Research Article

Morphological Filter-Assisted Ensemble Empirical Mode Decomposition

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In the ensemble empirical mode decomposition (EEMD) algorithm, different realizations of white noise are added to the original signal as dyadic filter banks to overcome the mode mixing problems of empirical mode decomposition (EMD). However, not all the components in white noise are necessary, and the superfluous components will introduce additional mode mixing problems. To address this problem, morphological filter-assisted ensemble empirical mode decomposition (MF-EEMD) was proposed in this paper. First, a new method for determining the structuring element shape and size was proposed to improve the adaptive ability of morphological filter (MF). Then, the adaptive MF was introduced into EMD to remove the superfluous white noise components to improve the decomposition results. Based on the contributions of MF in a single EMD process, the MF-EEMD was proposed by combining EEMD with MF to suppress the mode mixing problems. Finally, an analog signal and a measured signal were used to verify the feasibility of MF-EEMD. The results show that MF-EEMD significantly mitigates the mode mixing problems and achieves a higher decomposition efficiency compared to that of EEMD.

1. Introduction

Signal decomposition techniques, such as Fourier transform (FT), wavelet transform (WT), and empirical mode decomposition (EMD), are widely used in the field of structural health monitoring for denoising, parameter identification, and damage detection [1–3]. However, these techniques have considerable deficiencies. FT [4] takes the signal as a linear combination of sine waves with different frequencies, but the frequency and amplitude of the sine wave are immutable. Consequently, FT cannot analyze nonstationary or nonlinear signals [5]. Short-time Fourier transform (STFT) is a variation of FT, and it can address nonstationary signals by employing the window function technique. However, it is hard to balance the resolution between the time domain and the frequency domain [6]. WT [7] is suitable for decomposing nonlinear signals with multiple scales and multiple resolutions, but determining the appropriate mother wavelet function is difficult. Hence, the adaptive performance of WT is poor. EMD is a fully data-driven technique with the ability to decompose nonstationary and nonlinear signals; thus, it

possesses strong robustness and adaptive ability [5]. However, the mode mixing problems in EMD severely restrict its application [8, 9].

To overcome the mode mixing problem of EMD, Wu and Huang [10] proposed the noise-assisted ensemble empirical mode decomposition (EEMD). In the EEMD algorithm, EMD is performed repeatedly with the addition of different white noises, and an ensemble of the same order intrinsic mode functions (IMF) is made to obtain the final decomposition results. Flandrin and Rilling [11] noted that the white noise added in EEMD could be taken as a set of dyadic filter banks, and different frequency components in the original signal were projected to the corresponding banks. This characteristic of white noise helped to separate the different orders of IMFs.

The valuable components in the original signal are typically limited in quantity; in other words, the number of essential dyadic filter banks for EEMD can be counted. However, the added white noise contains all the dyadic filter banks in the frequency domain. The superfluous dyadic filter banks added to the original signal will not only reduce the

FIGURE 1: Different shapes of structuring elements.

decomposition efficiency but also cause additional mode mixing problems [12]. Based on the above problems, it could be speculated that the accuracy and efficiency of EEMD would be improved if the superfluous dyadic filter banks were removed.

The morphological filter (MF) is a type of nonlinear filter that is particularly sensitive to impulse noise and white noise; moreover, it will not cause sudden truncation in the frequency domain or phase delay in the time domain [13, 14]. Deng [15] adopted the MF along with other traditional filters to filter impulse noise, and the results demonstrated that the MF was superior to the other filters, especially when the noise level was high. Yuan [16] adopted the MF and a hybrid filter to detect and eliminate impulse noise in images, and superb denoising results were achieved for different signal-to-noise ratios. Lin [17] used the MF to eliminate the high-ratio impulse noise, and the MF achieved a better performance than other traditional digital filters, such as the mean filter and the median filter. Saniie [14] adopted the MF to suppress the impulse noise and the white noise in an ultrasonic signal; the MF could significantly improve the signal-to-noise ratio and maintain an undistorted signal. Mukhopadhyay [18] adopted the MF to filter different types of noise, and the results showed that the MF was effective for all types of noise and superior to other standard noise removal algorithms. The above literature review illustrates that the MF is a potentially powerful tool for filtering superfluous dyadic filter banks in EEMD.

