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Denoising Methods for Underwater Acoustic Signal

Vijaya Baskar Veeraiyan

Abstract

Underwater ambient noise is primarily a background noise which is a function of time, location, and depth. It is of prime importance to detect the signals such as sound of a submarine or echo from a target surpassing this ambient noise. It is also defined as the residual noise that remains after all easily identifiable sound sources are eliminated. In the absence of the sound from ships and marine life, underwater ambient noise levels are dependent mainly on wind speeds at frequencies between 500 Hz and 50 KHz. The detection of background noise is essential to enhance the signal-to-noise ratio of acoustic-based underwater instruments. Since there is a possibility of signal and noise present in the same frequency, it becomes essential to find out a suitable algorithm to perform denoising. In this chapter, various denoising techniques such as wavelet, empirical mode decomposition (EMD) in time domain, ensemble empirical mode decomposition (EEMD), and frequency domain-based EMD are studied, and the results are compared. The proposed frequency domain algorithm produced better results in the frequency ranging from 50 Hz to 25 KHz, with less signal error.

Keywords: underwater acoustics, ambient noise, denoising, wavelet, EMD

1. Introduction

The ocean is filled with sound. Underwater sound is generated by a variety of natural sources, such as breaking waves, rain, and marine life [1, 2]. It is also generated by a variety of man-made sources, such as ships and military sonars. Some sounds are present more or less everywhere in the ocean all of the time. The background sound in the ocean is called ambient noise [3, 4]. Ambient noise also excludes all forms of self-noise, such as the noise of current flow around the measurement hydrophone and its supporting structure and obviously must exclude all forms of electrical noise (Urick). In shallow water (depth of 10–100 m), acoustic

systems like sonar suffer a huge loss of acoustic signals due to ambient noise [5]. Wind noise is the most constant and most perennial of all components of ambient noise [3, 6]. Many theoreticians have predicted ambient noise that is caused by wind. Different actions are prevailing in a dissimilar component of the entire frequency band from 1 to 50 KHz [2]. The recovery of the signal buried in ambient noise is of important significance for target's signal detection, recognition, and classification at low signal-to-noise ratio.

2. Denoising methods

In science and engineering, noise is defined as an unwanted signal, particularly a stochastic and persistent form that dilutes the lucidity of a signal. In natural process, noise could be caused by the process itself, such as local and intermittent instabilities, irresolvable subgrid phenomena, or some concurrent processes in the environment in which the investigations are conducted. It could also be generated by the sensors and recording systems when observations are made. In general, all data are amalgamations of signal and noise, i.e.,

$$x(t) = s(t) + n(t) \tag{1}$$

in which $x(t)$ is the recorded data, and $s(t)$ and $n(t)$ are the true signal and noise, respectively.

The general algorithm of denoising can be written as:

i.   Convert the data from a time domain into a suitable domain where signal and noise can be separated.

ii.   Remove noise in the new domain using suitable algorithm.

iii. Then convert the data back to the time domain.

Identifying a suitable domain to eliminate the noise completely is a big challenge. Denoising has been performed using different denoising methods [wavelet, empirical mode decomposition (EMD), and ensemble EMD (EEMD)]. Here, a simulated signal was considered to be the sonar signal, and it was added with a real-time wind noise signal to get a noisy signal. This signal was applied as the stimulus to the denoising algorithm, and the denoised signal was obtained.

3. Denoising using wavelets

The wavelet transform is extensively used in several fields of processing a signal. It has the edge of employing variable sized time window for dissimilar bands of frequency. It has an advantage of higher resolution in frequency, particularly in lower bands and low resolution, when it comes to higher frequency bands. For the modeling of nonstationary signals, for

example, speech that possesses dull temporal variations when it comes to low frequency and sudden temporal deflections in higher frequency, the wavelet transform is a perfect answer. This is also used for denoising of the signal as well.

Denoising of underwater acoustic using wavelet is engineered in general with the following steps in place:

1. Source signal to be taken.

2. Real-time wind noise data are added to the source signal in obtaining the noisy signal.

3. Wavelet decomposition is carried out for the noisy signal using a suitable wavelet.

4. Updating noisy coefficients of a level should be done by setting threshold values. This setting is done by considering detailed noise coefficients.

5. In a similar manner, to update the approximate noisy coefficients of a level, the last level approximation noise coefficient is used to set the threshold value.

6. Next step is to compute modified noisy coefficient using different threshold functions such as hard, soft, and nonnegative garrote.

