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A hybrid denoising algorithm for HIFU echo signal based on ICEEMDAN combined with MMSVC and WT

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Abstract: High intensity focused ultrasound (HIFU) has been widely used in the biomedical field, and the noise processing for the HIFU echo signal has been a very critical problem. In order to obtain a purer and clearer HIFU echo signal, we propose a hybridt denoising method based on the improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN), minimum mean square variance criterion (MMSVC) and wavelet threshold (WT), which is called ICEEMDAN-MMSVC-WT. The ICEEMDAN can decompose the signal into a finite number of intrinsic mode functions (IMFs), which can avoid spurious modes and reduce the amount of noise contained in the modes. MMSVC is used to identify all IMFs by ICEEMDAN and divide these IMFs into two parts. The high frequency IMF components are denoised by WT first, and then combined with the low frequency IMF components to obtain the final denoised signal. In the experiments of simulation signal and actual HIFU echo signal, in comparison with other methods, the proposed denoising method retains the useful signal to the maximum extent, and removes the noise component largely, which has better denoising effect and application value.

Key words: high intensity focused ultrasound (HIFU); echo signal; improved complete ensemble empirical mode decomposition with adaptive noise(ICEEMDAN); minimum mean square variance criterion (MMSVC); wavelet threshold (WT)

0 Introduction

High intensity focused ultrasound (HIFU) is a biomedical emerging tumor and cancer treatment technology. In the process of HIFU treatment, HIFU beam is emitted from high power transducer and then focuses on the target area through soft tissue propagation. The energy in this area was transformed into heat, and the temperature rapidly increased in a few seconds, leading to tissue coagulative necrosis and protein denaturation[1-3]. The HIFU echo signal reflected back in the medium can reflect multi-state information of target tissue, such as the damage location, damage degree and tissue temperature[4]. However, in the real medical environment, noise is easy to disturb the important signal, mainly manifested as background noise, cavitation noise and scattering noise in the process of obtaining the HIFU echo signal[5-6]. The noise in the ultrasonic echo signal varies with propagation medium and the propagation time, and the received echo signal often has a low signal-to-noise ratio (SNR)[7]. Therefore, in order to better obtain real and reliable HIFU echo signals, extract various characteristics of biological tissues, and study the important mechanism of HIFU treatment, it is necessary to adopt effective noise suppression methods to denoise HIFU echo signals.

Aiming at the important research topic of noise suppression in the field of signal processing, some researchers have put forward many noise reduction methods, and a lot of work have been done to improve the SNR. Traditional noise reduction methods include short-time Fourier transform (STFT), adaptive filtering (AF), S transformation, and so on. These methods all have their unique advantages and disadvantages. For example, STFT is not suitable for processing time-varying unstable signals, the width of the window function cannot be changed once determined, and the time-frequency

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local performance of the signal cannot be expressed, thus the analysis is constrained. AF depends on the selection of reference signal, which is not always associated with the noise signal, and cannot be applied to the actual and uncertain signal[8-9]. The S transformation combines the multi-resolution analysis ability of wavelet transform (WT) with the phase holding ability of the STFT, and also adopts the Gaussian window function to meet the normalization characteristics, which can get the original signal from the converted time spectrum. However, the standard deviation of the Gaussian window function in the S transform is inversely proportional to the frequency and lacks flexibility, and therefore the S transform may output the result with poor time-frequency resolution[10].

Several noise reduction algorithms based on mode decomposition have been proposed in recent years, and the empirical mode decomposition(EMD) and the variational mode decomposition (VMD) are representative ones. EMD algorithm, proposed by Huang et al. in 1998, decomposes any complex data set into a finite number of intrinsic mode functions (IMFs). Since the decomposition is based on the local characteristic time scale of the data, it is suitable for nonlinear and non-stationary processes[11]. However, EMD has two major disadvantages, endpoint effect and mode mixing. Since it was proposed, several improved algorithms have been proposed to eliminate the defects of EMD, and therefore they have been applied in multiple fields. For example, Jia et al.[12] well removed the noise in the bearing vibration signal through ensemble empirical mode decomposition(EEMD) and gray scale theory. The principle of EEMD is to average the mode obtained by EMD after several Gaussian white noise is added to the original signal. However, due to the result of the algorithm, the reconstructed signal, mode, and final trend all contain residual noise. Furthermore, the signal addition of different noise may produce different numbers of modes, making the final averaging difficult. Sun et al.[13] combined complementary ensemble empirical mode decomposition (CEEMD) with compression sensing to seismic signals. This algorithm significantly improves the signal reconstruction problem by using complementary (addition and subtraction) noise, yet the final average problem remains unresolved. Later, Xiong et al.[14] proposed to apply complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) to electrocardio graph (ECG) signal. This method solves the reconstruction problem that is easily ignored and the problem of obtaining different mode numbers after different signals add noises signals. Although noise reduction is better than those by EEMD and CEEMD, it still needs improvement in some ways. For example, the mode still contains a lot of noise, the information is concentrated in the later modes. To solve these problems, Colominas et al. proposed a improved complete ensemble EMD(ICEEMDAN) algorithm in 2014[15], which greatly suppresses the false component and solves the mode mixing problem caused by decomposition process. It is a new and better mode decomposition algorithm, and has been widely used in the field of noise reduction. In Ref. [16], Thuraisingham et al. decomposed the EEG signal by ICEEMDAN and distinguished the IMF by the total overlap index (TIOF) in the frequency domain. In Ref. [17], Feng et al. proposed a method of combining ICEEMDAN with an improved wavelet threshold(IWT) for signal blind source separation, which well extracts the source signal with high SNR from the mixed signal. VMD was first proposed by Constantin et al. in 2014, which is a novel multi-component signal decomposition algorithm based on the Wiener filter, Hilbert transform and heterodyne demodulation[18]. In Ref. [19], Kaur et al. proposed a noise reduction method that combines the VMD with the wavelet and applied it to the EEG signal with good results. However, this algorithm has the problem of parameter setting. When the signal source is different, the selection of the penalty factor α and the mode number K will also change accordingly, which is difficult in selecting the optimal solution.

