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# Identification of Modal Parameters from Noisy Transient Response Signals


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# Identification of Modal Parameters from Noisy Transient Response Signals

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Abstract

In the process of impact testing of large-scale mechanical equipment, the measured forced response signals are often polluted by strong background noise. The forced response signal has a low signal-to-noise ratio, and this makes it difficult to accurately estimate the modal parameters. To solve this problem, the mean averaging of repeatedly measured frequency response function estimates is often employed in practical applications. However, a large number of impact testsare not practical for the modal testing of large-scale mechanical equipment. The primary objective of this paper is to reduce the number of averaging operations and improve the accuracy of the modal identification by using an adaptive noise removal technique. An adaptive denoising method is proposed by combining the Wiener and improved minimum mean square error short-time spectral amplitude estimators. The proposed method can adaptively remove both stationary and highly non-stationary noise, while preserving the important features of the true forced response signals. The simulation results show that the proposed noise removal technique improves the accuracy of the estimated modal parameters using only one impulse response signal. The experimental results show that the proposed two step method can accurately identify a natural frequency that is very close to a strong interference frequency in the modal test of a 600MW generator casing.

KEY WORDS: Modal identification; Adaptive noise reduction; Low SNR; MMSE-STSA estimator; WIENER-STSA estimator

# 1. Introduction

Modal identification estimates the modal model of a structure, i.e. natural frequencies, damping ratios and mode shapes, from measured input-output data. The accuracy of modal identification is highly sensitive to the signal-to-noise ratio (SNR) of the measured output signals(forced response signals). In modal tests of large-scale mechanical equipment, the measured forced response signals are always polluted by strong background noise, and the noise is rather complex as the contributing factors are diverse and complicated. The noise sources are thought to originate from test environment including non-linear effects, extraneous structural noise as well as 'noise' in electronic devices[1]. Hence, the forced response signals have a low SNR and this makes the estimation of the modal parameters difficult. To obtain the ideal forced responses the background noise should be removed from the measured forced response signals. Denoising methods have been proposed for noise removal from frequency response functions(FRFs). Kim and Hong [2] proposed a robust wavelet denoising method for FRFs estimation, which is based on a wavelet-related median filtering and wavelet shrinkage to reduce the effect of outliers and zero-mean Gaussian noise respectively. But the method requires many averaging operations for accurate FRF estimation, which reduces the scope of its application. Sanliturk and Cakar [1] presented a method based on the singular value decomposition(SVD) for the elimination of noise from measured FRFs so as to improve the accuracy of modal identification, but the method needs to set an appropriate threshold to avoid loss of valuable information. Alamdari et al. [3] introduced a Gaussian kernel algorithm to reduce unnecessary noise from noisy FRFs, and it is designed to localize damage in the presence of heavy noise influences by using FRFs of the damaged structure only. Huet al. and Bao et al.[4,5] introduced a Cadzow's algorithm to reduce unnecessary noise from noisy FRFs, but the denoising method needs to set a reasonable noise threshold based on the measured signals. The effectiveness of the denoising methods in [3-5] was illustrated by simulation and experimental data, but none of the results show that the two denoising methods can remove strong background noise mixed in a forced response signal.

Insert Figure 1 here

Figure 1 shows the basic breakdown of signals into different types[6,7]. The most fundamental division is into stationary and non-stationary signals. Stationary signals have statistical properties that are invariant with time, whereas for non-stationary signals the statistical properties vary with time. Figure 1 highlights that typical measured forced response signals contain both stationary and non-stationary components for modal tests on large-scale mechanical equipment. The ideal forced response signal has a transient component that is non-stationary, background noise that is mainly stationary, and often a continuous component that is non-stationary. The existing denoising algorithms cannot remove stationary noise and non-stationary noise simultaneously, and these different types of noise should be dealt with separately. The short-time spectral amplitude(STSA), Wiener filter(WIENER) and minimum mean square error(MMSE) methods have been widely used in denoising and coding [8-15]. The MMSE-STSA estimator is effective in removing stationary signals and the continuous components of non-stationary signals from measured speech signals[8], although the technique requires the SNR a priori. Hence this SNR is a key parameter in the MMSE-STSA estimator. The decision-directed(DD) approach[8] is a widely used method to estimate the a priori SNR, but has two inherent drawbacks:

- The estimated a priori SNR is biased since the DD approach depends on the estimate of the spectrum in the previous window[8,9].
- The estimated a priori SNR is distorted when the measured signal has a low SNR[8].

The first problem has been solved by an improved a priori SNR estimation method proposed by Plapouset et al.[9], which removes the bias in the DD approach. However, the second problem is still unsolved and hence the MMSE-STSA estimator method cannot be directly used to remove strong background noise mixed in a forced response signal. The Wiener filter is an optimal method to remove stationary noise in stationary environments[16],whereas the Wiener short-time spectral amplitude estimator (WIENER-STSA)improves the application scope of the Wiener filter. Here, the WIENER-STSA estimator can be used to eliminate stationary noise from the measured forced response signal, so as to solve the second problem. In this paper, we propose an adaptive denoising method combining WIENER-STSA and MMSE-STSA estimators with improved a priori SNR estimation. The proposed denoising method can adaptively remove stationary noise and continuous components of non-stationary noise, while preserving the important features of the true forced response signals. The proposed method can reduce the number of averaging operations and improve the accuracy of modal identification for low SNR measurements.

The paper is organized as follows. Section 2 introduces some background about denoising, and compares two a priori SNR estimation methods. Section 3 introduces the proposed method. In section 4, the proposed method is validated using simulated signals. Section 5 applies the proposed method to measured forced response signals collected from a 600MW generator. Finally, conclusion are given in Section 6.



## 2. Background

### 2.1. The MMSE-STSA estimator

Ephraim and Malah [8] proposed the minimum mean-square error short-time spectral amplitude(MMSE-STSA) estimator. Previous studies[8, 17] have shown that the MMSE-STSA estimator has a beneficial effect for the processing of non-stationary signals when the SNR level is high. Here the MMSE-STSA developed in [8] is reviewed.

In the usual additive noise model, the measured impulse response signal is given by

$$x(t) = s(t) + n(t),\ 0 \le t \le T \quad (1)$$

where $s(t)$ and $n(t)$ denote the noise-free impulse response signal and the noise signal, respectively, in the analysis interval $[0, T]$. Applying the Short Time Fourier Transform (STFT), we have

$$X_k(p) = S_k(p) + N_k(p) \quad (2)$$

where $p$ and $k$ denotethe short-time window and the frequency indices, respectively. Using exponential notation, the $k$-th spectralcomponent ofthe noise-free impulse response signal and the noisy signal can be expressed as$S_k(p) = A_k e^{j\alpha_k}$ and$X_k(p) = R_k e^{j\upsilon_k}$, respectively[8, 9].