7. Signal retrieval or denoised signal is done by applying inverse wavelet transform.

8. Calculate the error in the denoised signal for different threshold functions and also for different wavelets.

Here, a universal method for fixing the threshold value is modified by introducing two constants 'k' and '$m1$' to obtain higher quality output signal, and it is combined with nonnegative garrote threshold function in the denoising process.

The modified threshold equation is given by Aggarwal et al. [7].

$$\lambda = k.m1.\sigma\sqrt{2\log2(N)} \tag{2}$$

Where N denotes the number of samples of noise. It is noted that if two factors, i.e., k and $m1$ are introduced in the universal threshold equation, then new threshold value gives better results, especially to recover the original signal [1].

Here, the values of k and $m1$ are fixed after repeated trials. Initially, $m1$ value was fixed, and k value varied to obtain better result. After many trials, k value is fixed as '0.5', which gives a better result when compared to other k values. The root-mean-square error (RMSE) value is low when $k = 0.5$, and there is no change in the RMSE value above this k value. So k value was fixed as 0.5. Then, the value of $m1$ is varied, and the output was better for the value of $m1 = 3$. The RMSE value is less for $m1 = 3$, and above this value, there is no change in the RMSE value. So it has been concluded that the value of k is fixed as $k = 0.5$ and $m1 = 3$ to get better results.

The final step is by enforcing inverse wavelet transform to obtain the original signal. The denoised signal thus obtained should be similar to the original signal, i.e., RMSE of the signal should be low.

3.1. Denoising results obtained using wavelets

In this work, sine wave is taken as a sample signal. This signal is added with a real-time wind noise signal. This noisy signal is processed with the denoising steps, i.e., decomposition, wavelet thresholding, and inverse wavelet transform for reconstruction. Initially, the signal decomposition is done for a different level. After a series of test, it was found that the decomposition level 2 gives better output. Now for each level, the threshold values are calculated using the modified universal threshold equation. Then thresholding is applied to detailed noisy coefficient in order to obtain the modified detailed coefficient. The denoised signal was reconstructed using the true approximation coefficient of level 2 and the modified detailed coefficient of levels 1– 2.

In this work, decomposition was done using different wavelets. After decomposition by wavelet, the threshold is applied using different threshold functions, i.e., soft, hard, and nonnegative garrote threshold [8]. The RMSE value was calculated for different wavelet and threshold function. These values are presented in **Table 1**. From the table, it is clear that RMSE value is less for 'sym8' wavelet compared with other wavelets and most of the wavelets perform well along with nonnegative garrote threshold, i.e., RMSE value is less.

Then, the modified universal threshold along with nonnegative garrote threshold is applied to the decomposed signal. After applying threshold value, inverse wavelet is applied at last to obtain the original signal. The signal, noise, noisy, and the denoised signals are shown in **Figure 1**. The qualitative output, i.e., the comparison of original and denoised signals is presented in **Figure 2**.

Wavelet type	RMSE value for different threshold method		
	Hard	**Soft**	**Nonnegative garrote**
haar	0.001339103	0.001303089	0.001326211
db2	0.000836217	0.000837207	0.000836016
db4	0.000618673	0.000620417	0.000618689
db5	0.000602552	0.000603077	0.000602235
db8	0.000595174	0.000595174	0.000595174
sym4	0.000617997	0.000619197	0.000617785
sym8	0.000594376	0.000595753	0.000594325
coif4	0.000594698	0.000596959	0.000594531
coif2	0.000615408	0.000617598	0.000615114
dmey	0.000593861	0.000593861	0.000593861