Among these algorithms related to mode decomposition, it is often necessary to analyze, select and reconstruct the IMFs generated by the decomposition. How to choose the IMF with more information and less noise is a very critical problem, which will have a decisive impact on the effect of noise reduction. In this study, a noise reduction algorithm combined ICEEMDAN, minimum mean square variance criterion (MMSVC) and WT is proposed, which decomposes the HIFU echo signal into multiple IMFs through ICEEMDAN, and then identifies the noisy IMFs. Different from correlation coefficient(CC), entropy value, mutual information method, which measure the importance of each IMF by calculating the relationship between the IMF and the original signal, the MMSVC is an algorithm to calculate the relationship between IMFs, which has higher stability and accuracy[20-22]. Then the high frequency IMF components that requiring subsequent noise reduction can be determined, while the low frequency IMF components remain unchanged. This method avoids the direct loss of useful information about the high frequency components caused by EMD and the error caused by using threshold judgment[23-24]. As a relatively mature signal analysis method, WT can analyze the time domain and frequency domain of the signal simultaneously, and it is widely used in suppressing random noise due to its characteristics of multi-resolution, low legitimacy, multi-scale, decorrelation and flexibility of base selection. It is more suitable for the analysis and processing of non-stationary signals[25-27]. After selecting the appropriate wavelet basis, the decomposition layers and the wavelet threshold function, the WT is applied to the high frequency IMFs with much noise while still containing important information. The noise component is removed and the useful information is retained, and then reconstructed with the low frequency IMFs. This method largely overcomes the drawbacks of direct WT denoising. The final experiments and discriminant results also demonstrate the superiority of this method.

1 Basic theory

1.1 ICEEMDAN

Compared with CEEMDAN, the ICEEMDAN avoids the generation of spurious components, and also greatly reduces the noise contained in the components. Therefore, this study applies it to the HIFU echo signal denoising, which is to decompose the signal to be processed into a finite number of IMFs. The specific steps are as follows:

First, introducing two new operators: $M(\cdot)$ and $E_k(\cdot)$, where $M(\cdot)$ is the local mean of the original signal generated via the EMD, and $E_k(\cdot)$ is the function that produces the kth mode decomposed by EMD. Let $W^{(i)}$ be the Gaussian white noise with zero mean and zero unit variance.

1) Adding Gaussian white noise to the raw signal x, this is, $x^{(i)}=x+\beta_0 E_1(W^{(i)})$, where β_0 is the standard deviation of the added Gaussian white noise, $E_1(\cdot)$ is the function to calculate IMF_1, we obtain the first residal as

$$r_1=M(x^{(i)}). \tag{1}$$

2) Defining k as the kth mode generated by the ICEEMDAN decomposition, when $k=1$, the first mode is derived as

$$f_1=x-r_1. \tag{2}$$

3) When $k=2$, the second residual is obtained by calculating the local mean of r_1 after adding Gaussian white noise through EMD, the difference between r_1 and r_2 is then calculated to obtain the second mode, namely

$$r_2=M(r_1+\beta_1 E_2(W^{(i)})), \tag{3}$$

$$f_2=r_1-r_2=r_1-M(r_1+\beta_1 E_2(W^{(i)})). \tag{4}$$

4) When $k=3,4,\cdots,K$, calculating the kth residual by

$$r_k=M(r_{k-1}+\beta_{k-1} E_k(W^{(i)})). \tag{5}$$

5) Calculating the kth IMF by

$$f_k=r_{k-1}-r_k. \tag{6}$$

6) Repeating the calculation to obtain all IMFs until the residual cannot be further decomposed.

1.2 MMSVC

The MMSVC proposed in this study aims to distinguish high frequency IMF from low frequency IMF. Its specific steps are as follows:

Step 1) Defining $N(n)$ as the remaining component that removes the first n components from the original signal, which is expressed by

$$N(n)=\sum_{i=1}^{k} C_i(t),\quad k=1,2,\cdots,K, \tag{7}$$

where x is the original signal and $C_i(t)$ is the ith IMF where the original signal is decomposed by ICEEMDAN.