This paper proposes the morphological filter-assisted ensemble empirical mode decomposition (MF-EEMD) to overcome the mode mixing problems in EEMD. First, the concepts of MF were presented, and the adaptive ability of MF was improved by proposing a new method for determining the structure element shape and size. Then, the adaptive MF was applied to remove the superfluous white noise components in EMD to improve its decomposition results. Based on the contributions of MF in a single EMD process, the MF-EEMD was proposed by introducing MF into EEMD to suppress its mode mixing problems. Finally, MF-EEMD is compared with EEMD by decomposing an analog signal and a measured signal, and the effectiveness of MF-EEMD is validated.

2. MF Theory

In 1986, Serra [19, 20] proposed the MF based on the theory of mathematical morphology. The MF is a type of nonlinear temporal filter that can process a signal directly in the time domain without converting it into the frequency domain. In the MF algorithm, a structuring element is used to address the data points, and its common shapes are shown in Figure 1.

In the algorithm of MF, dilation and erosion are the two most basic operations [21]. The dilation operation on signal α with structuring element β is defined as $\alpha \oplus \beta$, and the erosion operation on signal α with structuring element β is defined as $\alpha \ominus \beta$, as shown in (1) and (2), respectively.

$$\alpha \oplus \beta = \max \{ \alpha(i - j) + \beta(j) \} \quad (1)$$

$$\alpha \ominus \beta = \min \{ \alpha(i + j) - \beta(j) \} \quad (2)$$

where $1 < i < n$, $1 \leq j \leq k$, $i + j \leq n$, n is the length of α , and k is the width of β .

Based on the dilation and erosion operations, the opening operation on signal α with structuring element β is defined as $\alpha \circ \beta$, and the closing operation on signal α with structuring element β is defined as $\alpha \bullet \beta$, as shown in (3) and (4), respectively.

$$\alpha \circ \beta = (\alpha \ominus \beta) \oplus \beta \quad (3)$$

$$\alpha \bullet \beta = (\alpha \oplus \beta) \ominus \beta \quad (4)$$

However, the opening operation can only address the local maximums, while the closing operation can only address the local minimums [22]. To address both the local maximums and local minimums of the signal, the opening and closing operations should be combined by (5).

$$\alpha' = (\alpha \circ \beta) \bullet \beta \quad (5)$$

$$\text{or } \alpha' = (\alpha \bullet \beta) \circ \beta$$

To eliminate the effect of different operational sequences, the average of opening-closing and closing-opening is taken as the final filtering result. The complete operational flow of the MF is shown in Figure 2.

FIGURE 2: Operational flow of the MF.

3. Adaptive MF

The shape and size of the structuring element are the two most important parameters in MF, and they have significant influences on the filtering results. The determination of the two parameters relates to multiple factors, such as the sample frequency, the dominant frequency, and the noise type. The shape and size of the structuring element are generally determined by empirical methods [14, 15], and the disadvantages of those methods are low adaptive ability and poor versatility.

To construct an adaptive MF algorithm, the determination method of the appropriate structuring element parameters were investigated in this paper.

A composite signal of sinusoid and white noise is constructed based on (6)-(8).

$$S_{sin} = \lambda \cdot \sin\left(2\pi f \times \frac{n}{sf}\right) \quad (6)$$

$$S_{wn} = k \cdot \text{rand}\left(\frac{n}{sf}\right) \quad (7)$$

$$S_c = S_{sin} + S_{wn} \quad (8)$$

where S_{sin} is a pure sinusoid, S_{wn} is white noise, S_c is the composite signal, sf is the sample frequency, $n = 1, 2, 3 \dots N$, N is the length of S_c , f is the dominant frequency, λ is the amplitude of the pure sinusoid, and k is the amplitude of the white noise.

To make an objective evaluation of the effectiveness of the MF, the signal-to-noise ratio (SNR) [23] is introduced as the evaluation index, as shown in (9).

$$SNR = 10 \times \log\left(\frac{\text{Std}(S_{sin})}{\text{Std}(S_{MF} - S_{sin})}\right) \quad (9)$$

where the operator $\text{Std}()$ is the expression of standard deviation and S_{MF} is the filtering result of S_c . When S_{MF} and S_{sin} are more similar, the value of SNR is greater.