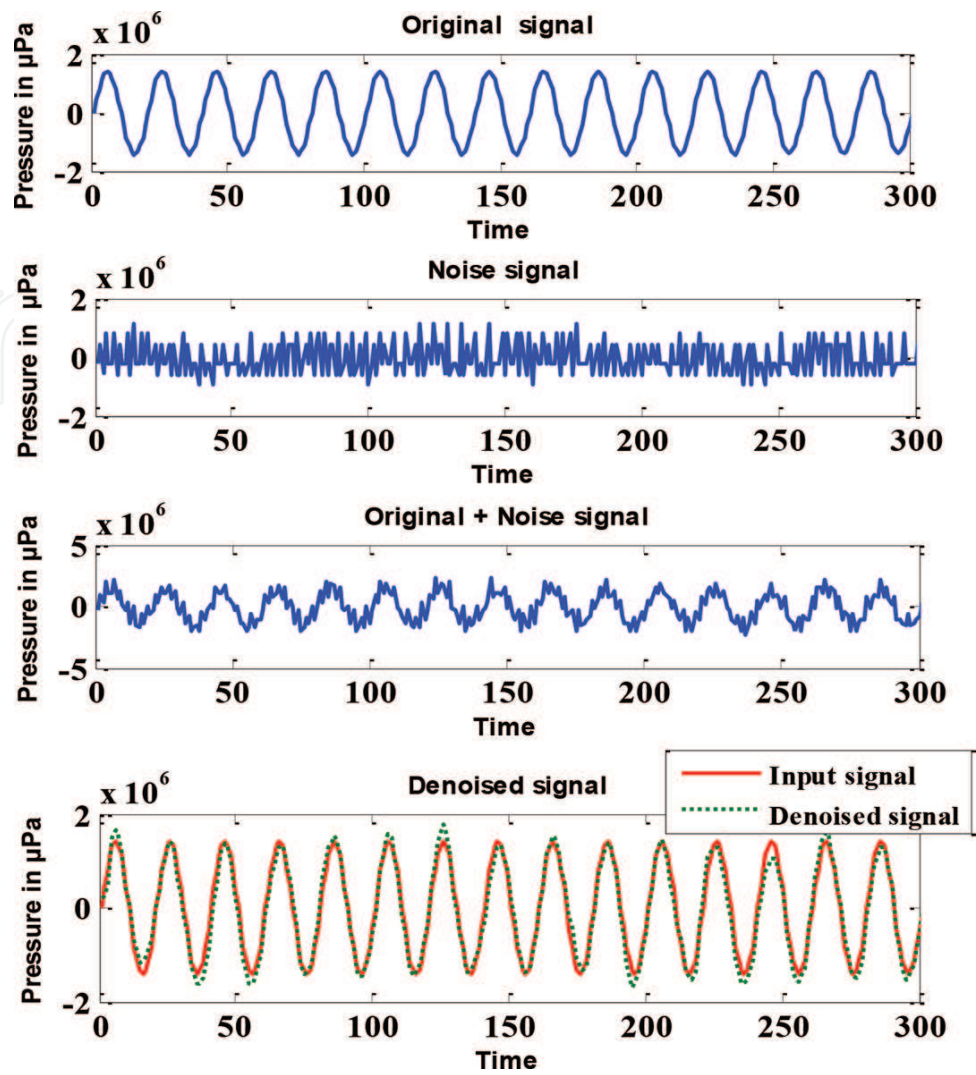**Table 1.** RMSE value for different threshold function.

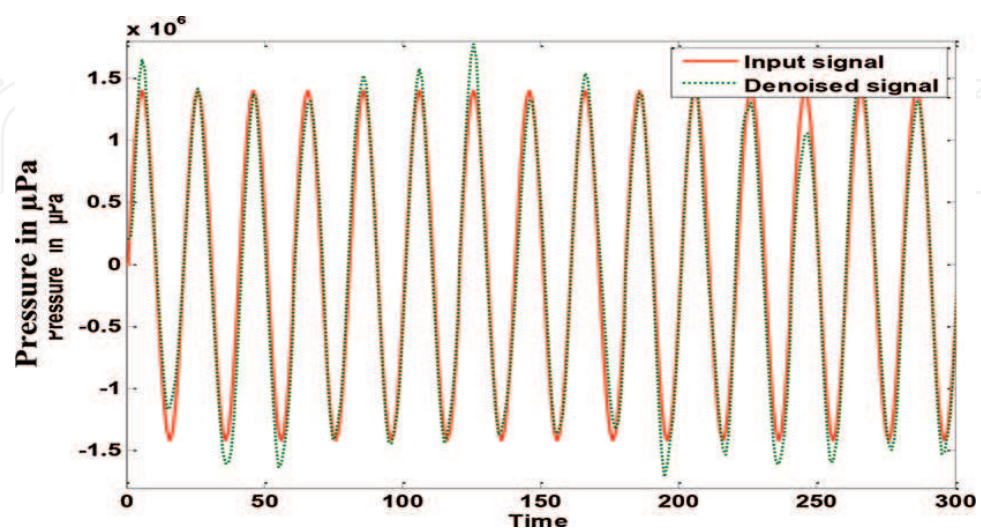**Figure 1.** Process of denoising using wavelet.

