Residual Stress Recognition Method for Welded Structures based on An Improved Multiple Differential Empirical Mode Decomposition

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Abstract. To overcome the difficulty in accurately identifying the residual stress of complex large welded parts, a multiple differential empirical mode decomposition (MDEMD) method based on grey mean GM(1,1) prediction and mirror symmetry (MS) extension combined with energy entropy is proposed to identify the residual stress state of components. Firstly, the vibration signal of the welded steel plate is collected by the hammering method and preprocessed by MD algorithm. Secondly, GM(1,1) is used to predict the extreme points at the endpoints and mirror symmetry continuation is used to obtain the intrinsic mode function (IMF). Then, the energy value of IMF component is calculated and normalized by energy entropy, and the characteristic parameters are extracted to realize the identification of the residual stress state. The experimental results show that this method can effectively identify the residual stress state of welded components, and the recognition rate reaches 98.7%.

1. Introduction

The application of advanced welding technology in metal structures such as airplanes and automobiles is recognized as one of the most potential methods to further reduce weight and save costs. However, residual stress will be introduced during the welding process, which will affect the integrity assessment of the structure [1]. Therefore, accurate assessment of the magnitude and distribution of residual stresses has very important practical engineering application value for predicting the fatigue strength, durability, and stability of parts, and avoiding deformation and cracking during service.

A large number of studies have proved that the existence of residual stress will affect the structural vibration characteristics of mechanical parts [2]. However, the measurement of these characteristic parameters is often extracted by excitation and vibration response. Through the modal analysis of the vibration signal of the mechanical parts, the characteristic parameters such as its own natural frequency and damping ratio are extracted, and then the residual stress of the mechanical parts can be effectively judged [3].

The Empirical Mode Decomposition (EMD) method has strong adaptive ability and does not require prior signal knowledge. It can decompose the time-frequency according to the local time-varying characteristics of the signal. The decomposition process is completely driven by the data itself and has a high time-frequency resolution. After the vibration response signal of the mechanical system
undergoes EMD, a series of Intrinsic Modal Functions (IMF) are obtained, and there is a physical mapping relationship between these functions and the system’s natural vibration mode functions.

Aiming at the above problems, this paper explores a multi-differential empirical mode decomposition method (MDEMD) based on the combination of grey mean GM(1,1) prediction and mirror symmetry extension. The vibration signal of the component is collected by the hammering method, and the IMF component reflecting the local characteristics of vibration signal is obtained by GMMS-MDEMD. Combined with the energy entropy theory, the residual stress discrimination mechanism is constructed, which provides a new idea for the residual stress assessment of large and complex welded structures, and has a certain engineering practical value.

2. Methodology

2.1. Empirical mode decomposition (EMD)

EMD is the process of separating IMF from complex signals. The signal is decomposed into a series of IMF \( c_i \) and a residual term \( r \) at different frequencies from high to low. The original times series data represent the summation of all the IMFs and the signal decomposition is as follows:

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

Where \( x(t) \) is the analytic signal, \( c_i \) is the \( i \)th order IMF, \( n \) is the number of IMF and \( r \) is the residual term. The EMD algorithm can be summarized as follows:

1) Identify all local extrema of \( x(t) \) and connect all local extrema with a cubic spline line to generate the upper \( E_{up} \) and lower \( E_{low} \) envelopes;

2) Calculate the mean value of the envelopes by

\[
m = \frac{E_{up} + E_{low}}{2}
\]

3) Extract the first component \( h(t) = x(t) - m \);

4) Test whether \( h(t) \) satisfies the zero-crossing point condition and mean value condition of IMF component. The mean value condition is judged by the threshold value, usually \( 0.2 \sim 0.3 \). If the condition is not met, \( h(t) \) is not an IMF component, replace \( h(t) \) with \( x(t) \);

5) Repeat the step from (1) to (4) until the stop criterion is met.

2.2. Multi-differential empirical mode decomposition (MDEMD)

MDEMD method is to perform multiple mathematical differentiations on the original signal before EMD, which changes the proportion of different frequency components in the signal. The energy of the high-frequency part of the signal is greater than that of the low-frequency part. Multi-differential enhances the frequency decomposition ability of EMD and effectively suppresses the mode aliasing phenomenon.

