Wavelet Denoising of Flight Flutter Testing Data for Improvement of Parameter Identification

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Abstract: The accuracy of modal parameter estimation plays a crucial role in flutter boundary prediction. A new wavelet denoising method is introduced for flight flutter testing data, which can improve the estimation of frequency domain identification algorithms. In this method, the testing data is first preprocessed with a gradient inverse weighted filter to initially lower the noise. The redundant wavelet transform is then used to decompose the signal into several levels. A "clean" input is recovered from the noisy data by level dependent thresholding approach, and the noise of output is reduced by a modified spatially selective noise filtration technique. The advantage of the wavelet denoising is illustrated by means of simulated and real data.

Key words: identification; denoise; wavelet; redundant wavelet transform; threshold; spatial correlation

用于提高辨识效果的颤振试验数据小波去噪. 唐 炜, 史忠科. 中国航空学报(英文版), 2005, 18(1): 72-77.

摘 要: 准确估计模态参数在飞机颤振边界的预测中具有重要意义。为了提高频域辨识算法的辨识效果, 提出了一种用于颤振飞行试验数据处理的小波去噪方法。该方法引入梯度倒数加权滤波器对数据进行预处理, 处理后的数据运用冗余小波进行小波分解, 然后对输入信号在不同尺度下分别进行阈值降噪, 对输出信号则采用了一种改进的小波空域相关滤波法去噪。最后通过仿真计算和实际数据证明该方法有效。

关键词: 辨识; 去噪; 小波; 冗余小波变换; 阈值; 空域相关
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New or modified aircraft often necessitates flight flutter tests to verify safety margins and to prevent catastrophic flutter. These tests typically consist of flight under different conditions of airspeed and altitude while applying some form of excitation to the structure. Most commonly used method of predicting the onset of flutter is to extrapolate trends of modal damping ratio. It is drawn from the fact that the damping of at least one mode becomes zero at the onset of flutter. Further information of flutter testing and analysis has been reviewed in references[1, 2].

Flight data often has so low signal-to-noise ratio that sophisticated techniques are required. Classical frequency transfer function identification has been used for modal parameter estimation. The GTLS (Generalized Total Least Squares) and BTLS (Bootstrapped Total Least Squares) have been implemented successfully to get consistent estimation from noisy data[3]. But this way need considering the noise frequency covariances of input and output, which are almost impossible to know for an impulse excitation testing with finite testing and without reference signal. In order to reduce the effect of noise under this condition, the true signal from the noisy data would be recovered. When using "clean" data, accurate modal parameter still can be achieved by simple identification algorithm. Therefore, denoising of testing data plays an important role in flutter testing carried out by impulse excitation.

Recently several wavelet methods have been

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proposed and showed success in removing noise from noisy signal[4-6]. But it is still difficult to recover signal form low SNR signal such as the flutter testing data.

This paper focus on investigating wavelet-based denoisng method for flight flutter testing excited by impulse. A new wavelet denosing method combined with the gradient inverse weighted filter is introduced. The adopted techniques will be described in detailed in Section 2. In Section 3, performance of the method will be valued by artificial noise and real noisy signal. Section 4 illustrates the conclusions.

1 Theory and Description of the Method

A discrete model of noisy signal is considered

$$\boldsymbol{F}(i) = \boldsymbol{S}(i) + \boldsymbol{T}(i) \quad (i = 1, \cdots, N) \quad (1)$$

where $\boldsymbol{F}$ is the noisy signal; $\boldsymbol{S}$ is the true signal; $\boldsymbol{T}$ is the noise caused by atmospheric turbulence.

The discrete wavelet transform can be represented as a matrix multiplication

$$\boldsymbol{w} = \boldsymbol{WF}$$

where $\boldsymbol{F}$ is a $1\times N$ input vector; $\boldsymbol{W}$ is $N(L+L)\times N$ matrix; L is the number of levels of decomposition; $\boldsymbol{w}$ is the wavelet coefficients matrix.

Then the noise would be removed according to the different properties of noise and signal such as the coefficients level or correlation.

The denoising procedure is shown in Fig. 1. The flutter signal is first preprocessed with a gradient inverse weighted filter. A redundant wavelet transform is then applied to decompose the corrupted signal into sub-bands. The level dependent adaptive thresholding approach is used to get a "clean" input. While a modified spatially selective filtration technique is used to suppress the noise in response. Finally, the inverse transform synthesizes the enhanced signal. Each of the stage is further detailed in the following section.