Step 2) Calculating the mean square variance of $N(n)$ and $N(n+1)$ by

$$M(n)=\frac{2[N(n)-N(n+1)]}{N}. \tag{8}$$

Step 3) Calculating the minimum value of all mean square variances by

$$\min_{0<n<K-1} M(n). \tag{9}$$

This minimum is defined as the critical point of the IMFs. If the nth mean square variance is the minimum, it means that the first $n-1$ IMFs are the high frequency IMFs with more noise.

1.3 WT

WT is a multi-resolution analysis method that can be used to obtain the time-frequency representation of ultrasonic signals, and wavelet threshold method is one of its extension methods. The standard thresholding methods only retain coefficients that exceed the estimated threshold. In hard threshold processing, the coefficients whose absolute values are lower than the threshold are set to be zero, while in soft threshold processing, the remaining nonzero coefficients are reduced to zero. Soft threshold processing avoids the problem of spurious oscillation, while hard threshold processing usually leads to smaller mean square error[28]. WT method is generally divided into three steps:

1) Wavelet decomposition. Select a wavelet and set its number of decomposition layers, then the decomposition is calculated.

2) Thresholding quantification processing. The wavelet function is selected to quantify the high-frequency coefficient of each layer.

3) Wavelet reconstruction. The treated wavelet reverse transformation is used to reconstruct high frequency wavelet coefficient and low frequency wavelet coefficient to obtain noise reduction signal.

The WT denoising method will adopt different thresholds according to different scales, which makes the noise propagation characteristics consistent on different scales of wavelet transformation. The effect of WT denoising method is closely related to the choice of threshold function, wavelet basis, and decomposition layers, and therefore there are multiple determination criteria. Common threshold selection methods include fixed threshold estimation (sqtwolog), maximal minimum threshold estimation (minimaxi), unbiased risk estimation (rigsure), heuristic threshold estimation (heursure), etc[25]. After comparing the effect of the multiple wavelet bases and the threshold function, the soft threshold denoising method is adopted, the threshold function is heursure, the wavelet basis is symlets 10, and the setting of decomposition layer is 4.

2 Denoising procedure

The flow chart of the hybrid denoising method based on ICEEMDAN-MMSVC-WT method is shown in Fig. 1. Its specific steps are as follows:

1) The HIFU signal is decomposed by ICEEMDAN to obtain finite IMFs.

2) MMSVC is used to calculate IMFs to obtain the minimum value of multiple root square variance values, and then distinguish IMFs into two components.

3) Selecting the appropriate wavelet basis, threshold function and decomposition layer, and then using the WT to denoise the high frequency IMF components that covered by a large amount of noise.

4) Combining the high frequency IMFs component with the low frequency IMFs component to obtain the final denoised signal.

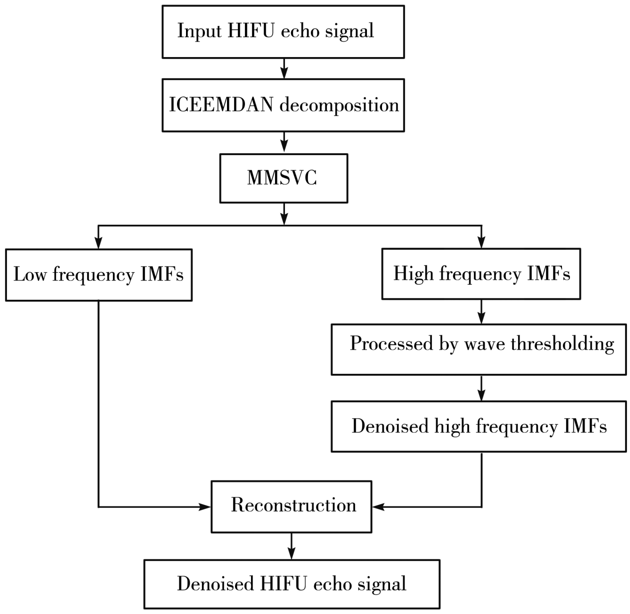
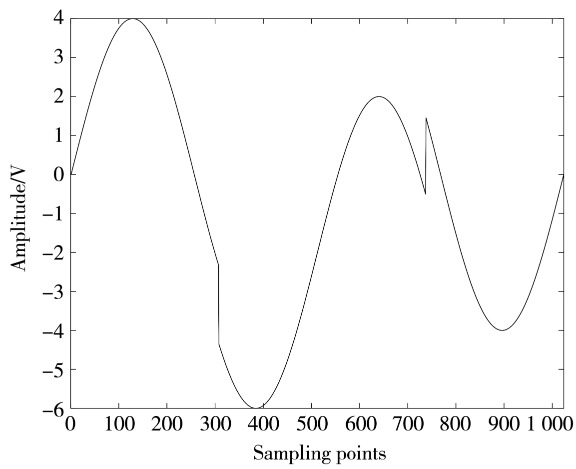