2.3. Grey mean prediction system

The core of the grey forecasting system is the GM(1,1) model, which is a first-order differential equation model for variable prediction. Its discrete time response function is approximately exponential [5]. The method of establishing the GM(1,1) model is as follows: Supposing original data are in original series of raw data contains \( k \) entries as in:

\[
x^{(0)}(k) = x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)
\]

Where \( x^{(0)} \) stands for the non-negative original historical time series data. Structure \( x^{(1)} \) by accumulated generating operation (AGO) method, which is:

\[
x^{(1)}(k) = x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)
\]
Where $x^{(1)}(k) = \sum_{n=1}^{k} x^{(0)}(n), k = 1, 2, 3 \cdots n$. The prediction of AGO is similar to the first order linear differential equation:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b$$

(4)

It is the original form of the GM(1,1) model. The original form of the GM(1,1) model is essentially a difference equation. Among them, the vector parameters can be estimated by the least square method.

$$x^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1)$$

(5)

$k$ is a time point, $a$ is called the development coefficient, and $b$ is called driving coefficients. Applying the least square method, in which it can estimate the values of $a$ and $b$.

$$\hat{a} = \begin{pmatrix} \hat{a} \\ \hat{b} \end{pmatrix} = \left( B^T B \right)^{-1} B^T Y_n$$

(6)

Where $B$ and $Y^N$ are defined as follows

$$B = \begin{bmatrix} -z^{(1)}(1) & \cdots & 1 \\ -z^{(1)}(2) & \cdots & 1 \\ \vdots & \ddots & \vdots \\ -z^{(1)}(n) & \cdots & 1 \end{bmatrix}$$

(7)

$$Y^N = \begin{bmatrix} x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), x^{(0)}(4), \cdots, x^{(0)}(n) \end{bmatrix}^T$$

(8)

Furthermore, the parameters and GM(1,1) prediction equation can be obtained by the least square method:

$$x^{(1)}(k+1) = x^{(0)}(1) - \frac{b}{a} \exp \left( \frac{a}{b} \right)$$

(9)

### 2.4. Improved MDEMD with grey mean prediction and mirror symmetry extension

Firstly, the grey mean GM (1,1) prediction model is used to forecast the data, and then the mirror image method is used to mirror the new signal to form a closed loop. Finally, it is applied to MDEMD, in the screening process, the contaminated data at both ends are discarded and the original data is not affected by the endpoint effect to obtain the IMF component of the real effect. The grey mean GM (1,1) prediction model can get better fitting effect through a small number of data points, which avoids the problem of poor effect when only using mirror extension to deal with short time series whose endpoints are not extreme points. The problem of end effect and mode aliasing is avoided, so that the signal has real accuracy. The decomposition process of MDEMD based on grey mean GM (1,1) prediction and image extension method is as follows:

1) The grey mean GM (1,1) prediction model is established by taking the original signal data as samples and taking at least four data from each end.

2) The two ends of the sequence are extended to a certain extent, and a maximum point and a minimum point are added respectively.

3) Place the "mirror" at the extreme point obtained in step (2) to make the signal form closed-loop data.

### 2.5. Intrinsic mode energy entropy

The most significant and important information in mechanical vibration signal is often concentrated in the first few-order IMF components. IMF has its own energy. Based on the information entropy theory and EMD normalization algorithm, the energy entropy of IMF components is calculated, and a certain
measure of the unknown degree of the system is given. After the original signal is decomposed, the energy $E_i (i=1, 2, \cdots, n)$ of $n$ IMF components is obtained, which forms an automatic division in frequency domain. Ignore the residual $r$, total energy $E = \sum_{i=1}^{n} E_i$ and normalize the energy. Then the intrinsic energy entropy of each IMF component is

$$H_i = -\sum_{i=1}^{n} q_i \ln q_i$$

(10)

Then the normalized IMF energy entropy vector is obtained

$$H_0 = (H_1, H_2, H_3, \cdots, H_n)$$

(11)

Use the correlation between the vibration signal under different residual stress states and the vibration signal under no residual stress or meet the requirements of component use but contain less residual stress to reflect the degree of characteristic parameter change, and use the time domain and time-frequency domain Information measurement value to quantify this relationship. Energy entropy can identify false modal components, and can reflect the energy distribution of each time-frequency region of the EMD spectrum, thereby describing the state of residual stress of the component. The larger the energy entropy is, the larger the proportion in the high frequency region is, and the larger the lag time is, and vice versa. When the residual stress state of the component remains unchanged, the energy distribution in each time-frequency region of the EMD spectrum does not change much, and the energy entropy remains basically constant.