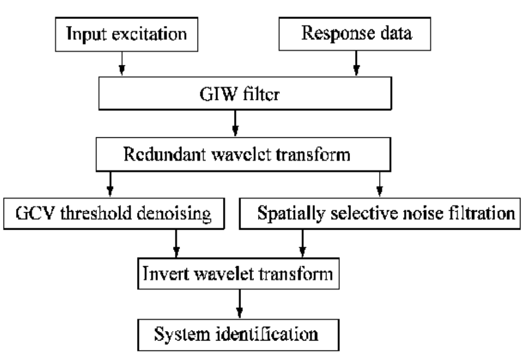

Fig. 1 Algorithm structure of flutter test data enhancement based on wavelet denoising

1.1 Gradient inverse weighted filter

Wavelet denoising has the best performance when the noise level is not too high. Accordingly, the purpose of preprocessing is to initially lower the noise level of the noise signal while minimizing the distortion of the true signal. For this, a nonlinear filtering algorithm GIW (gradient inverse weighted) presented by Wang[7] is implemented. The filter is based on the general form of Eq. (3). Experiments have shown that it can preserve edge and smooth noise effectively. Meanwhile, the modal frequency of aircraft mostly distributes at low frequency, the response has smooth curve, and the filter could get better performance.

The inverse gradient of ith point of signal is defined as

$$\delta(i,k) = \begin{cases} 1/d(i,k), & \text{if} \quad d(i,k) \neq 0 \\ 2 & \text{if} \quad d(i,k) = 0 \end{cases} \quad (2)$$

where $d(i,k) = |x(i+k) - x(i)|,\ k \in V$.

with

$$V = \left\{-(m-1)/2, \cdots, -2, -1, 1, 2 \cdots (m-1)/2\right\}.$$

The general form of the filter is

$$\hat{\boldsymbol{x}}(i) = \boldsymbol{K}(i)\boldsymbol{x}(i) + (1 - \boldsymbol{K}(i))\boldsymbol{y}(i) \quad (3)$$

with $\boldsymbol{K}(i) = \boldsymbol{D}(i)/(1+\boldsymbol{D}(i))$,

$$\boldsymbol{D}(i) = \sum_{k\in V} \boldsymbol{W}^2(k),$$

$$\boldsymbol{y}(i) = \sum_{k\in V} \boldsymbol{W}(i,k)\boldsymbol{x}(i,k),$$

$$\boldsymbol{W}(i,k) = \delta(i,k)/\sum_{k\in V}\delta(i,k).$$

where m is the length of window and it is odd; $\boldsymbol{K}(i)$ is an optimal weighted coefficient; $\boldsymbol{x}(i)$ is the center point in the window; $\boldsymbol{y}(i)$ is the weighted sum of local point in filtering window; $\hat{\boldsymbol{x}}(i)$ is the output value.

1.2 Redundant wavelet transforms

Level-dependent threshold is applied to deal with the correlated noise[8] and GCV (Generalized Cross Validation) is used to estimate the threshold. The problem occurs from the fact that the GCV estimation is only asymptotically optimal, but the flutter test data is finite and the number of available wavelet coefficient decreases if the scale gets coarser when using decimated wavelet transform. Here an alternative wavelet transform known as Non-decimated Wavelet Transform, or Redundant Transform will be used to deal with the problem, which can provide the same number of coefficients at all scales. The number is equal to the size of original input data. Ref. [9] has mentioned it. The other advantage is the coefficients of "clean" response at each scale with the similar curve. Coefficients show strong correlation across scales, which could be used to recover the signal.

1.3 Wavelet threshold denoising for input

The measured impulse input signal has a high SNR, so a wavelet threshold way will be used directly after preprocessing. The threshold is chosen by a GCV algorithm[10], which do not need any estimation of the noise energy. The estimated threshold valve is the minimum of the following Generalized Cross Validation function

$$\mathrm{GCV}(\lambda)=\frac{\frac{1}{N}\|\boldsymbol{y}-\boldsymbol{y}_\lambda\|}{\left(\frac{N_0}{N}\right)^2} \tag{4}$$

where N is the total number of wavelet coefficients and N_0 is the number of those coefficients that are replaced by zeros; $\boldsymbol{y}$ is the noisy data; $\boldsymbol{y}_\lambda$ is the restored data; the threshold $\lambda=\arg\min \mathrm{GCV}(\lambda)$.