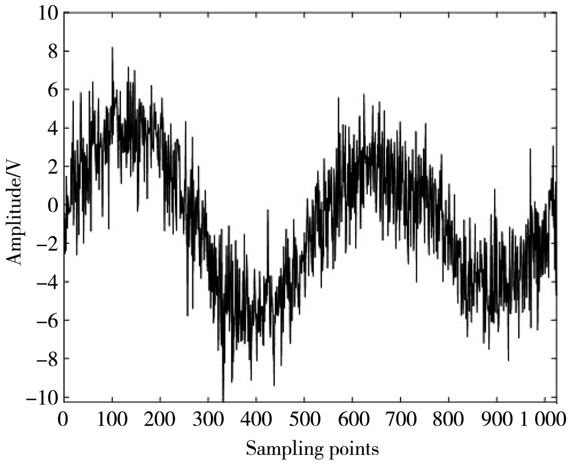
Fig. 1 Flow chart of proposed algorithm

3 Denoising of simulation signals

To demonstrate the availability and superiority of the proposed method, a heavysine signal with 5 dB after adding Gaussian white noise is selected for testing by ICEEMDAN-MMSVC-WT method, and the data length is 1 024, as shown in Fig. 2.



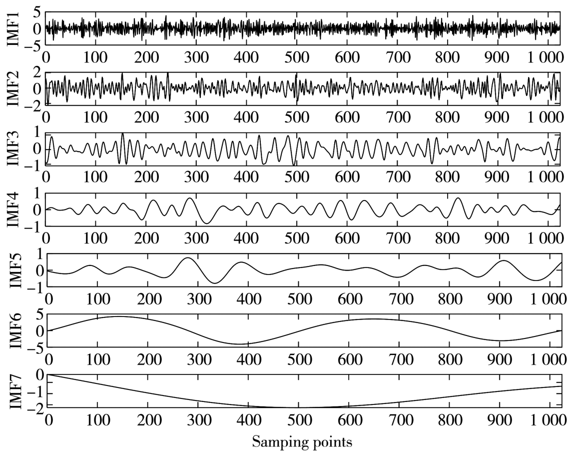
(a) Pure heavysine signal



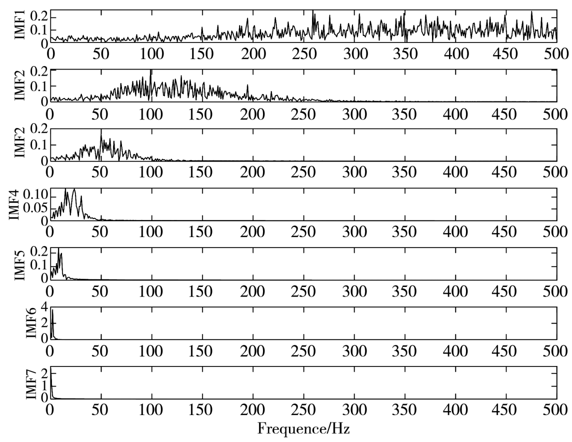
(b) Noisy heavysine signal

Fig. 2 Pure and noisy heavysine signals

First, the heavysine signal is decomposed by the ICEEMDAN to obtain seven IMFs, Fig. 3 shows the time and frequency domains of each IMF. It can be seen that the frequencies of these IMFs are distributed from high frequency to low frequency, while the noise is mainly concentrated in the high frequency component.



(a) Time domain



(b) Frequency domain

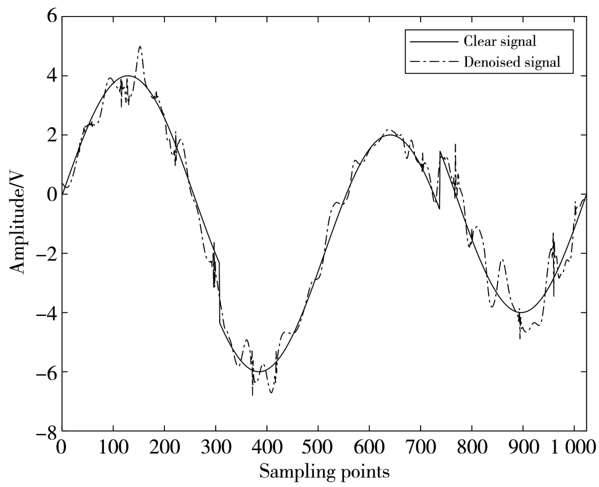
Fig. 3 Time and frequency domains for noisy heavysine signal after ICEEMDAN decomposition

After the signal is decomposed by ICEEMDAN, the IMFs are calculated by MMSVC, and the results are listed in Table 1. M_1 represents the root mean square variance between the original signal and that removing the first IMF, M_2 is the mean square variance of the original signal with the first IMF removed and the original signal with the first two IMFs removed, and so on. Finally, this signal has six mean square variance values. .