Figure 2. Input and denoised output signal comparison graph.

4. Denoising using EMD

Empirical mode decomposition (EMD) is different from other methods of analyzing data from nonstationary and nonlinear processes. This has been introduced by Huang et al.. This is used to decompose signals in an adaptive manner into a sum of AM and FM components containing raw intrinsic building blocks. These define the complex waveform. There is no need to fix the functional basis in advance. EMD sifting methods are usually employed to procure these basis functions in an adaptive manner [9].

EMD identifies the intrinsic oscillatory modes by their characteristic time scales in the data through empirical observation and then decomposes the data into the corresponding IMFs through shifting processes. Intrinsic Mode Functions (IMF) may contain variable amplitude and frequency functions those are dependents of time. It is an algorithm to assign an instantaneous frequency to each IMF in order to decompose an arbitrary data set.

Since in EMD, decomposition is based on and derived from the data, it is an adaptive method. Here, the data $x(t)$ is decomposed in terms of IMFs, i.e.,

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \tag{3}$$

Here r_n is the residue of data $x(t)$, after n number of IMFs being extracted. IMFs are simple oscillatory functions with varying amplitudes and frequencies [10].

4.1. Denoising using EMD based on existing time domain approach

The importance of a given model is estimated with the information pertained to IMF datum at times where the noise makes its presence.

In this algorithm, EMD was applied to the noisy signal. Then, the noisy signal was decomposed into a set of IMFs. The energy of each IMF had been calculated and then the threshold value. The IMFs were shrunken using the nonnegative threshold function and then added to get the denoised output [1, 11, 12].

The energy of the first IMF is defined as

$$W_H[1] = \sum_{n=1}^{N} c_1^2(n) \tag{4}$$

c_1 represents the first IMF coefficients.

The energy of each IMF is defined as

$$\text{energy(count)} = \frac{\text{energy}(1)}{0.719} * 2.01^{-\text{count}}, \text{count} = 2, 3, \ldots \tag{5}$$

Where *energy* (1) is the noise energy that can be achieved by the first IMF variance using equation (4) and *count* is a variable that specifies the IMF number.

Then, the threshold value of each IMF can be calculated by

$$\text{threshold}(\text{count}) = \sqrt{\left(\frac{\text{energy}(\text{count})}{x\text{size}}\right) * 2 * \log(x\text{size})} \tag{6}$$

The first IMF can be discarded as it captures most of the noise, and for other IMFs, the adaptive threshold can be calculated using Eq. (6). Then, the coefficients of each IMF was shrunken using nonnegative garrote threshold function that is calculated for values of IMF greater than or equal to the threshold value using

$$\text{mode}(\text{count}) = \text{mode}(\text{count}) - \left(\frac{\text{threshold}(\text{count})^{\text{count}}}{\text{mode}(\text{count}^{(\text{count}-1)})}\right) \tag{7}$$

Where *mode* represents the IMF, and the variable count specifies the IMF number.

For values of IMF less than the threshold value,

$$\text{mode}(\text{count}) = 0 \tag{8}$$

Finally, the shrunken IMFs were added to obtain the denoised signal. The denoising algorithm is shown in **Figure 3**.
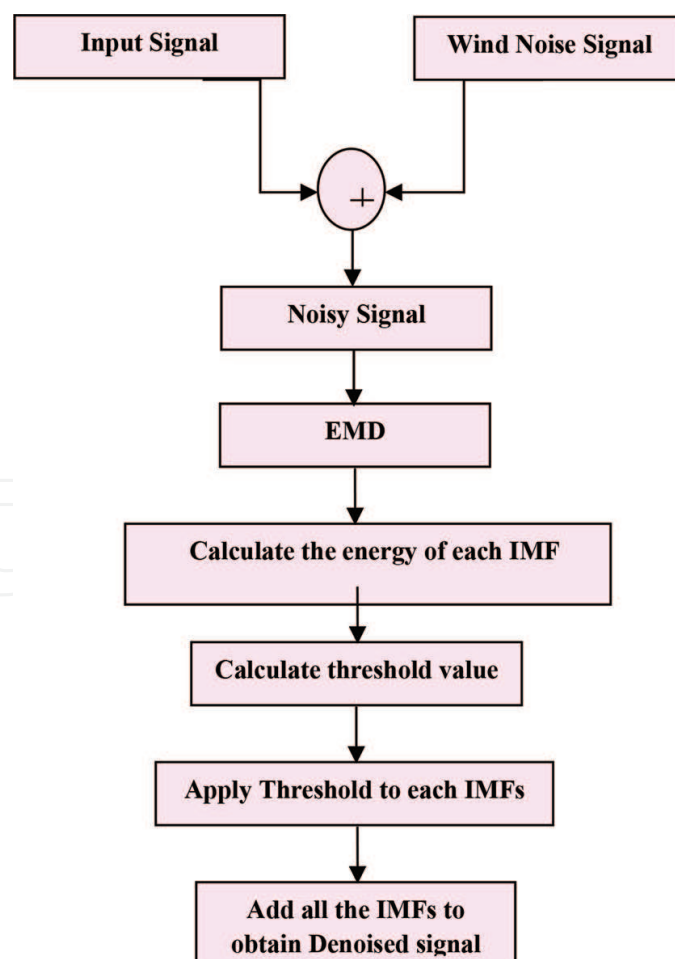
Figure 3. EMD-based denoising algorithm using time domain thresholding.