3.1. Shape Selection. To investigate the characteristics of different structuring element shapes, a composite signal with one dominant frequency was constructed by (6)-(8) with the parameters $sf=256$ Hz, $N=512$, $f=5$ Hz, $\lambda=1$, and $k=0.3$, as shown in Figure 3.

TABLE 1: Parameter settings of S_c with one dominant frequency.

No.	sf	f	λ	k
#1	256	5	1	0.1
#2	256	5	1	0.3
#3	256	5	1	0.5
#4	512	4	1	0.3
#5	512	8	1	0.3
#6	512	16	1	0.3
#7	64	3	1	0.3
#8	128	3	1	0.3
#9	512	3	1	0.3

Three types of structuring elements were constructed, each with linear, sinusoidal, or triangular shapes. The range of the structuring element width (W) was set as 3-35, and the range of the structuring element height (H) was set as 0.1-5 times the standard deviation of S_c . Then, the three types of structuring elements with varying sizes were adopted to filter the signal, and the corresponding SNR of each S_{MF} was calculated. In Figure 4, the initial SNR of S_c is shown as a plane surface with a value of 14.35, and the SNR of S_{MF} is shown as a curved surface.

In Figure 4(a), the changes in SNR values only relate to W . The appropriate distribution range of W is 3-11, and the best filtering result is achieved with an SNR value of 19.56 when $W=5$. In Figure 4(b), the changes in SNR values relate to both W and H . W and H have wide appropriate ranges, and the best filtering result is achieved with an SNR value of 23.72 when $W=11$ and $H=0.7$. The filtering result in Figure 4(c) is similar to that in Figure 4(b), but the appropriate ranges of W and H are narrower. The best filtering result is achieved with an SNR value of 22.61 when $W=9$ and $H=0.5$.

Although the filtering results with different white noises are not constant due to the white noise randomness, still some patterns can be observed as follows. The best filtering results of the sinusoidal and triangular structuring elements are similar, and they are superior to that of the linear element. Additionally, the distribution range of the appropriate element sizes of the triangular structuring element is narrower than that of the sinusoidal structuring element and, thus, the distribution law of the appropriate element size of the triangular structuring element is more obvious.

According to the above patterns, the triangular structuring element was selected for the follow-up studies in this paper.

3.2. Size Determination. To investigate the distribution laws of the appropriate W and H , multiple composite signals with one dominant frequency were constructed using (6)-(8). The corresponding parameter settings are listed in Table 1. A triangular structuring element with varying sizes was adopted to filter the signals, and the corresponding SNR values of each S_{MF} were calculated, as shown in Figure 5.

In signals #1-3, k is the only parameter that is varied. The distribution range of appropriate sizes becomes wider with increasing k ; however, the ridgeline (colored yellow) of the

FIGURE 3: Composite signal with one dominant frequency.

FIGURE 4: Filtering results with different structuring element shapes.

SNR surface remains relatively unchanged. In signals #4-6, f is the only parameter being varied. When f is small, the ridgeline is close to axis W , and vice versa. In signals #7-9, sf is the only parameter being varied, and the effect of sf on the ridgeline is opposite that of f .

Figure 5 illustrates that the location and direction of the ridgeline of SNR surface are mainly dominated by sf and f . The intersection point of the ridgeline and $H=0.1$ has a larger value with increases in sf or decreases in f . The value of W/H also has the same relationship with sf and f . The above laws can be summarized as (10)-(12).

$$W_{H=0.1} \sim \frac{sf}{f} \quad (10)$$

$$W/H \sim \frac{sf}{f} \quad (11)$$

$$W \sim \frac{sf}{f} + H \cdot \frac{sf}{f} \quad (12)$$

A linear regression was performed to fit (12) using 650 samples with the value of sf/f varying from 4 to 1,024. The fitting result is shown in (13).

$$W = 0.33\sqrt{\frac{sf}{f}} + 0.24H \cdot \frac{sf}{f} \quad (13)$$

In Figure 6, three examples with different values of sf/f were selected to demonstrate the prediction precision of (13). The black points are the predictions of the appropriate structuring element sizes, and they are very close to the ridgelines

TABLE 2: Parameter settings of S_c with two dominant frequencies.