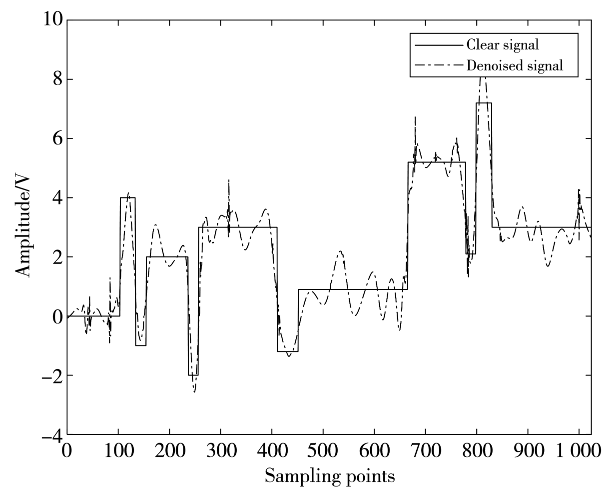
Table 1 Mean square variances between adjacent IMFs

Root mean square	M_1	M_2	M_3	M_4	M_5	M_6
Value	1.757 3	0.538 8	0.233 1	0.112 9	0.107 6	7.686 2

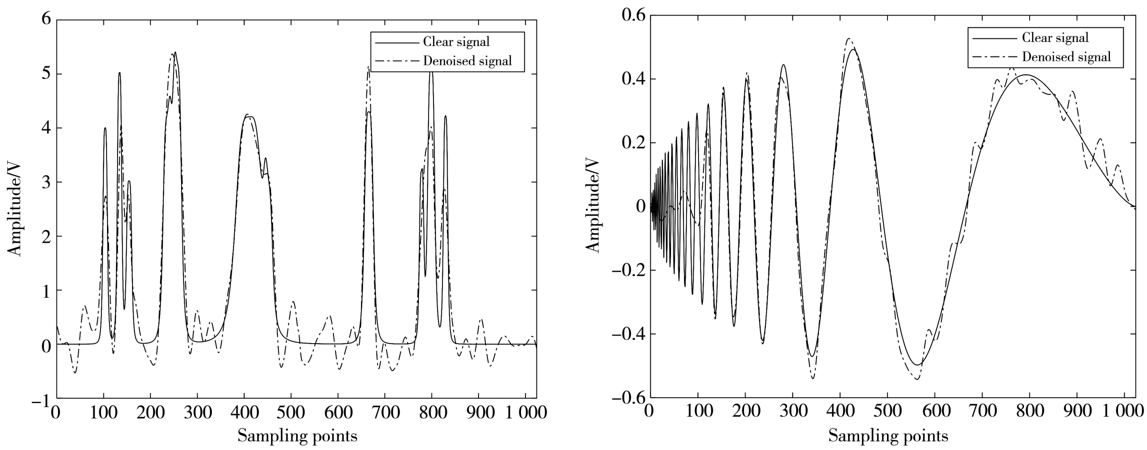
It can be seen that M_5 in Table 1 is the minimum value, which means that the important information in the first five IMFs is covered by more noise, so the first five IMFs are defined as the high frequency IMFs. Then, WT is used to denoise them. Finally, they are combined with the low frequency IMFs to obtain the final reconstructed signal, as shown in Fig. 4(a).



(a) Heavysine



(b) Blocks



(c) Bumps (d) Doppler

Fig. 4 Denoising results for four noisy signals

In addition, three other test signals, blocks, bumps and doppler, are also used for noise reduction experiments. After the same processing, their denoised results are shown in Fig. 4(b), Fig. 4(c) and Fig. 4(d), respectively. Their trajectories are almost consistent with that of the original pure signal, and the noise components are removed largely, therefore the denoising effect is obvious.