The objective of the MMSE-STSA estimator is to determine$\hat{A}_k$, the estimate of the spectral amplitude $A_k$ of the noise-free impulse response signal$s(t)$. Ephraim and Malah [8] estimated $\hat{A}_k$through the minimization of a Bayesian cost function which measures the mean square error between$\hat{A}_k$ and $A_k$. Thus the Bayesian cost function can be expressed as:

$$J = \mathbf{E}\left\{\left(A_k - \hat{A}_k\right)^2\right\} \quad (3)$$

where $\mathbf{E}\{\cdot\}$ is the expectation operator. The Bayesian estimator is then given by

$$\hat{A}_k = \mathbf{E}\{A_k | x(t),\ 0 \leq t \leq T\} \quad (4)$$

Assuming the individual spectral components are statistically independent of one another, the expected value of $A_k$given$\{x(t),\ 0 \leq t \leq T\}$is equal to the expected value of $A_k$given$X_k$only. We therefore have

$$\hat{A}_k = \mathbf{E}\{A_k | X_k\} = \frac{\int_0^\infty \int_0^{2\pi} a_k p(X_k | a_k, \alpha_k) p(a_k, \alpha_k) da_k d\alpha_k}{\int_0^\infty \int_0^{2\pi} p(X_k | a_k, \alpha_k) p(a_k, \alpha_k) da_k d\alpha_k} \quad (5)$$

where the symbol $a_k$ denotes the sample value of $A_k$,and $p(\cdot)$ denotes a probability density function(PDF). In order to develop the theory along the lines that it has been done in the past it is necessary to treat the Discrete Fourier Transform(DFT) coefficients as Gaussian distributions, the assumption is quite poor in some cases but it appears that the resulting algorithm can still provide useful results. With the Gaussian distribution assumption of each individual spectral component of the noise-free impulse response signal and the noisy signal, the conditional PDF of the observed spectral component given $a_k$and $\alpha_k$, $p(X_k | a_k, \alpha_k)$, is given by

$$p(X_k | a_k, \alpha_k) = \frac{1}{\pi \lambda_n(k)} \exp\left\{-\frac{1}{\lambda_n(k)} |X_k - a_k \exp(j\alpha_k)|^2\right\} \quad (6)$$

and the joint PDF of the impulse response signal spectral amplitude, $p(a_k, \alpha_k)$, is given by

$$p(a_k, \alpha_k) = \frac{a_k}{\pi \lambda_s(k)} \exp\left\{-\frac{a_k^2}{\lambda_s(k)}\right\} \quad (7)$$

where $\lambda_n(k) \triangleq \mathrm{E}\{|N_k|^2\}$ and $\lambda_s(k) \triangleq \mathrm{E}\{|S_k|^2\}$ are the variance of the $k$-th spectral component of the noisy signal and the noise-free impulse response signal, respectively. Substituting Eqs. (6) and (7) into Eq. (5), the MMSE-STSA estimator of the impulse response signal spectral amplitude is obtained as

$$\hat{A}_k = \sqrt{\left[\frac{1}{\lambda_s(k)} + \frac{1}{\lambda_n(k)}\right]^{-1}} \cdot \Gamma(1.5) \cdot M\left(-0.5; 1; -\frac{SNR_{prior}(k)}{1 + SNR_{prior}(k)} SNR_{post}(k)\right) \cdot A_k \quad (8)$$

where$\Gamma(\cdot)$is the gamma function, with$\Gamma(1.5) = \frac{\sqrt{\pi}}{2}$,$M(a; b; c)$is the confluent hyper geometric function, and $SNR_{prior}(k)$ and$SNR_{post}(k)$ represent the a priori Signal-to-Noise Ratio (SNR) and the a posteriori SNR, respectively.$SNR_{prior}(k)$ and $SNR_{post}(k)$ are defined by

$$SNR_{post}(k) = \frac{|X_k|^2}{\mathrm{E}\{|N_k|^2\}} \tag{9}$$

$$SNR_{prior}(k) = \frac{\mathrm{E}\{|S_k|^2\}}{\mathrm{E}\{|N_k|^2\}}. \tag{10}$$

Finally, applying the inverse STFT operation and the phase information of the measured signal, the estimator of the noise-free impulse response signal can be obtained. In practical implementations of the MMSE-STSA estimator, $\mathrm{E}\{|S_k|^2\}$ and $\mathrm{E}\{|N_k|^2\}$ are unknown since only the measured signal spectrum $X_k$is available. Thus, both $\mathrm{E}\{|S_k|^2\}$ and $\mathrm{E}\{|N_k|^2\}$ have to be estimated. In practice,$\mathrm{E}\{|N_k|^2\}$can be easily estimated during pauses in the impulse response using a classic recursive relation [17], continuously using Minimum Statistics [18] or Minima Controlled Recursive Averaging [19],whereas the priori SNR is a key parameter in the MMSE-STSA estimator. The estimation of the priori SNR will be discussed in detail in the following sections.

**2.2. The a priori SNR estimation method**

A widely used method to determine the a priori SNR from distorted speech is the decision-directed(DD) approach. Ephraim and Malah [8] defined the DD approach as a linear combination of the a posteriori SNR and the instantaneous SNR, with a weighting parameter, $\beta$, that is constrained to be $0 < \beta < 1$.The linear combination gives

$$S\widehat{N}R_{prior}^{DD}(p,k) = \beta\frac{|\hat{S}(p-1,k)|^2}{\hat{\gamma}_n(p,k)} + (1-\beta)\mathrm{P}\left[S\widehat{N}R_{post}(p,k) - 1\right] \tag{11}$$

where $p$ and $k$denote the short-time window and frequency indices, respectively,$\mathrm{P}[x] = x$ if $x \geq 0$ and $\mathrm{P}[x] = 0$ otherwise. The parameter $\beta$ is set to a typical value of 0.98 for the DD approach. However, Plapous et al. [9] showed that the DD algorithm introduces a window delay when the parameter β is close to one, and this delay introduces a bias in the SNR estimation. Consequently, the DD algorithm computed at the current window $p$ matches that at the previous window $p-1$. Thus, Plapous et al. [9] proposed to compute the SNR for the next window $p+1$ using the DD approach and toapply it to the current window because of the window delay. Hence, an improved a priori SNR estimation method is

$$S\widehat{N}R_{prior}^{TSNR}(p,k) = \beta\frac{|G_{mmse}^{DD}(p,k)X(p,k)|^2}{\hat{\gamma}_n(p,k)} + (1-\beta)\mathrm{P}\left[S\widehat{N}R_{post}(p+1,k) - 1\right] \tag{12}$$

The improved a priori SNR estimation method solves the bias problem while maintaining the benefits of the DD approach [9]. In order to measure the performance of SNR estimators, it is useful to compare the estimated SNR values to the true(actual) ones, as shown in Figure 2 where the estimated SNRs are displayed versus the true SNRs. The SNRs are plotted for a simulated signal(to be described in detail in Section 4) to focus the analysis on the behavior of the SNR estimators for forced response components.