No.	sf	f_l	f_h	λ_l	λ_h	k
#1	256	8	16	0.4	0.6	0.3
#2	256	2	8	0.5	0.5	0.3
#3	256	4	32	0.6	0.4	0.3

of the SNR surfaces, which indicates that the prediction of appropriate structuring element sizes has a high precision.

To investigate the applicability of (13) to signals with multiple dominant frequencies, three composite signals with two dominant frequencies were constructed with the parameter settings listed in Table 2. The SNR values of the filtering results along with the predictions of the appropriate structuring element sizes are shown in Figure 7, where the blue points represent the predictions with f_h and the red points represent the predictions with f_l .

Figure 7 illustrates that the ridgeline of the SNR surface is between the two predictions but very close to the blue points, indicating that the distribution of appropriate structuring element sizes is mainly dominated by f_h . Therefore, the ridgeline of the SNR surface can be approximately estimated by (13) with f_h .

In actual operation, one pair of appropriate size (W, H) is sufficient for the MF, and the value of W for the triangular structuring element is $W=2n+1$, which means that the smallest value of W is 3. In this paper, a simplified and practical size determination method for the triangular structuring element was proposed as follows: (1) Extract the highest valuable frequency f of the signal. (2) Introduce sf and f into (13),

FIGURE 5: Filtering results with varying structuring element sizes.

FIGURE 6: Fitting results of the SNR ridgeline with one dominant frequency.

FIGURE 7: Fitting results of the SNR ridgeline with two dominant frequencies.

increase H from 0.1 with a step length of 0.1, and calculate the corresponding odd-value of W . (3) Stop the calculation when $W \geq 3$, and obtain one pair of appropriate size (W, H) .

4. MF-EEMD

The superfluous white noise components in EEMD may cause additional mode mixing problems and reduce the decomposition efficiency [12]. In this paper, the MF was adopted to filter out the superfluous white noise components to improve EEMD.

4.1. EMD Combined with MF. A composite signal with two dominant frequencies was constructed by (6)-(8), as shown in Figure 8, and the parameters were set as $f_1=2$, $\lambda_1=0.5$, $f_2=5$, $\lambda_2=0.5$, $sf=256$, $N=512$, and $k=0.3$.

EMD was directly adopted for the composite signal in Figure 8(c). The stoppage criterion of EMD was that the number of zero crossing points of IMF must be larger than N/sf , and the decomposition shall be stopped after the appearance of the first unqualified IMF. This stoppage criterion was also applicable to EEMD and MF-EEMD. There were 9 orders of IMFs in the decomposition results of EMD, as shown in Figure 9. The 1st- to 3rd-order IMFs are noise, the 4th-order IMF consists of noise and a 5 Hz component, the 5th-order IMF consists of 5 Hz and 2 Hz components, the 6th-order IMF is mainly a 2 Hz component, and the 7th- to 9th-order IMFs are trends. These results illustrate that there are obvious mode mixing problems in the EMD results.

There is typically no prior knowledge about the highest valuable f in the signal; thus, the application of (13) is limited. To address this problem, an extraction method for f based on the decomposition results of EMD or EEMD was proposed.

First, the original signal is decomposed with EMD or EEMD. Then, the criterion ET proposed by Wu and Huang [24] is used to distinguish the noise components from the valuable components. The criterion $E_n T_n$ of the n^{th} IMF is defined by (14) and (15).

$$E_n = \frac{1}{N} \sum_{i=1}^N [\text{IMF}_n(i)]^2 \quad (14)$$

$$T_n = \frac{2N}{N_{zc}} \quad (15)$$

where E_n is the energy density, T_n is the averaged period, N is the length of IMF_n , and N_{zc} is the number of zero-crossings of IMF_n . When IMF_n is a noise component, the value of $E_n T_n$ is small; otherwise, the value of $E_n T_n$ is considerably larger.