Table 2 Results for different denoising methods

Test signal	Input SNR/dB	Results	Denoising methods			
			ICEEMDAN-MMSVC-WT	ICEEMDAN-MMSVC	CEEMDAN-MMSVC	ICEEMDAN-MMSVC-CC
Doppler	−10	SNR/dB	3.701 7	2.363 0	3.213 9	2.627 5
		RMSE	0.191 2	0.223 1	0.202 3	0.216 4
	−5	SNR/dB	6.597 6	5.644 0	6.160 7	6.097 4
		RMSE	0.137 0	0.152 9	0.144 1	0.145 1
	0	SNR/dB	9.468 4	7.834 4	8.823 6	9.130 6
		RMSE	0.098 5	0.118 8	0.106 0	0.102 4
	5	SNR/dB	12.225 1	12.020 3	11.786 0	11.807 7
		RMSE	0.071 7	0.073 4	0.090 9	0.075 2
Bumps	−10	SNR/dB	4.291 2	4.275 7	2.484 6	3.251 0
		RMSE	1.098 0	1.100 0	1.351 9	1.237 7
	−5	SNR/dB	6.455 7	5.463 8	4.966 0	6.163 4
		RMSE	0.855 8	0.959 4	1.016 0	0.885 1
	0	SNR/dB	10.263 5	8.892 8	7.783 7	9.570 5
		RMSE	0.552 1	0.646 5	0.734 5	0.597 9
	5	SNR/dB	13.709 9	13.012 9	12.423 0	12.665 3
		RMSE	0.371 3	0.402 3	0.430 3	0.418 7
Blocks	−10	SNR/dB	4.743 0	3.316 2	2.827 0	3.962 6
		RMSE	1.720 4	2.027 5	2.145 0	1.882 1
	−5	SNR/dB	6.803 7	5.817 4	5.329 0	5.807 5
		RMSE	1.476 9	1.520 2	1.608 1	1.521 9
	0	SNR/dB	10.044 1	8.214 9	9.087 9	9.520 7
		RMSE	0.934 5	1.153 5	1.043 2	0.992 5
	5	SNR/dB	13.275 6	13.146 4	12.585 2	12.915 5
		RMSE	0.644 2	0.653 8	0.697 4	0.671 4
Heavysine	−10	SNR/dB	9.613 8	8.927 3	7.135 7	9.105 4
		RMSE	1.020 2	1.104 1	1.357 0	1.087 9
	−5	SNR/dB	12.664 3	12.018 7	11.463 8	11.802 6
		RMSE	0.718 0	0.773 5	0.824 5	0.792 9
	0	SNR/dB	17.022 4	16.827 3	15.539 7	16.340 9
		RMSE	0.721 0	0.444 6	0.515 7	0.470 2
	5	SNR/dB	19.143 7	18.660 0	18.455 2	19.092 5
		RMSE	0.340 6	0.360 1	0.368 6	0.342 6

To prove the validity of the ICEEMDAN-MMSVC-WT method, the other three methods are used for comparison, namely ICEEMDAN-MMSVC, CEEMDAN-MMSVC and ICEEMDAN-CC-WT. The four simulation test signals selected are blocks signal, bumps signal, heavysine signal and doppler signal. The four input SNRs are −10 dB, −5 dB, 0 dB and 5 dB, respectively. Denoising effect was evaluated by SNR and root mean square error (RMSE) of reconstructed signal, as shown in Table 2. It can be seen that the denoising effect of the proposed method is better than those of other three methods and has higher SNR and lower RMSE.

4 Denoising of HIFU echo signal

4.1 Acquisition for experimental signal

To demonstrate the effectiveness and practicability of the proposed method, this method is applied to the collected actual HIFU echo signal. The signal acquisition device is shown in Fig. 5[4]. The experimental material was fresh porcine muscle tissue. Povidone was mixed with 95% alcohol in a ratio of 1∶4, and then mixed with water in a ratio of 1∶20 to remove oxygen from the water. Afterwards, poured it into a water tank, and then let it stand for 1 h before the experiment. Porcine muscle tissue was mounted on a rubber plate to prevent sink glass damage from HIFU energy during the experiment and was immersed in water (PRO2008, ShenZhen, China). The needle hydrophone probe was installed on the HIFU transducer. The HIFU energy was irradiated on the porcine tissue through the HIFU transducer, and then it was received in the hydrophone probe. The received central frequency was 1.39 MHz, the second harmonic was 2.78 MHz, the tertiary harmonic was 4.17 MHz, and the number of collected data points were set at 10 000.

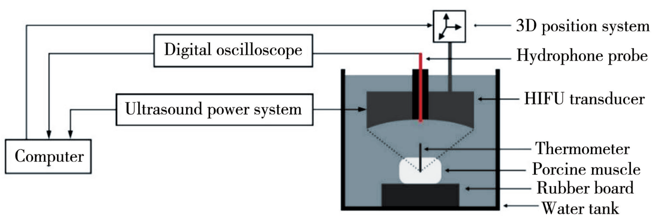


Fig. 5 Experiment equipment

4.2 Comparison of mode decomposition

Fig. 6 shows the time and frequency domain diagram of the collected HIFU echo signal. It can be seen that the HIFU echo signal is covered with much noise, and the signal will be processed next.