A compromise threshold[11] between hard and soft threshold is used, that is,

$$\hat{w}_{j,k}=\begin{cases}\mathrm{sign}(w_{j,k})\left(|w_{j,k}|-\alpha\lambda\right) & |w_{j,k}|\geqslant\lambda\\ 0 & |w_{j,k}|<\lambda\end{cases} \tag{5}$$

where $w_{j,k}$ is the kth wavelet coefficient at jth level; $\hat{w}_{j,k}$ is the wavelet coefficient after thresholding; λ is the estimated threshold; α is a comprise factor and $0\leqslant\alpha\leqslant 1$. The parameter can be regulated to get the best result, here $\alpha=0.5$.

Fig. 2 illustrates the wavelet thresholding the noisy impulse excitation, and the result is shown in Fig. 3. The dashed lines indicate the boundaries between two successive frequency resolution level. The horizontal lines are the thresholds at deferent level.

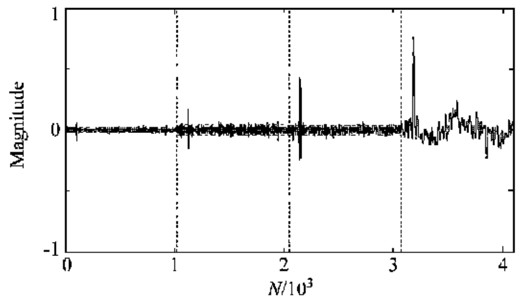

Fig. 2 Wavelet thresholding the noisy impulse excitation

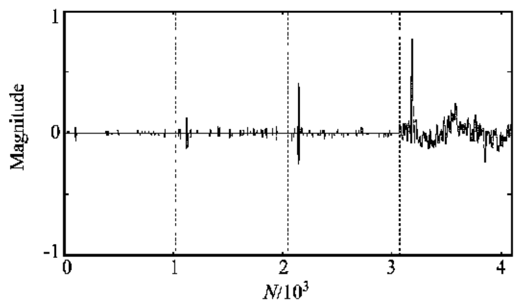

Fig. 3 Wavelet coefficients after thresholding

1.4 Improved spatially selective noise filtration technique for response

Wavelet threshold denoising works well for impulse, but this method fails to deal with response signal. The problem arises form the low SNR and decayed envelope of response. As illustrated in Fig. 4, most coefficients of true signals below the high thresholds estimated by GCV will be replaced by zeros, which will lead to the distortion of signal. As an alternative method, a modified spatially selective noise filtration technique has been used in the response signal denoising, which is proposed by Xu[7].

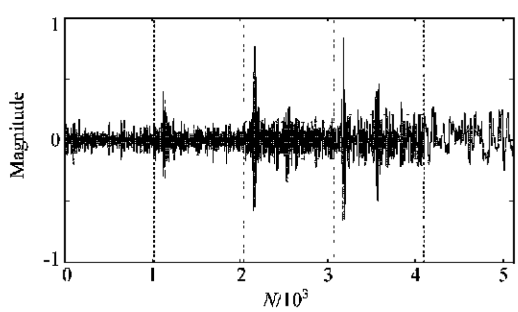

Fig. 4 Thresholding the response signal

Wavelet transform of a simulated true response has been shown in Fig. 5. The coefficients at each scale form a similar curve with the original data. The coefficients have strong correlation with other scales. In Xu's paper, the correlation of wavelet coefficients at several adjacent scales is used detect the locations of edges. If Xu's algorithm is used directly in flutter testing data, the correlation calculation depending on the noisy reference scale would be inaccurate, because the coefficients at adjacent fine scales all have a high noise level.