By observing the values of $E_n T_n$, the noise components and valuable components are distinguished, and the IMF with the desired f is selected. Finally, the auto-power spectrum analysis is adopted for the selected IMF, and the frequency of the peak point in the spectrum is taken as f .

The ET values of the IMFs in Figure 9 are shown in Figure 10, where there is a sudden increase between the 3rd and 4th ET values. This result indicates that the frequency of the 4th IMF can be taken as f . The auto-power spectrum of the 4th IMF is shown in Figure 11 with $f=5$ Hz.

The appropriate structuring element size was derived as $W=3$ and $H=0.1$ by (13) with $sf=256$ and $f=5$. Then, the composite signal in Figure 8(c) was filtered by the MF, as shown in Figure 12.

The Fourier spectrum of the noise component is shown in Figure 13. The amplitude of the low-frequency domain, where the frequencies of the valuable components are located, is smaller than that of the high-frequency domain. In other words, the superfluous dyadic filter banks are removed while the valuable ones are retained in S_{MF} .

Then, the EMD was applied again to the filtering result in Figure 12(a), and 7 orders of IMFs were obtained, as shown in Figure 14. The 1st- to 3rd-order IMFs are noise, the 4th-order IMF is a 5 Hz component, the 5th-order IMF is mainly a 2 Hz component, and the 6th- and 7th-order IMFs are trends. Only slight mode mixing problems are observed in the decomposition results, indicating that the mode mixing problems are suppressed. Moreover, the number of IMFs is reduced from 9 to 7, which means that the decomposition efficiency of EMD is also improved.

4.2. EEMD Combined with MF. The decomposition results of a single operation of EMD were improved with the addition of MF. EEMD is an ensemble of numerous EMD; therefore, the EEMD results would also be improved by the MF. Hence, MF-EEMD was proposed in this paper by introducing MF into EEMD.

FIGURE 8: Composite signal with two dominant frequencies.

FIGURE 9: EMD results.

FIGURE 11: Auto-power spectrum of the 4th IMF.

FIGURE 10: ET values of the IMFs.

The main flows of MF-EEMD are as follows: (1) Decompose the original signal by traditional EMD or EEMD and determine the appropriate structuring element size based on the decomposition results. (2) Add white noise to the original signal and employ the MF to filter the polluted signal. (3) Adopt EMD to decompose the filtering signal. (4) Repeat the second and third processes by adding different series of white noise. (5) Make an ensemble of the numerous decomposition results and achieve the final decomposition results of EEMD. The above flows of MF-EEMD are shown in Figure 15, where the additional operations proposed in this paper are marked with a gray shade.

5. Application Instance

5.1. Analog Signal Decomposition. To verify the feasibility of the proposed method, the composite signal S_c in Figure 8(c)

FIGURE 12: Filtering result of the MF.

FIGURE 13: Fourier spectrum of the noise component.

FIGURE 14: Results of the EMD combined with MF.

was selected again to be decomposed by EEMD and MF-EEMD. During operations of the two methods, the level of white noise added in each operation of EMD was set as 0.1 times the standard deviation of S_c , and the number of ensembles was set as 500. The appropriate size of triangular structuring element was set as $W=3$, $H=0.1$. Nine IMFs are present in the traditional EEMD results, as shown in Figure 16, while there are 7 IMFs in the MF-EEMD results, as shown in Figure 17. The corresponding Hilbert spectra of the EEMD and MF-EEMD results are shown in Figures 18 and 19, respectively.

In Figure 16, the 1st- to 4th-order IMFs are noise, the 5th-order IMF is a 5 Hz component, the 6th-order IMF is a 2 Hz component, and the 7th- to 9th-order IMFs are trends. However, the waveform of the 4th-order IMF from 1 s to 2 s is

quite similar to that of the 5th-order IMF; there are slight mode mixing problems in the EEMD results. The mode mixing problems can also be observed in Figure 18, where there are disturbances around the 5 Hz spectrum.

In Figure 17, the 1st- to 3rd-order IMFs are noise, the 4th-order IMF is a 5 Hz component, the 5th-order IMF is a 2 Hz component, and the 6th- and 7th-order IMFs are trends. In Figure 19, the 5 Hz and 2 Hz spectra are straight, and the background is quite clean. No obvious mode mixing problem is found in the MF-EEMD results.

