtained. In the next step, the first IMF will be separated from the signals.

\[
x(t) - c_i = r_i
\]  
(5)

Step6: Because \( r_i \) still contains other different time-scale signals, it will be treated as new signals to repeat the above process until \( r_n \) is a monotone function. An equation can be obtained.

\[
x(t) = \sum_{i=1}^{n} c_i + r_n
\]  
(6)

2.2. Problems of EMD

The EMD algorithm itself has some weakness [11,12]. Although the extreme envelope method and the three spline method play a role in EMD, the envelopes of the three spline interpolation don’t
completely fit the signals, and the amplitude is very serious increased at the end, which is called the endpoint effect. The simulated signals in figure 1 are used to illustrate the three-spline weakness.

From figure 1, it is easily found that when the spline function is used to fit the envelope, there is no other information to constrain the endpoint. The endpoint is not guaranteed to be the extreme point. Therefore, the envelope has a large swing at the endpoint, which can cause serious deviation from the decomposition result. Because of the sifting, this deviation will widen and eventually contaminate the whole signals, making the whole process meaningless. In order to reduce the endpoint effect, the endpoints need to be suppressed.

![Figure 1. The envelope vs. the given signals.](image)

**2.3. Improved EMD**

The defect of the EMD algorithm is that the three-spline envelope is not complete, which is hoped to resolve in the improved algorithm so as to improve the envelope quality [13,14].

Two improved algorithms are applied and compared in this paper. One is to extend the signals to make the envelope more complete. The other is to calculate several extreme points by the internal extreme points, and then extend them to achieve the perfect envelope. By comparison, the better algorithm is chosen to deal with cavitation signals.

Figure 2 is the improved flow chart.

![Figure 2. Algorithm improvement flow chart.](image)

According to the literatures [15,16], two indicators are used to evaluate the endpoint effect.

The similarity coefficients between each component signals and the corresponding original signals after EMD decomposition are calculated to evaluate the inhibitory effect.

\[
p(x_i(t), IMF_i(t)) = \frac{\text{cov}(x_i(t), IMF_i(t))}{\sigma(x_i)^2(\sigma(IMF_i))^2}
\]

(7)

Where: \(\text{cov}()\) represents covariance, \(p\) is the variance. The bigger is the \(p\), the better is the decomposition.
The average relative error between the obtained IMF components by EMD and the original signals are calculated.

\[
error = \frac{\sqrt{\sum_{i=1}^{n} (x_i(k) - IMF(k))^2)}}{n}
\]  

(8)

The specific steps of this method are as follows.
Step 1: The simulation signals are processed by two kinds of extension, and processed by EMD.
Step 2: Evaluation indices are calculated according to Equation (7) and Equation (8).
Step 3: The errors and coefficients are estimated and compared.
Step 4: The best extension method is determined.

2.4. Simulation analysis
In order to verify the effectiveness of the improved algorithm, the simulation signals were processed by two extension methods with the sampling point 1000. The simulation signals are described as \( y = \cos(2\pi t/50) + 0.6\cos(2\pi t/25) \). The improved EMD aims to restrain the endpoint effect by signal extension, so both high frequency and low frequency signals are effective. Because the endpoint of the high frequency signals are difficult to directly observe, the low-frequency signals are used to make clearer and improve the effect.

![Simulation signal](image)

**Figure 3.** Simulation signals. The yellow line represents the signals, the black line represents the signals’ envelope by mirror extending, and the red line represents the signals’ envelope by average extremum extension.

![Improved EMD decomposition](image)

**(a)** Improved EMD decomposition by mirror extension  
**(b)** improved EMD decomposition by average extremum extension.


The evaluation indices are listed in table 1.

**Table 1.** Evaluation indices.

| Coefficients | Mirror  | Average extremum |
|--------------|---------|------------------|
| p_IMF1       | 0.9957  | 0.9812           |
| p_IMF2       | 0.9996  | 0.9920           |
| Error IMF1   | 0.0030  | 0.0249           |
| Error IMF2   | 0.0030  | 0.0213           |
| Time(s)      | 0.1715  | 0.1335           |

As can be seen from table 1 and figure 4, there are apparent differences between two methods. The similarity of each IMF component to the original function is more than 0.99 by using mirror extension. The error coefficient is 0.003. However, the error is over 0.02 by using average extremum extension, and the similarity ratio is smaller than the mirror extension decomposition. So, the mirror extension is better than average extremum one.

The envelope of the simulation shows that the red envelope of the average extremum algorithm cannot meet the requirements of the envelope because it cannot fit the signals at the two ends; and the black envelope of the mirror extension basically meets.

From the EMD decomposition process, the IMF component of the average extremum algorithm is obviously divergent, and the end effect of the mirror extension is better suppressed.

3. **Analysis on cavitation AE signals**

A cavitation test of a Francis turbine model was implemented on a domestic close-loop turbine model test bench which has an international advanced level and a comprehensive precision less than ±0.2%. AE signals under different operating conditions were collected. The AE signals sampling frequency were set 2.0 MHz, and the bandpass filter frequency range was 20–500 kHz. AE signals with a sampling point of 2048 were taken to test the effectiveness of the improved EMD method on the actual cavitation AE signals. The experimental data of the cavitation AE signals were decomposed by the improved EMD method, and the absolute energy of each IMF was calculated. The data decomposed by EMD were shown in figures 5. The absolute energy of each IMF and its energy change with cavitation coefficients were listed in figure 6. The absolute energy is calculated as:

\[ E_{IMF(i)} = \text{sum}((\text{abs}(\text{IMF}(i,:)))^2) \]  

(9)
Figure 5. (a) (b) Non-cavitating signals decomposed by improved EMD (c) (d) (e) and (f) the intensifying cavitating signals decomposed by improved EMD.

With the decrease of cavitating coefficient, condition (a) to (f) shows the development that cavitation develops from nothing to severe. The size and number of vacuoles in water bodies will change significantly. The energy of the acoustic emission signals changes as well.

Figure 6. Cavitation coefficient vs. absolute energy. The black line represents IMF 1, the fuchsia line represents IMF 2, the blue represents IMF 3, the red line represents IMF 4.
From figure 5, no significant increased amplitudes are observed at the two ends of all IMF components, indicating that the improved EMD algorithm is valid.

From figure 6, it can be seen that the energy of cavitation signals are mainly concentrated on IMF 1 and IMF 2, and the energy distribution decreases from the lower order IMF to the higher one. This energy distribution is consistent with the high-pass filtering property of the EMD algorithm, which shows that the decomposition effect is valid.

It is easily found that the energy trends of IMF 1 and IMF 2 in each state increase at first and then decrease. It is shown that when cavitation occurs, the energies of IMF 1 and IMF 2 will increase significantly. These are more pronounced signals that the cavitation response occurs with the characteristic of energy explosion.

4. Conclusions
In this paper, an improved EMD for feature extraction of cavitation AE signals of hydraulic turbine was provided.

The decompositions of the simulated signals and the measured cavitation AE signals verify the effectiveness of the improved EMD.

According to the extracting the cavitation signals features, the absolute energies under the different time-scale are regarded as the feature vector of the cavitation AE signals. Compared to the traditional methods, the EMD extracting features of cavitation AE signals can clearly reveal the cavitation information and easily be observed, which makes improved EMD more advantageous.

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