Insert Figure 2 here

Figure 2 compares the actual SNR versus the estimated SNRs using the posteriori algorithm, the improved algorithm and the DD algorithm given by Eqs.(9), (11) and (12), respectively. In this case, the solid line corresponds to the actual SNR that can be used as a reference. From Figure 2, it is obvious that the a priori SNR estimator based on the improved algorithm is closer to the actual SNR than the a priori SNR estimator based on the DD algorithm at higher SNR levels. However, the a priori SNR estimator based on the improved algorithm departs from the true SNR at lower SNR levels. The improved algorithm is superior to the traditional DD algorithm when the measured impulse response signal has a higher SNR, but is distorted when the measured impulse response signal has a low SNR. In order to avoid the low SNR situation, the WIENER-STSA estimator will be introduced to improve the SNR.

**2.3 The WIENER-STSA estimator**

The Wiener filter is an optimal method to remove stationary noise in stationary environments [16]. Here, the WIENER-STSA estimator is introduced to enhance the application scope of the Wiener filter. Adopting the noise model mentioned in Section2.1, we assume $s(t)$ and $n(t)$ to be uncorrelated stationary random process, with power spectral density functions denoted by $S_s(k)$ and $S_n(k)$respectively, where $k$denotes the frequency index. One approach to recover the desired signal$s(t)$ relies on the additivity of power spectra

$$S_x(k) = S_s(k) + S_n(k) \quad (13)$$

To recover a sequence $s(t)$ corrupted by additive noise $n(t)$, that is from the sequence

$x(t) = s(t) + n(t)$, a linear filter $h(t)$ is found, such that the sequence $\hat{s}(t) = h(t) * x(t)$ minimizes the expected value of the nosie, under the condition that the signals $s(t)$ and $n(t)$ are stationary and uncorrelated. The frequency domain solution to this stochastic optimization problem is given by

$$H(k) = \frac{S_s(k)}{S_s(k) + S_n(k)} \quad (14)$$

which is referred as the Wiener filter. Since the Wiener filter is derived under uncorrelated and stationary conditions, the Wiener filter provides noise suppression without significant distortion in the estimated signal and the background residual. The STFT is applied when the background and desired signals are non-stationary, and then $S_s(k)$ and $S_n(k)$ can be expressed as time varying functions $S_s(p,k)$ and $S_n(p,k)$, where $p$ represents the short-time window. Thus every time window is processed by a different Wiener filter, defined as

$$H(p,k) = \frac{\hat{S}_s(p,k)}{\hat{S}_s(p,k) + \hat{S}_n(p,k)} = \frac{\frac{\hat{S}_s(p,k)}{\hat{S}_n(p,k)}}{1 + \frac{\hat{S}_s(p,k)}{\hat{S}_n(p,k)}} = \frac{\mathrm{S\hat{N}R}(p,k)}{1 + \mathrm{S\hat{N}R}(p,k)} \quad (15)$$

The reduction of the noise is based on obtaining an accurate SNR [20]. In order to effectively remove stationary noise, an instantaneous SNR will be introduced, defined as

$$SNR_{inst}(p,k) = \frac{|X(p,k)|^2 - \mathrm{E}[|N(p,k)|^2]}{\mathrm{E}[|N(p,k)|^2]} \quad (16)$$

where $X(p,k)$ is available, and the estimators of $\mathrm{E}[|N(p,k)|^2]$ have been introduced in Section 2.1. Hence, the WIENER-STSA estimator is obtained as

$$\hat{S}(p,k) = H(p,k) \cdot X(p,k) = \frac{SNR_{inst}(p,k)}{1 + SNR_{inst}(p,k)} \cdot X(p,k). \quad (17)$$

Finally, applying the inverse STFT operation and the phase information of the measured signal, the estimator of the noise-free impulse response signal can be obtained.

## 3. Proposed Method

We assume that the ideal forced response signal is the transient component of non-stationary signal, and the background noise has a stationary component and a continuous component that is non-stationary. An adaptive denoising method is proposed to obtain the ideal forced response signal. In the first step, the WIENER-STSA estimator is used to remove the stationary signal components, which is very helpful in improving the SNR of the measured forced response signals and make the filtered signals suitable for further processing. In the second step, the MMSE-STSA estimator with an improved a priori SNR estimation method is introduced, which can be used to remove the continuous component of the non-stationary signal. The flow chart of the proposed method is shown in Figure 3.

Insert Figure 3 here



The implementation of the proposed denoising method is summarized below:

(1) Estimate the noise PSD $\mathrm{E}[|N(p,k)|^2]$ during no forced response using the Minima Controlled Recursive Averaging approach [19].

(2) Calculate the instantaneous SNR using Eq. (16).

(3) Remove stationary noise components from the measured forced response signal using the WIENER-STSA estimator with an instantaneous SNR estimation method.

(4) Re-estimate the noise PSD $\mathrm{E}[|N(p,k)|^2]$ during no forced response using the Minima Controlled Recursive Averaging approach [19].

(5) Calculate the improved a priori SNR using Eq. (12).

(6) Remove residual non-stationary noise from the filtered forced response signals using the MMSE-STSA estimator with the improved a priori SNR estimation method.

In this paper, the a priori SNR estimation always uses the improved a priori SNR estimation method, and the following parameters have been chosen: short-time window $p = 0.06$s, windows overlap 50% and weighting parameter $\beta$=0.98.

