A Novel Approach for Stress Cycle Analysis based on Empirical Mode Decomposition

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In real industrial stress/strain analysis applications, calculating equivalent constant amplitude cycles is important. Rainflow counting is a process to obtain equivalent constant amplitude cycles. The method is designed to count reversals in accordance with the material's stress/strain relationship including hysteresis loops. However, Rainflow counting needs to identify the peaks/valleys in the collected sensor signal and it is sensitive to noise. In this paper, a novel approach is proposed to count the fatigue cycles. The approach first uses empirical mode decomposition method to decompose the signal adaptively. Then a systematic count method is developed to calculate the cycles based on the decomposed signal components. The effectiveness and the performance of this method are compared with the Rainflow counting algorithm on simulated data with different frequencies and levels of noise.

Keywords: Rainflow count, Empirical mode decomposition, Stress cycle analysis, fatigue analysis

1. Introduction

Fatigue analysis is one of the main challenges in man-made structures health monitoring. It is more challenging these days due to excessive usage of modern technology. Advances in the field of fatigue monitoring helped to reduce the amount of failure in structures. Recent understanding of how the materials fail has been considerably increased in the recent years.

One of the main factors in fatigue analysis is calculating the number cycles (i.e. loading history). There are different methods to estimate this number. One very popular method is Rainflow counting, which was first proposed by Matsuishi and Endo[1] . It is now widely applied to estimate the fatigue cycles in different industry applications, such as, railway, aircraft, bridge, and automotive industries [2, 3, 4]. However, Rainflow counting algorithm has a complicated procedure, which makes it difficult to apply when their statistical properties are to be studied [5, 6]. Moreover, Rainflow counting algorithm is very sensitive to noise as it is depending on the local minima and local maxima of the sensor signal.

In this paper, a new stress cycle counting algorithm has been developed. The approach first uses empirical mode decomposition to decompose the signal into different narrowband signals and then estimates the stress counts based on the decomposed signals. The performance of the developed method is evaluated with simulated data with different frequency and noise levels. The reminder of the paper is organized as follow. Section 2 describes the Rainflow counting algorithm, empirical mode decomposition (EMD) and the proposed framework. Section 3 presents a case study comparing the Rainflow counting algorithm and the developed method. Section 4 summarizes the work and concludes this paper.

2. Theoretic Basis

2.1 Rainflow counting algorithm

Rainflow counting algorithm is widely used in estimating the stress cycles of the structure [7]. The procedure of conducting the Rainflow counting algorithm can be summarized in the following five steps [8],

Assume X denotes range under consideration; Y denotes the previous range adjacent to X; and S denotes the starting point in the stress history.

(a) Read next peak or trough. If out of data, go to step (f).

(b) If there are less than three points, go to step (a). Form ranges X and Y using the three most recent peaks and trough that have not been discarded.

(c) Compare the absolute values of ranges X and Y.

If $X < Y$, go to step (a).

If $X > Y$, go to step (d).

(d) If range Y contains the starting point S, go to step (e); otherwise, count range Y as one cycle; discard the peak and trough of Y and go to step (b).

(e) Count range Y as one-half cycle; discard the first point in range Y; move the starting point to the second point in range Y and go to (b).

(f) Count each range that has not been previously counted as one-half cycle.

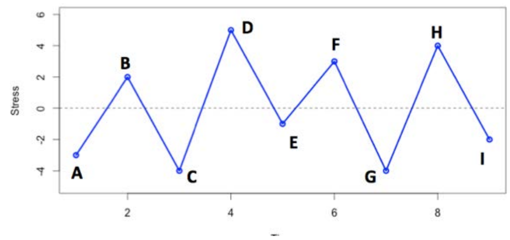

Figure 1. Example Stress vs Time Plot

A simple example is applied here to illustrate how Rainflow counting algorithm works. The stress versus time plot is shown in Figure 1. And the number of cycles corresponding to stress range illustrated in Fig. 3 is summarized in Table I.

Table I. Stess cycle count

Path	Cycles	Sress Range
A-B	0.5	5
B-C	0.5	6
C-D	0.5	9
D-G	0.5	9
E-F	1.0	4
G-H	0.5	8
H-I	0.5	6

2.2 Empirical mode decomposition

EMD was first proposed by Huang et al. as part of the Hilbert–Huang transform (HHT) [9]. Recently, EMD has been widely applied in different fields, such as acoustic emission signal processing [10], medical image processing [11], vibration analysis [12].

Assuming X represent the time series of the signal, the procedures of implementing the EMD algorithm is shown below,

(a) Find the local maxima and local minima of the signals.

(b) Construct the lower and upper envelopes of the signals by the cubic spline based on the local maxima and local minima, respectively.