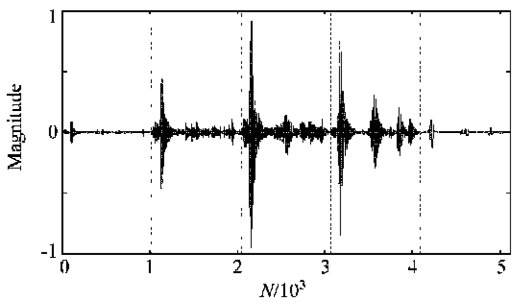

Fig. 5 Coefficients of true output signal

A modification has been made in this paper to adapt the practical application. In practice, true signals of flutter test almost distribute at low frequency, while the noise at high frequency band, therefore the wavelet transform at coarser scale will have a high SNR. In order to achieve better results, the coarse scale is chosen, which has the highest SNR as reference scale. So the correlation calculation in Xu's algorithm is rewritten as Eq. (6)

$$\mathbf{Corr}_2(m, n) = \mathbf{W}(m, n)\,\mathbf{W}(L, n),$$
$$n = 1, 2, \cdots, N$$
$$m = 1, 2, \cdots, L-1, L+1, \cdots, M+1 \quad (6)$$

where $\mathbf{W}$ denotes the wavelet coefficients (containing lowpass coefficients); M is the total number of levels; N is the number of coefficients at each scale; and L is the reference level that has the highest SNR.

Here the forth level is used as reference to calculate the correlation with others. Fig. 6 illustrates the result by improved algorithm. Fig. 7 illustrates the result by Xu's algorithm. It can be seen that the improved method can extract signal coefficients more efficiently from noise and has less distortion in comparison with original algorithm.

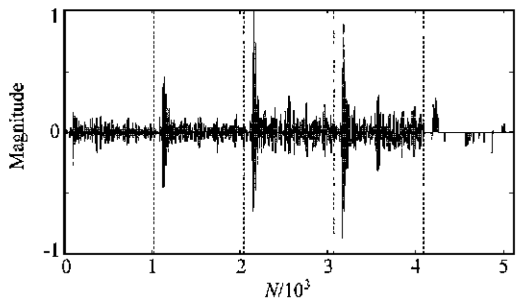

Fig. 6 Coefficients of noisy output filtered by the improved algorithm

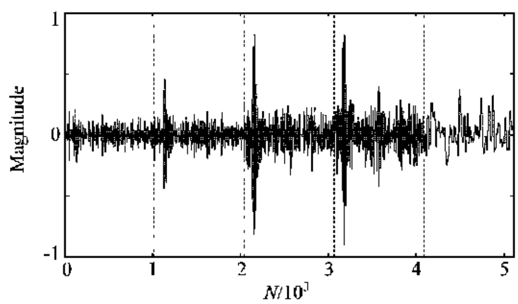

Fig. 7 Coefficients of noisy output filtered by Xu' algorithm

2 Results

2.1 Simulation

A two degree freedom model is established to simulate the measurements. The natural frequencies are $f_1 = 14$Hz, $f_2 = 30$Hz; the damping ratios are $\xi_1 = 0.065$, $\xi_2 = 0.027$. The system is excited by an impulse signal and the response is measured from accelerometer. The continuous transfer function is written as

$$H(s) = \frac{s^2}{s^2 + 2\xi_1\omega_1 s + \omega_1^2} + \frac{s^2}{s^2 + 2\xi_2\omega_2 s + \omega_2^2} \quad (7)$$

In order to simulate the unmeasured atmosphere turbulence of real condition, a random white noise (stander deviation $\sigma = 0.03$) is added to the excited signal as the unknown input signal. A total measurement time of 4s is simulated. Two random noises (stander deviation $\sigma = 0.1$) are added to the input and the response as the measurement noise. The sample frequency is 256Hz; the data length is 1024.

The denoising method mentioned above is applied to reduce the noise of signal. The forth order Daubechies is selected as the wavelet basis. In the simulation, in order to test the improvement of identification, an extended discrete transfer function model[12] is adopted to identify the transfer function and estimate the modal parameter by using a WLS (Weighted Least Squares) identification algorithms in frequency domain[13].

One hundred runs (for each run new noise sequence is generated to as unknown input, and measurement noise on the input and output) of a Monte Carlo simulation are performed. In each run of the Monte Carlo, the denoised signal and noisy signal are used to identify the modal parameters and transfer function. The natural frequency and damping ratio statistically processed. The mean value and the standard deviation of natural frequency (m_f, σ_f) and damping ratio (m_ξ, σ_ξ) are compared in Table 1. The denoised data lead to much better modal parameter estimation than noisy data although the standard deviations are slightly larger than the noisy data estimation. Of course, a more accurate result can be achieved when more complicated frequency identification algorithm is applied.