## 4. Simulated Example

To validate the proposed method, a simulated signal, $x(t)$, is generated according to the model

$$x(t)=\sum_{i=T}\begin{pmatrix} s_1\cdot e^{-\zeta_1(t-i)}\cdot\cos\left(2\pi f_{n1}(t-i)\right)+s_2\cdot e^{-\zeta_1(t-i)}\cdot\cos\left(2\pi f_{n2}(t-i)\right)\\ +s_3\cdot e^{-\zeta_1(t-i)}\cdot\cos\left(2\pi f_{n3}(t-i)\right)+s_4\cdot e^{-\zeta_2(t-i)}\cdot\cos\left(2\pi f_{n4}(t-i)\right)\end{pmatrix}$$
$$+\left(\left(s_5\cdot\cos\left(2\pi f_{r1}t\right)\right)\cdot\left(s_6\cdot\cos\left(2\pi f_{r2}t\right)+s_7\cdot\cos\left(2\pi f_{r3}t\right)+1\right)\right)\cdot random\ noise \quad (14)$$

The parameters of the simulated signal are given in Tables 1 and 2, and the sampling frequency is 1024Hz.

Insert Table 1 here

Insert Table 2 here

The simulated signal, $x(t)$, is composed of two terms. The first term represents a forced response signal, where $s_1$, $s_2$, $s_3$ and $s_4$ are the amplitudes of the impulse response signal, $f_{n1}$, $f_{n2}$, $f_{n3}$ and $f_{n4}$ are the corresponding natural frequencies and $i$ is the sample time increment. The second term represents noise components. According to the mathematical model and the parameters the simulated signal has the following three characteristics.

(1) The forced response signal has a low SNR(SNR=-4.6dB).

(2) The noise components contain stationary noise and non-stationary noise.

(3) The noise components contain a base frequency($f_{r1}$), which is very close to a natural frequency($f_{n2}$) and makes it difficult to accurately estimate the natural frequency($f_{n2}$).

The simulated signal $x(t)$ is shown in Figure 4; the simulated signal contains significant environmental noise, and the forced response signal has a low SNR. The proposed denoising method was applied to the simulated signal, and the results are shown in Figure 5 and Figure 6. Figure 5 compares the filtered signals from the MMSE-STSA and the proposed methods in the time domain, and Figure 6 compares the results in the frequency domain. Figure 6 shows that the natural frequencies cannot be accurately estimated using the raw simulated forced response signal spectrum.

Insert Figure 4 here

Insert Figure 5 here

Insert Figure 6 here

Figure 5 shows that both the MMSE-STSA and the proposed method can remove most of the environmental noise. The zoomed part of Figure 5 shows that the filtered signal with only the MMSE-STSA method is distorted in the time domain. According to the simulated signal parameters, the first two true natural frequencies are 44.0Hz and 50.0Hz; however Figure 6 shows that the filtered first two natural frequencies using the MMSE-STSA method are predicted to be 42.0Hz and 49.5Hz. Figure 5 and Figure 6 show that the filtered signal with the proposed method has a good consistency with the ideal forced response signal in both the time and frequency domains. Meanwhile, the strong colored noise frequency(49.5Hz) disappears after the filter operation of the proposed method, and the two close natural frequencies (44.0Hz, 50.0Hz) are accurately estimated. The simulation results indicates that using the WIENER-STSA estimator before the MMSE-STSA estimator under low SNR conditions significantly improves the estimation. The proposed noise removal technique can improve the accuracy of the estimated modal parameters using only one impulse response signal in a strong background noise environment.

# 5. Experiment Results from a 600MW Generator

## 5.1. Experimental setup

In this section, the proposed method is validated using the measured forced response signals collected from a 600MW generator. The generator exhibits excessive vibration during operation, and the rotating frequency of the generator is 50Hz. Figure 7 shows the image of the generator, and the generator shell located inside a sound-proof housing. Figure 8 shows the bode diagram of the generator; the generator has a resonance frequency at 48.5Hz, which is not the natural frequency of the rotor according to the simulated results. Hence, this resonance frequency is likely to be a natural frequency of the generator shell. A modal test was performed to obtain the natural frequencies of the generator shell. However, the measured forced response signal is polluted by highly non-stationary noise, and the measured forced response signal has a low SNR. The spectral analysis of the measured signal shows that the forced response signal contains a strong colored noise; the strong colored noise frequency is 49.8Hz, which is very close to the resonance frequency at 48.5Hz.This makes it difficult to accurately estimate the natural frequency of the generator shell. It should be mentioned that the state-of-the-art method (PolyMAX algorithm) estimates the natural frequency to be 49.8Hz, which indicates that the strong colored noise signal has a great influence on modal parameter identification.

Insert Figure 7 here

Insert Figure 8 here

**5.2. Experimental results**

The time domain waveform of the measured signal is shown in Figure 9.The measured signal contains high levels of environmental noise, and the forced response signal has a low SNR. The proposed denoising method was applied to the measured forced response signal, and the results are shown in the time and frequency domains in Figure 10 and Figure 11 respectively. The filtered signal from the MMSE-STSA and the proposed methods are compared. Figure 11 shows that the natural frequencies cannot be accurately estimated from the raw measured forced response signal spectrum. Figure 10 shows that most of the environmental noise has been removed by both the MMSE-STSA and proposed methods. Figure 11 shows that the colored noise frequency(49.8Hz) has been filtered using both the MMSE-STSA method and the proposed method, but a natural frequency close to the interference frequency(49.8Hz) disappears with the MMSE-STSA method. This demonstrates that the MMSE-STSA method may lead to distortion of the estimated modal parameters in noisy environments. In contrast, Figure 11 shows that a natural frequency at 48.9Hz appears after using the proposed method, and the result is consistent with the Bode diagram during the rotor startup. Thus, the application of the WIENER-STSA estimator is necessary before the MMSE-STSA estimator under low SNR conditions, and the proposed method can help to accurately identify natural frequencies in modal tests of large-scale mechanical equipment.

Insert Figure 9 here

Insert Figure 10 here

Insert Figure 11 here

# 6. Conclusion

In this paper, we focus on modal parameter identification when the forced response signal has a low SNR. An adaptive denoising method based on the WIENER-STSA estimator and an improved MMSE-STSA estimator was proposed. Comparing the proposed method with some state-of-the-art denoising methods in Ref. [1,2], the proposed method does not need to set an appropriate threshold to avoid loss of valuable information, and does not require many averaging operations. The proposed method can adaptively remove stationary and non-stationary noise components, while preserving the important features of the true forced response signals. The simulation shows that the proposed noise removal technique improves the accuracy of the estimated modal parameters using only one impulse response signal, which demonstrates that the proposed method can reduce the number of averaging operations when the measured forced response signal has a low SNR. In the modal test of a 600MW generator shell, the measurement results show that, in contrast to the state-of-the-art method (PolyMAX algorithm), the proposed method can accurately identify a natural frequency that is very close to a strong interference frequency. Consequently, the proposed adaptive method is a powerful tool to improve the accuracy of modal identification when the forced response signal has a low SNR.