(c) Calculate the mean values $m(t)$ by averaging the lower envelope and the upper envelope.

(d) Subtract the mean values from the original signals to produce the IMF candidate component $h_1(t) = X(t) - m(t)$. If it is the true IMF, go to the next step. In addition, the IMF component $C_i(t) = h_m(t)$ is saved. If it is not the IMF, repeat Steps a)–d). The stop condition for the iteration is given by

$$\sum_{t=0}^{T} \frac{[h_{m-1}(t) - h_m(t)]^2}{h_{m-1}^2(t)} \leqq SD$$

where $h_{m-1}(t)$ and $h_m(t)$ denote the IMF candidates of the $m - 1$ and m iterations, respectively, and, usually, SD is set between 0.2 and 0.3.

(e) Calculate the residual component by subtracting the IMF component obtained in Step d) from the original signals $res_i(t) = X(t) - C_i(t)$. This residual component is treated as new data and is subjected to the same processes described previously to calculate the next IMF component.

(f) Repeat Steps a)–e) until the final residual component becomes a monotonic function and no more IMF component can be extracted or the envelopes become smaller than a predetermined value. Through Steps a)–f), the original signals X.

A simulated example is used here to demonstrate how EMD process works. In the simulation, we add two sine waves (0.2 Hz and 3 Hz) together to generate a synthetic data. EMD is applied to decompose the signal into different components. From the Figure 2, we could see that the synthetic signal has been successfully separated into two components with 0.2 Hz and 3 Hz respectively.

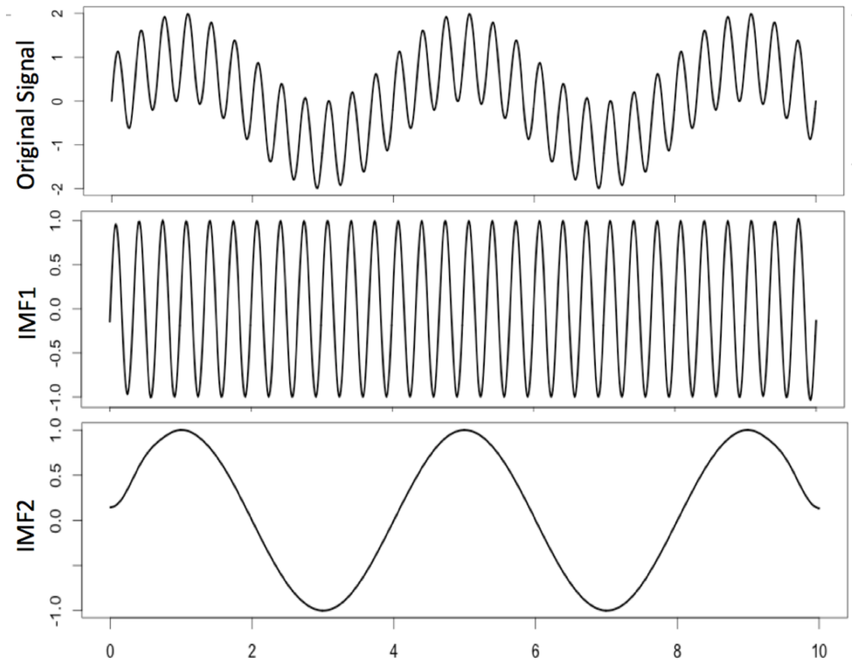

Figure 2. Simulated signal and IMF decomposition components

2.3 EMD-based Stress Cycle Counting Methodology

The framework of the developed methodology is shown in Figure 3.

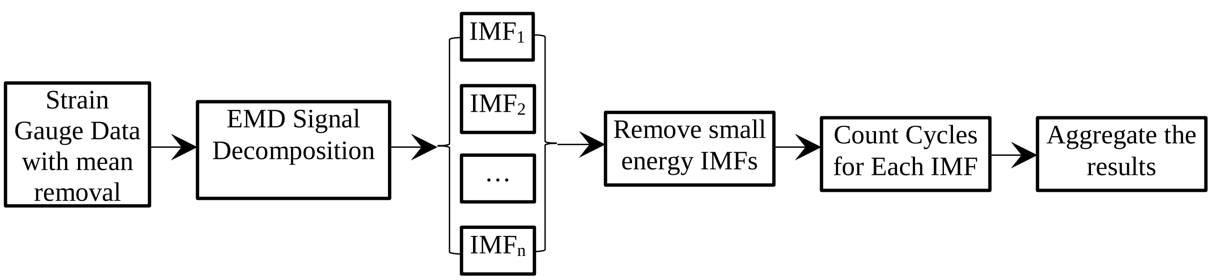

Figure 3. The framework of the developed methodology

As shown in Figure 3, the mean is first estimated and removed from the collected strain data. The estimated mean value is also used as the mean stress for fatigue analysis. Then the EMD is applied to decompose the strain data with mean value removed into multiple IMF components. To make the developed algorithm more robust to the noise, the energy ratios between each IMF component and the original signal are estimated and a threshold is set to remove any IMF component with energy ratio less than the threshold value. In this paper, 0.1 is used as the threshold to remove the IMF components. The energy ratio is calculated by using the following equation.