3. Experiment and application

3.1. Signal acquisition

Build a residual stress vibration test platform and conduct signal acquisition. The welded steel plates are suspended by rubber bands, and the components are excited by the hammering method. The signal acquisition equipment mainly includes DH5922D dynamic signal test analyzer, 1A102E general piezoelectric acceleration sensor, force hammer and computer. Set the sampling frequency to 2000Hz. At the same time, in order to ensure the accuracy of the test, the components are collected at multiple points and multiple times, and incomplete mode shapes and invalid data appearing in the collection process are eliminated.

![Figure 1. Vibration signal of welded components in different states](image)

Figure 1 shows the time-domain waveforms of vibration signals of welded components in different states. As can be seen from the figure below, the time-domain waveforms of the vibration signals of the
welded components that have not been heat-treated and those that have been heat-treated have great similarities, and it is difficult to distinguish their residual stress states. Therefore, this paper proposes a new method to improve EMD and combines energy entropy to extract the residual stress state of components.

3.2. Feature extraction
Firstly, the vibration signals of each measuring point are processed by multiple differential processing, then the GMMS-MDEMD is used to decompose the signals, and then the same number of integration is performed to output the IMF component, and then the energy entropy of the corresponding modal component is calculated. The energy entropy is used as the feature of the residual stress state of the component to realize the rapid identification of the residual stress state of the mechanical component.

The signal is decomposed by EMD and GMMS-MDEMD to get IMF component. The number of IMF is related to different frequency components contained in the original signal. In order to screen out irrelevant or weakly correlated IMF components, the correlation coefficients of each IMF component and the original signal are calculated respectively. After correlation analysis, only the first five IMF components are taken for further analysis.

Taking the welded steel plate without heat treatment as an example, as shown in Fig. 2 (a), using EMD method will produce very serious end flying wings, the amplitude deviation is too large, and each low-frequency component has obvious distortion; at the same time, there is a serious mode mixing problem between IMF components decomposed by EMD, which is bound to affect the extraction of vibration characteristics of mechanical components. As shown in Figure 2 (b), the grey image method solves the endpoint effect in EMD algorithm, and eliminates part of the mode aliasing problem.

![EMD and GMMS-MDEMD](a) EMD (b) GMMS-MDEMD)

Figure 2. Decomposition results of vibration signals of welded components by different methods

3.3. Identification of residual stress state
A new signal is obtained by n-th differential processing of the vibration signal of the welding component, which is decomposed by gray image empirical mode decomposition, and then restored to the IMF components and residuals of the original signal through the same number of integration of each order of IMF, and then the IMF component energy value of each group of vibration signal is calculated and screened, and then the energy entropy of IMF component is calculated and normalized, finally the energy value is calculated. The state of residual stress is evaluated by entropy. It can be seen from Table 1 that the energy entropy of welded steel plates under different conditions shows that the energy entropy of welded steel plates with residual stress is smaller than the other two cases. This is because the welded steel plate after heat treatment has almost no residual stress, the vibration signal energy distribution is relatively uniform, and the entropy value is larger.
Therefore, if the energy entropy value is known in the normal state, the residual stress state of the component can be judged by measuring the energy entropy value of the test piece. If the energy entropy is less than the normal state, it indicates that there is residual stress, and the smaller the entropy value, the greater the residual stress. After testing and analyzing 100 samples, the accurate recognition rate of residual stress state reached 98.7%.

| Status of welded steel plate | Energy entropy |
|-----------------------------|----------------|
| Without heat treatment      | 0.763          |
| (There is residual stress)  |                |
| First heat treatment        | 1.3212         |
| (Normal state)              |                |
| Second heat treatment       | 1.3483         |
| (Normal state)              |                |

### Table 1 Energy entropy of welded steel plates in different states

4. Conclusion

(1) An improved multiple differential empirical mode decomposition (EMD) algorithm is proposed, in which the gray mean GM (1,1) prediction model is used to predict the end points of the data, and the mirror extension is used to avoid the end effect of EMD decomposition; the multiple differential is more conducive to EMD decomposition, which can make the energy of IMF component gradually change more clearly, and has a good anti mode aliasing performance.

(2) EMD decomposition has unique advantages in processing non-stationary excitation vibration signal, which has good adaptability and high decomposition efficiency. The IMF component energy value and energy entropy obtained after decomposition are used as the characteristic quantity to identify the residual stress state of the component. The experiment shows that it can accurately reflect the residual stress change of the welded component.

(3) This method opens up a new way to extract the residual stress state of mechanical components, especially for some large and complex structural components that cannot be detected by existing methods, which has certain research significance and engineering practical value.

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