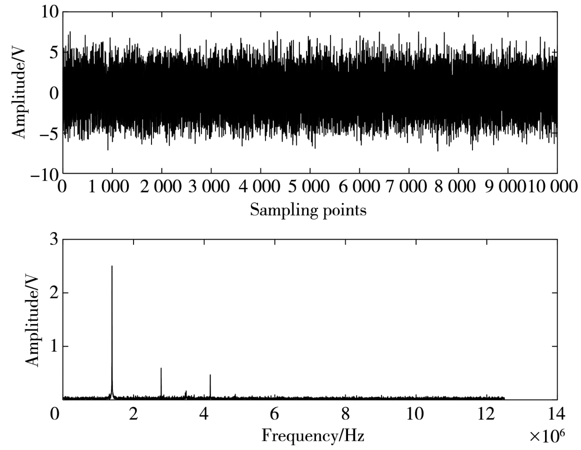
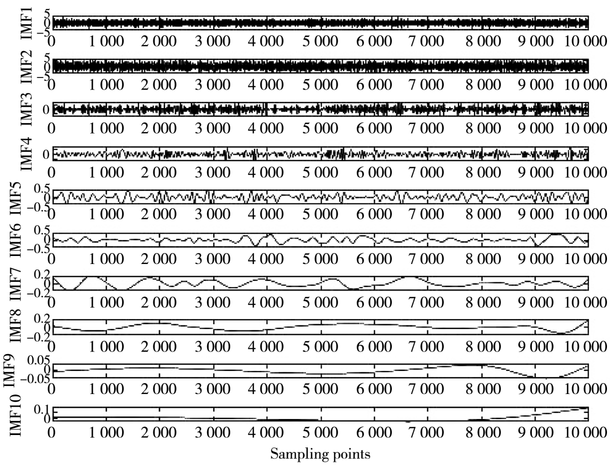
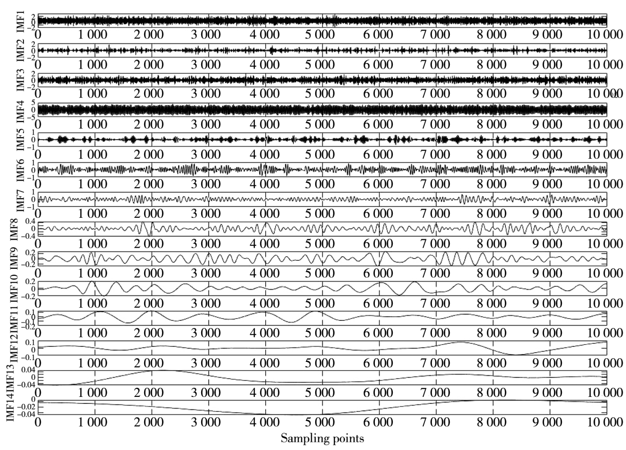


Fig. 6 Time domain waveform and spectrum of noisy signal

Fig. 7 shows the mode decomposition results of this HIFU echo signal by ICEEMDAN and CEEMDAN, respectively.



(a) ICEEMDAN



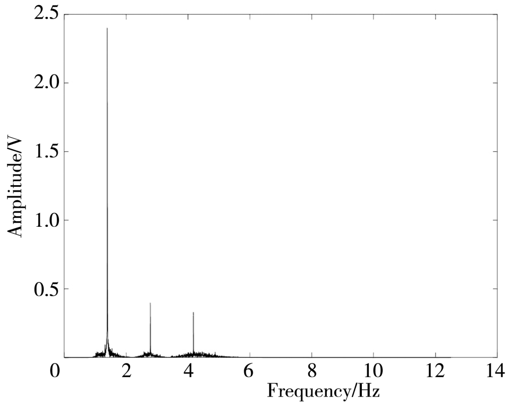
(b) CEEMDAN

Fig. 7 Results of two decomposition algorithms

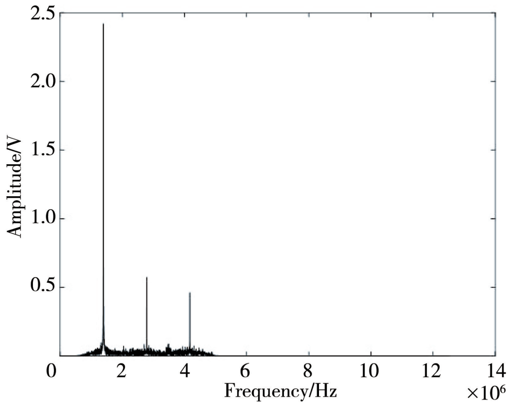
It can be seen that the noise is mainly distributed in the high frequency components. By comparison, the number of modes generated by CEEMDAN decomposition is too large, resulting in many false components, and the efficiency will be very low when the data amount is too large. ICEEMDAN decomposition avoids the generation of a large number of spurious components and solves the problem of mode mixing and end point effect of EMD.

4.3 Comparison of signal reconstruction

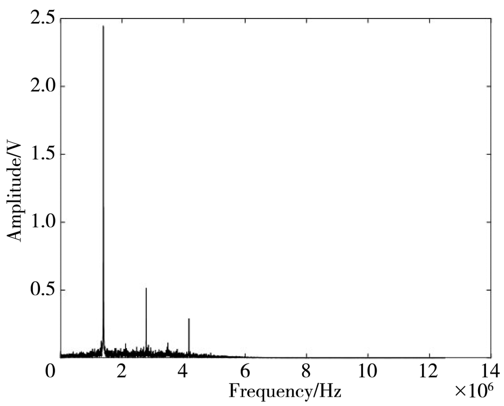
Next, the IMFs generated by decomposition will be reconstructed by four methods, namely ICEEMDAN-MMSVC-WT, ICEEMDAN-MMSVC, CEEMDAN-MMSVC and ICEEMDAN-CC-WT. The frequency domain diagrams of the reconstructed signal are shown in Fig. 8.