$$EnergyRatio_k = \frac{\sum_{i=1}^{N}(IMF_k^2(i))}{\sum_{i=1}^{N}(X^2(i))}$$

where, IMF_k is the k^{th} IMF component, X is the original signal, i is the i^{th} sampling point, and N is the number of the sampling points of signal X.

For stress cycle counting, the zero crossings of each selected i^{th} IMF component are counted as fatigue cycles (N^i) and the amplitude between zero crossings are calculated as the alternating stress (σ_{ai}) to be used for N_f calculation . After the cycle counts and its corresponding alternating stress have been estimated, they are combined with the mean stress (σ_m), which is the mean value of the original signal, to calculate the fatigue damage. The following equation is used to compute the accumulative fatigue damage (AFD).

$$AFD_i = \sum_{i=1}^{K} \frac{N_i}{N_{fi}}$$

Where N_i is the number of cycles in i^{th} IMF component, k is the total number of the selected IMFs, and N_{fi} in the i^{th} IMF is calculated as following,

$$N_{fi} = 10^{\text{intercept}} \times \sigma_0^{\text{slope}}$$

$$\sigma_0 = \frac{\sigma_{ai}}{1 - \left(\frac{\sigma_m}{\sigma_u}\right)^2}$$

where σ_u is ultimate stress, which is a material property, σ_{ai} is the alternating stress of the ith IMF component, σ_m is the mean stress, and intercept and slope are two constant related to material property.

3. Experimental Analysis

We have simulated five groups of signals. The simulated signals are composed by sine wave, random noise and a constant offset. For each group, it contains 100 simulated datasets with same level Gaussian noise. The simulated signals in group 1 have the lowest frequency content for sine wave and those in group 5 have the highest frequency content for sine wave. For each dataset, 200 Hz sampling frequency is used and 10 seconds' signal is simulated.

To obtain the accumulative fatigue value, a fatigue curve for a typical material (1050HR) was considered in this analysis. The relationship between number of cycles before failure (N_f) and corrected alternating stress (σ_0) is shown below

$$N_f = 1.298 \times 10^{38} \times \sigma_0^{-12.853}$$

Where

$$\sigma_0 = \frac{\sigma_a}{1 - \left(\frac{\sigma_m}{\sigma_u}\right)^2}$$

Where σ_a is alternating stress, σ_m is mean stress and σ_u is ultimate stress (630 MPa for 1050HR). For each cycle, corrected alternating stress (σ_0) and number of cycles before failure (N_f) need to be calculated. The accumulative damage (AFD) is introduced by N/N_f .

An example of the theoretical value for damage due to a 4.5 cycles of sine wave with 215 amplitude is summarized in table II.

Table II Theoretical damage

σ_a	σ_m	N	σ_0	N_f	AFD (N/N_f)
215	450	4.5	439.0	14,132	3.184E-04

All damage calculation for Rainflow and EMD are compared with their theoretical values. The calculated cycles are converted to be the AFD based on the SN curve approach described above. The performance of each model is measured by the percentage of the ratio difference, which is defined in the following equation.

$$AverageErrorPercentage = \sum_{i=1}^{J} \frac{\left| \frac{AFD_i}{AFD_{Theory}} - 1 \right|}{J}$$

where AFD_i is the AFD for ith signal in the same group, AFD_{Theory} is the theoretical AFD for that group, J is the number of the signals in that group. The performance comparison is shown in Table III.

Table III Average of Error Percentage of different models

	Rainflow counting	EMD counting
Error percentage Group 1	9.8%	5.02%
Error percentage Group 2	13.17%	5.47%
Error percentage Group 3	9.17%	7.89%
Error percentage Group 4	14.7%	12.59%
Error percentage Group 5	19.99%	15.24%

From the results in Table III, one could see that EMD based counting approach works better than Rainflow counting algorithm, especially when the noise level is high.

4. Conclusions

In this paper, a novel robust approach was developed to count the fatigue cycles. The approach applied EMD algorithms to decompose the signal into IMFs. The stress cycles are estimated based on the IMFs. The performance of the developed method was evaluated with simulated data with different level of noise added to the signal. The experimental results had shown that the developed EMD based stress cycle counting algorithm outperformed the Rainflow counting algorithm and was more robust to the signal with noise.

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