Table 1 Comparison of estimation results using denoised signal and noisy signal. 1-denoised signal; 2-noisy signal

f/Hz	M_{f1}/Hz	σ_{f1}/Hz	m_{f2}/Hz	σ_{f2}/Hz
14	14.8305	0.2141	15.0603	0.2504
30	30.0036	0.2080	30.0782	0.1894
ξ	$m_{\xi1}$	$\sigma_{\xi1}$	$m_{\xi2}$	$\sigma_{\xi2}$
0.065	0.0366	0.0101	0.0238	0.0092
0.027	0.0161	0.0053	0.0061	0.0036

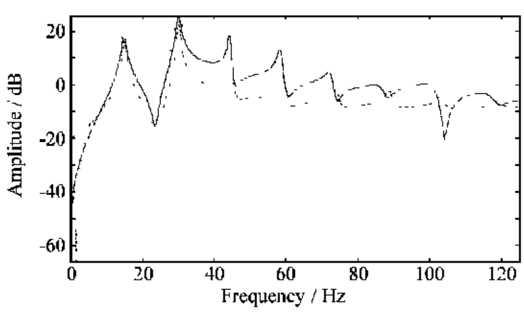

Fig.8 Denoised averaged FRF (solid line), exact FRF (dotted line) and noisy averaged FRF (dashed line)

The comparisons amony averaged frequency response function (FRF) of denoised signal, exact discrete FRF, and averaged transfer function of noisy signal are shown in Fig. 8. It is clear that the averaged FRF derived from the denoised signal compares favorably with the "exact" FRF, especially at low frequency, whereas that obtained from the noisy signal is unsatisfactory.

2.2 Real measurement example

The denoising method mentioned above is used for practical flight flutter data. The measurements are carried out by using an impulse excitation. The sample frequency is 256Hz; the data length is 1024.

The measurement response function $H(f)$ shown in Fig. 6 and Fig. 7 is defined as

$$H(f) = \frac{Y(f)}{X(f)} \tag{8}$$

In Fig. 9, $H(f)$ is calculated directly from the Fourier spectral of noisy measurement. While in Fig. 10, $H(f)$ is calculated by using the denoised signal. In Fig. 10, two peaks (frequency of flutter mode) are clearly at about 14Hz and 50Hz, which can not be seen in Fig. 9. Obviously, the denoised data will lead to a better result. The synthesized transfer function using denoised data is shown in Fig. 11.

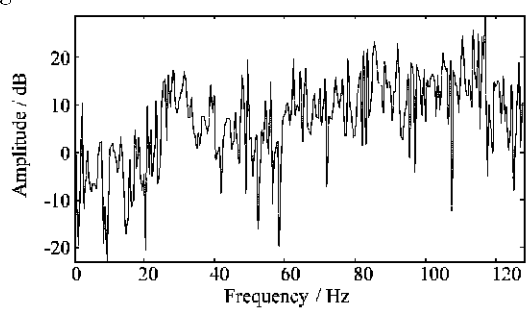

Fig.9 Measured response function estimated by noisy data

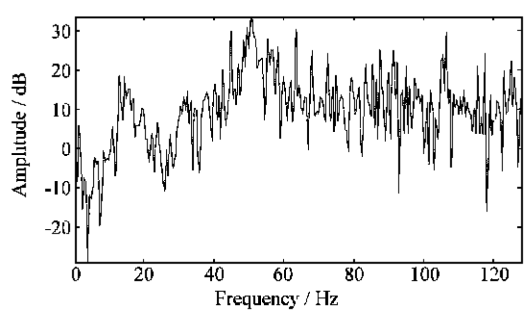

Fig. 10 Measured response function estimated by denoised data

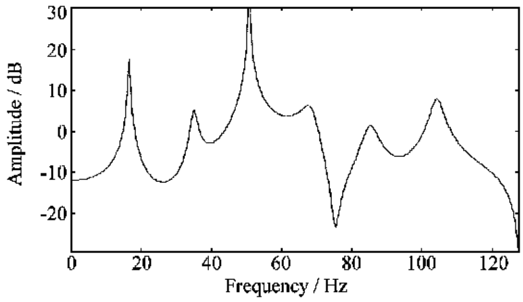

Fig. 11 Synthesized measured response function using WLS

3 Conclusions

A wavelet denoising method is presented to process the flight flutter testing data. The applicability of this technical is verified by means of Monte Carlo simulations and application to real flight flutter data. The comparisons show that this denoising method makes it possible to give an accurate result by a simple linear frequency identification algorithm with a short data.

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