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# Table list

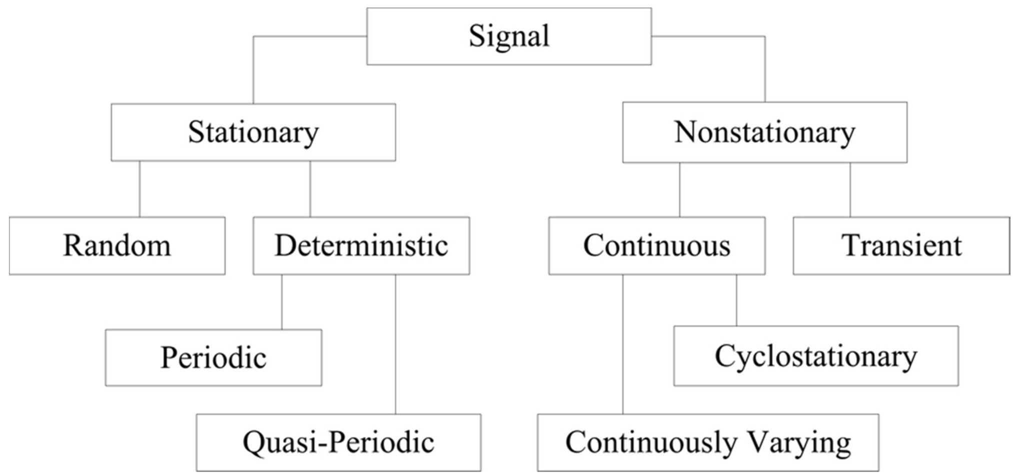
Table 1. The frequencies of the simulated signal

| $f_{n1}$(Hz) | $f_{n2}$(Hz) | $f_{n3}$(Hz) | $f_{n4}$(Hz) | $f_{r1}$(Hz) |
|---|---|---|---|---|
| 44.0 | 50.0 | 65.0 | 80.0 | 49.5 |

Table 2. The parameters of the simulated signal

| $s_1$ | $s_2$ | $s_3$ | $s_4$ | $s_5$ | $s_6$ | $s_7$ | $\zeta_1$ | $\zeta_2$ | $T(s)$ |
|---|---|---|---|---|---|---|---|---|---|
| 8.00 | 14.00 | 12.00 | 13.00 | 5.90 | 0.13 | 0.16 | 10 | 6 | 6.3 |

# Figure list

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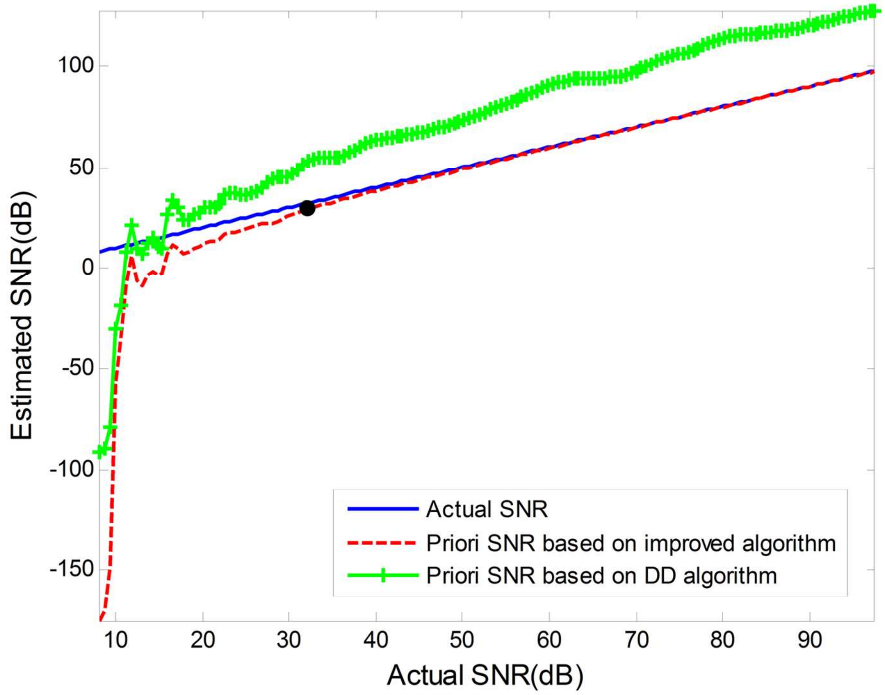