5.2. Measured Signal Decomposition. For further verifying the proposed method, the acceleration signal measured from a shaking table test of a cable-stayed bridge model was taken as another instance. A photograph of the cable-stayed bridge model is shown in Figure 20. The input of the test was white noise with a peak value of 0.1 g, and the input direction was lateral. A set of acceleration responses of the tower top with a sample frequency of 256 Hz was selected, as shown in Figure 21.

In this instance, the level of white noise added in each operation of EMD was set as 0.2 times the standard deviation of the measured signal, and the number of ensembles was set as 2,000. First, the measured signal was decomposed by EEMD, and 11 IMFs were obtained. The decomposition results along with the ET values are shown in Figures 22 and 23. There is a sudden increase between the 3rd and 4th ET values, indicating that the desired f is in the 4th-order IMF. The auto-power spectrum of the 4th-order IMF is shown in Figure 24, and the frequency of the peak point is 10.38 Hz. The appropriate size of the structuring element was derived as $W=3$ and $H=0.3$ by (13) with $sf=256$ and $f=10.38$. Then, the measured signal was decomposed by MF-EEMD, and 9 IMFs were obtained, as shown in Figure 25.

To compare the mode mixing problems in detail, the local waveforms of the IMFs of the two methods are presented in Figures 26 and 27. Mode mixing problems are present in the 5th-order IMF of EEMD, and the waveforms marked with the red circle are similar to that of the 4th-order IMF. The waveforms marked with the blue circles are similar to that of the 6th-order IMF. However, there are no evident mode mixing problems in the IMFs of MF-EEMD.

The Hilbert spectra of the EEMD and MF-EEMD results are shown in Figures 28 and 29, respectively. In Figure 28, there are serious mode mixing problems in the two spectra of

FIGURE 15: Operational flow of the MF-EEMD.

FIGURE 16: EEMD results.

FIGURE 18: Hilbert spectrum of EEMD.

FIGURE 17: MF-EEMD results.

FIGURE 19: Hilbert spectrum of MF-EEMD.

FIGURE 20: Cable-stayed bridge model.

FIGURE 21: Acceleration response of the tower top.

FIGURE 22: EEMD results.

FIGURE 23: ET values of IMFs.

FIGURE 24: Auto-power spectrum of the 4th IMF.

FIGURE 25: MF-EEMD results.

approximately 4 Hz, and the fluctuations of their frequencies cannot be easily tracked. The spectrum of approximately 10 Hz is widely distributed in the frequency domain, which means that the corresponding waveforms of this spectrum are not smooth. In Figure 29, the mode mixing problems in the two spectra of approximately 4 Hz are mild, and the fluctuations of their frequencies are clear and easy to track. The distribution band of the spectrum of approximately 10 Hz is narrow, which means that the smoothness of its waveforms is improved. The comparison results show that the mode mixing problems in EEMD are effectively suppressed by MF-EEMD.

6. Conclusion

MF-EEMD was proposed to suppress the mode mixing problems in EEMD. Structuring elements with different shapes and sizes were used in the MF to filter a series of analog signals. Based on the filtering results, the triangular shape was found to be superior to the linear and sinusoidal shapes, and an equation for calculating the appropriate sizes of the triangular structuring element was established. Then, the MF was used to filter the superfluous white noise components during the EMD operation. The MF could help suppress the mode

FIGURE 26: Local waveforms of the IMFs of EEMD.

FIGURE 27: Local waveforms of the IMFs of MF-EEMD.

mixing problems and improve the decomposition efficiency. Based on the above results, an improved MF-EEMD method was proposed by combining the EEMD with MF. To verify the proposed method, an analog signal and a measured signal were decomposed by EEMD and MF-EEMD, respectively. The comparison results show that the mode mixing problems in EEMD are effectively suppressed by the MF-EEMD. Moreover, under the same stoppage criterion, fewer IMFs are archived by the MF-EEMD, which means that the proposed method also has a higher decomposition efficiency.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

FIGURE 28: Hilbert spectrum of EEMD.

FIGURE 29: Hilbert spectrum of MF-EEMD.

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