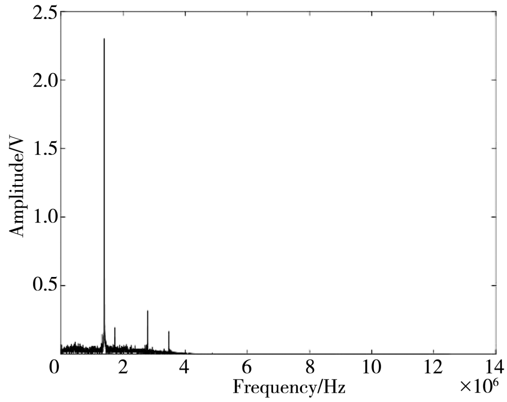
(a) ICEEMDAN-MMSVC-WT



(b) ICEEMDAN-MMSVC



(c) CEEMDAN-MMSVC



(d) ICEEMDAN-CC-WT

Fig. 8 Spectra of HIFU echo signal after noise reduction by four methods

It can be seen from the spectra in Fig. 8 that the denoising effect of the proposed method is better than those of other three methods, and the noise part is removed more.

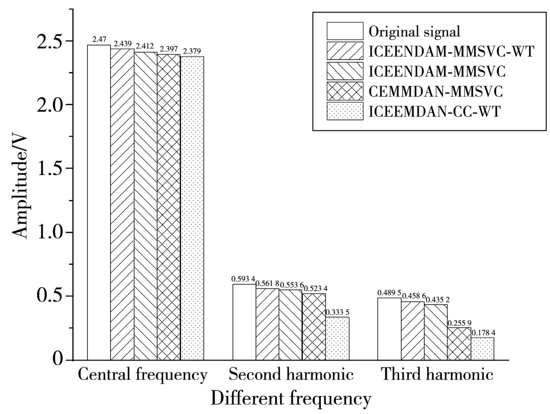


Fig. 9 Comparison of signal amplitudes after four denoising methods

By compaing the effects of four denoising methods on the central frequency and harmonics and calculating their amplitude values, it can be seen from Figs. 8 and 9 that the proposed method not only removes more noise, but also preserves the important part of the signal relatively well.

Moreover, in the process of signal decomposition and reconstruction, the useful signals and the noise are difficult to be distinguished, some modes or important information contained in the modes are easily removed as noise. Since, the noise is not separated completely and remains in the modes, compared with the proposed method, the other three methods can obtain lower amplitude values of the second and third harmonics. In this study, we combine the advantages of ICEEMDAN, MMSVC and WT to preserve the important information in the mode to the maximum extent, and therefore higher harmonic amplitude value is in the reconstructed signal.

5 Conclusions

This paper presents a denoising method for HIFU echo signal based on ICEEMDAN-MMSVC-WT. The signal decomposition by ICEEMDAN not only avoids the problem of EMD mode mixing and the parameter setting of VMD, but also solves redundant spurious IMFs problem when CEEMDAN decomposes a large amount of data. Besides, it also reduces the amount of noise contained in the modes. The MMSVC method can clearly distinguish all modes into high frequency component and low frequency component. After selecting the appropriate wavelet parameters, the decomposed high frequency IMF components are processed by the WT while the low frequency IMF components remain unchanged. Finally, these IMFs are reconstructed to obtain the complete denoised signal.

In the test of simulation signal, this method has higher SNR and lower RMSE compared with other three methods, the denoised signal is smoother, and the trajectory is also more consistent with that of the original signal. In the denoising of actual HIFU echo signal, it can be seen from the frequency domain that this method removes more noise, and compared with the results of the other three methods, the center frequency and harmonic are preserved more completely, which is a better application in the denoising problem of HIFU echo signal.

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基于 ICEEMDAN 结合 MMSVC 和 WT 的 HIFU 回波信号联合去噪算法

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摘　要： 高强度聚焦超声(High intensity focused ultrasound，HIFU)已广泛应用于生物医学领域，其回波信号中的噪声处理是一个非常关键的问题。为了获得更纯净、更清晰的 HIFU 回波信号，提出了一种基于改进的完全自适应噪声集成经验模态分解(Improved complete ensemble empirical mode decomposition with adaptive noise，ICEEMDAN)、最小均方方差准则(Minimum mean square variance criterion，MMSVC)和小波阈值(Wavelet threshold，WT)的联合去噪方法。ICEEMDAN 将信号分解为有限个本征模态函数(Intrinsic mode functions，IMF)，从而避免杂散模态，减少模态中所含的噪声。MMSVC 用于识别被 ICEEMDAN 分解得到的所有 IMF，并将这些 IMF 分为两部分，高频 IMF 部分通过 WT 进行去噪，之后与低频 IMF 分量重构得到最终去噪信号。在仿真信号的实验中，与其他方法相比，本文所描述的基于 ICEEMDAN-MMSVC-WT 的降噪方法最大限度地保留了有用信号，大量去除了噪声成分，因而具有更好的去噪效果和应用价值。

关键词： 高强度聚焦超声；回波信号；改进的完全自适应噪声集成经验模态分解；最小均方方差准则；小波阈值

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