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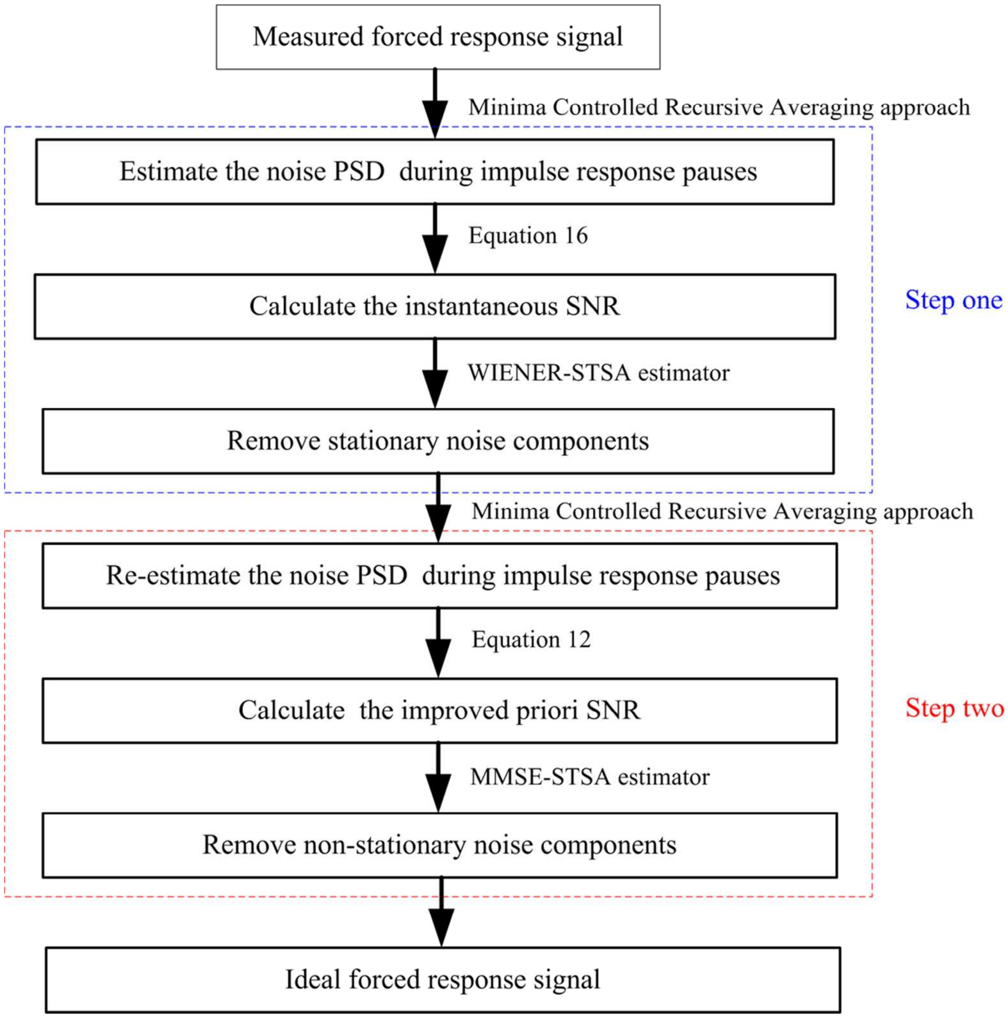


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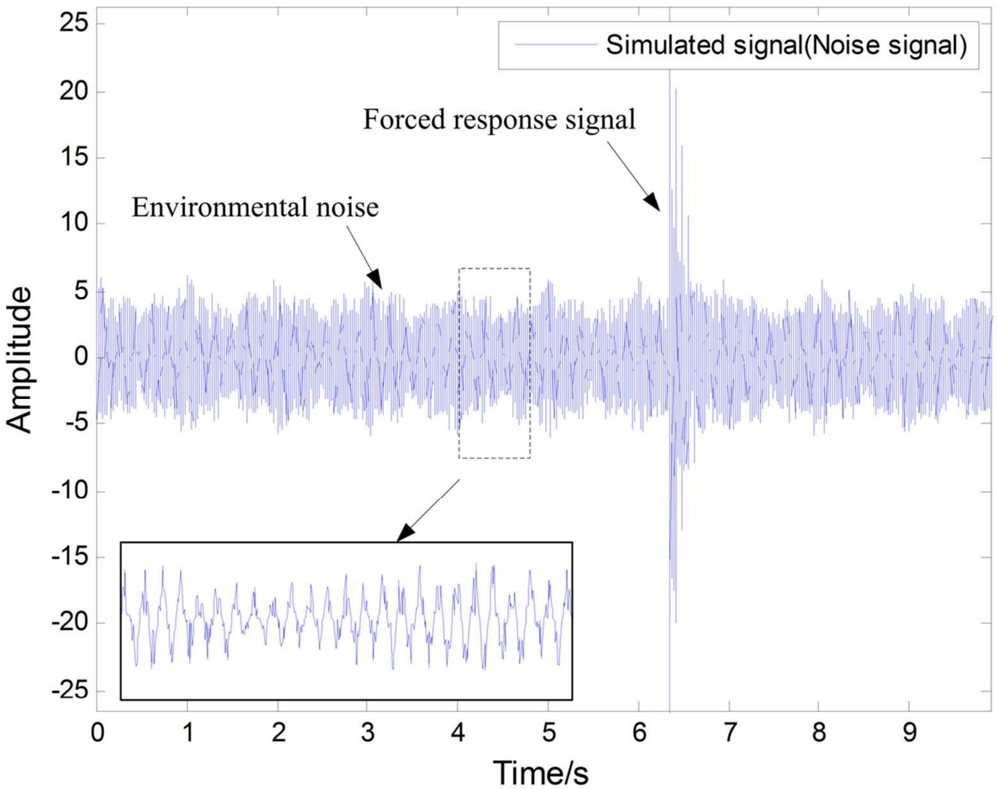


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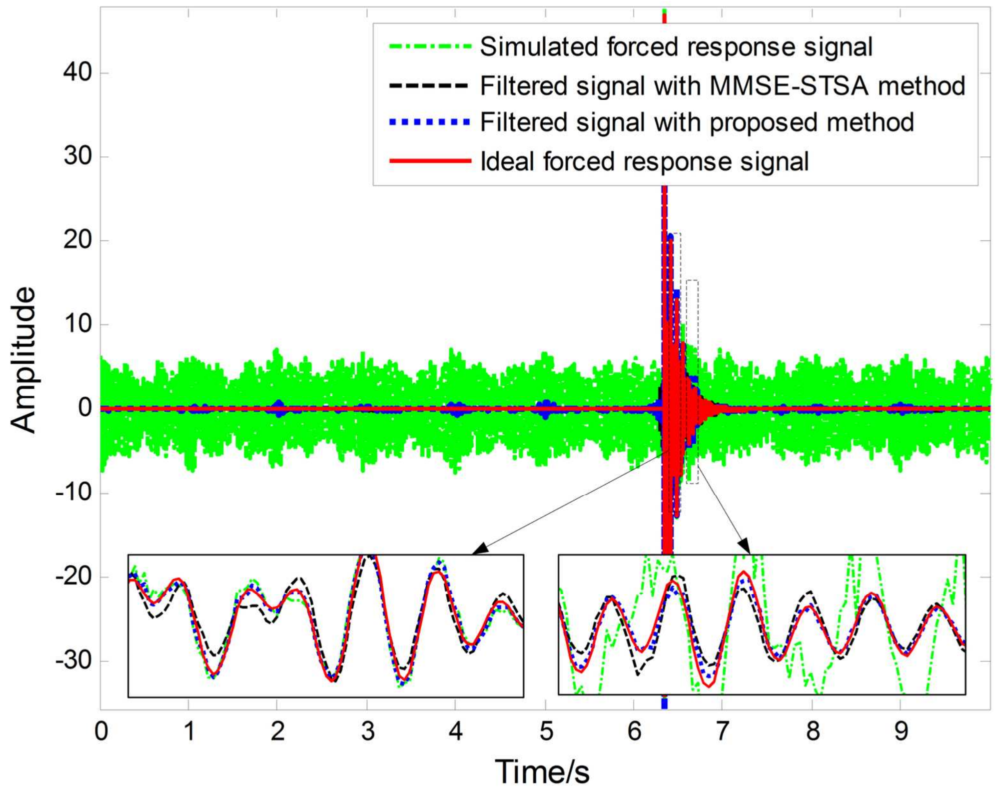


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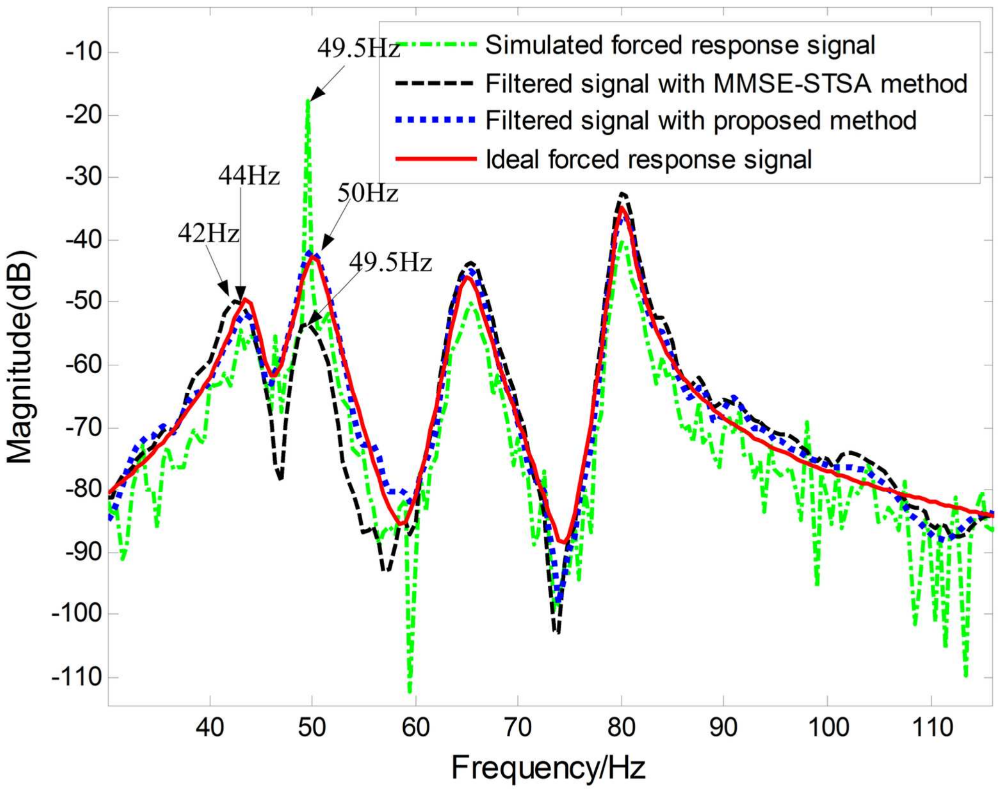


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(a) (b)

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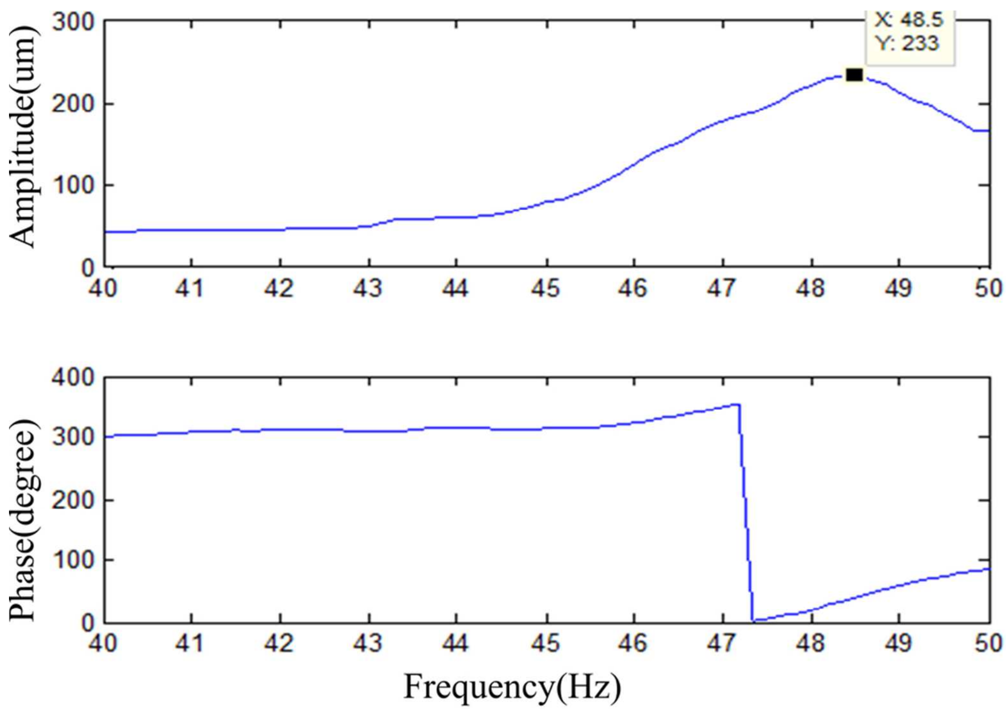


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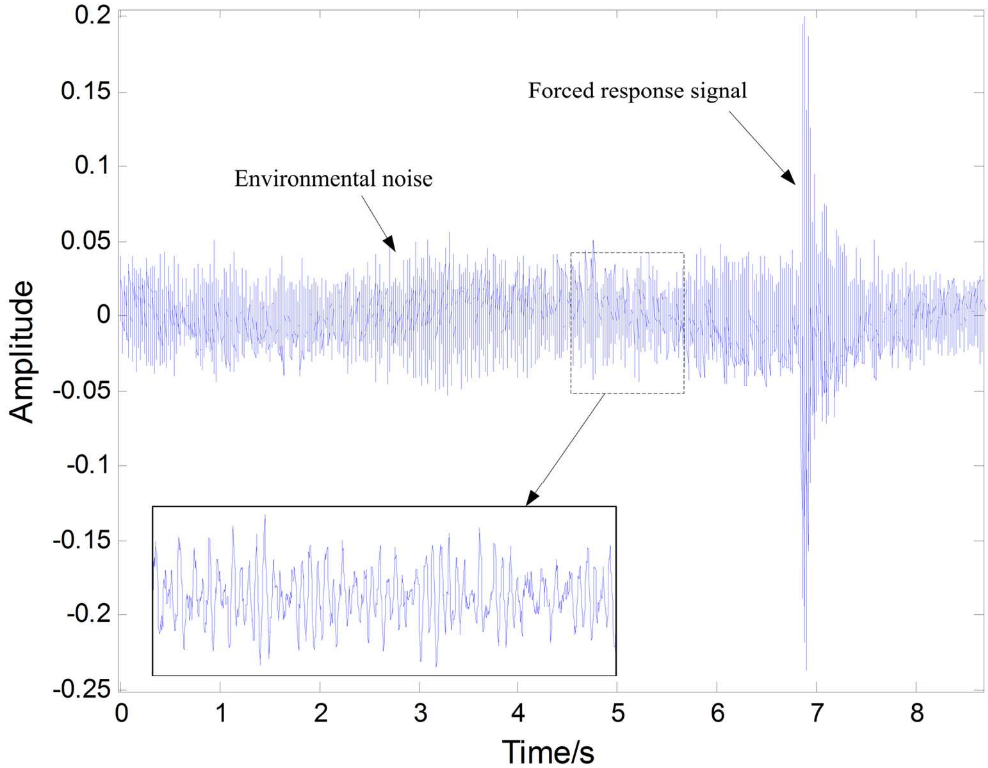


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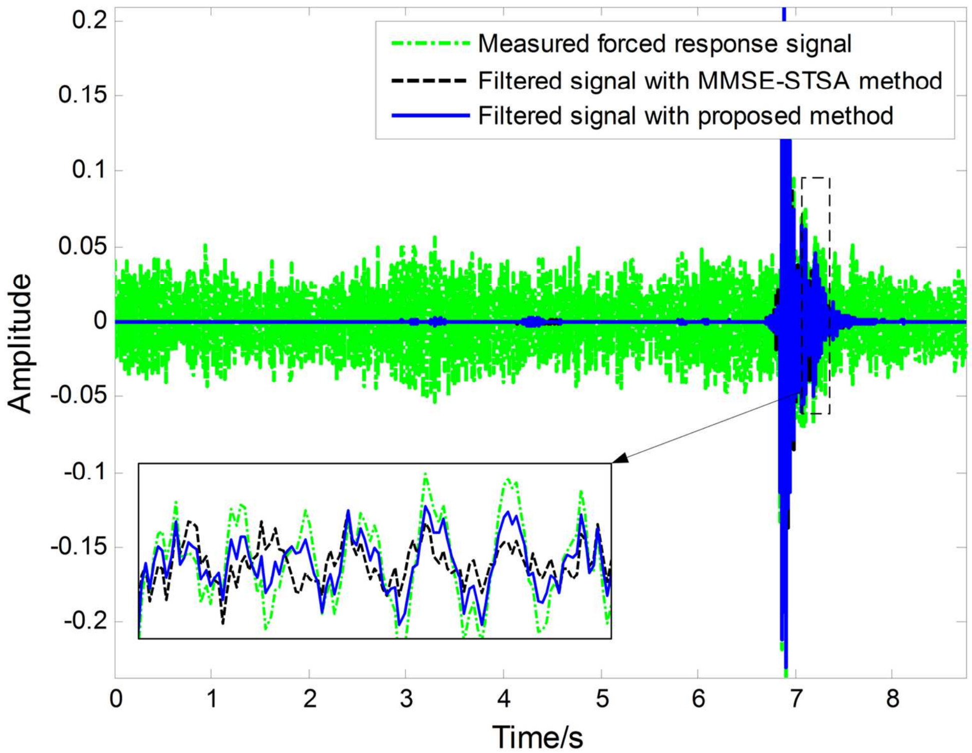


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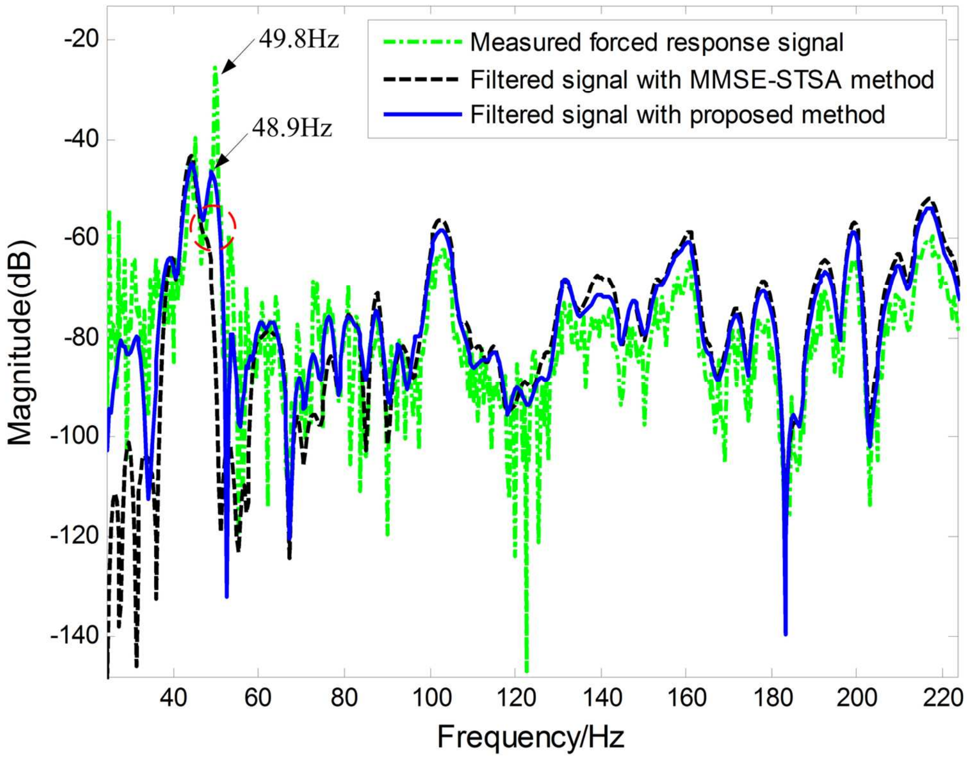


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