A sinusoidal signal was considered as the input test signal, and then, a real-time wind-driven ambient noise signal that was collected at the wind speed of 5.06 m/s was added with the input signal to obtain the noisy signal. The input, noise, and noisy signals are presented in **Figures 4–6**. The noisy signal was decomposed into a set of IMFs by using EMD function and is shown in **Figure 7**. Each of the IMF was shrunken using the nonnegative garrote threshold function. Then, the denoised signal was reconstructed by adding the shrunken IMFs, which is shown in **Figure 8**.

This algorithm performs well until the noise amplitude is less than the signal amplitude. The output is not acceptable whenever the noise amplitude is higher than 50% of the signal
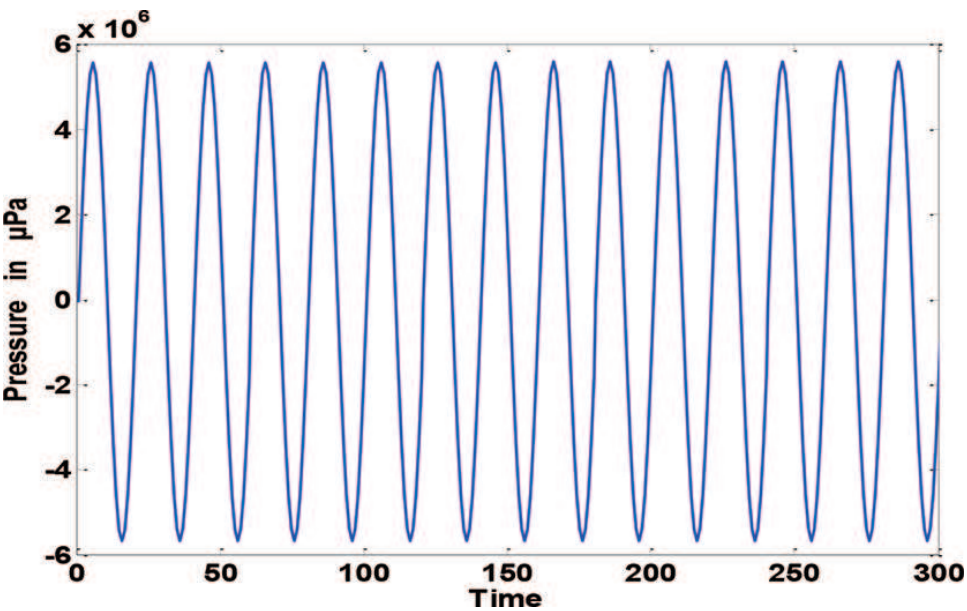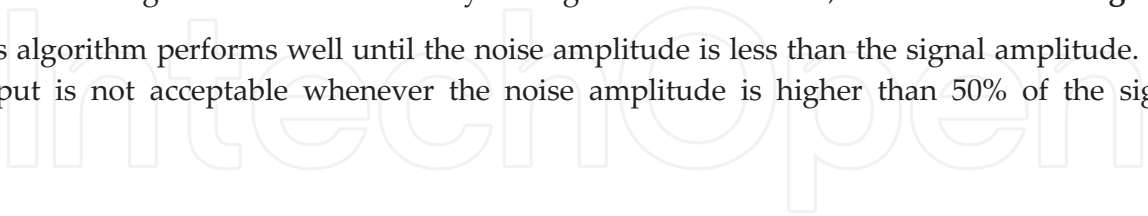
Figure 4. Input signal.
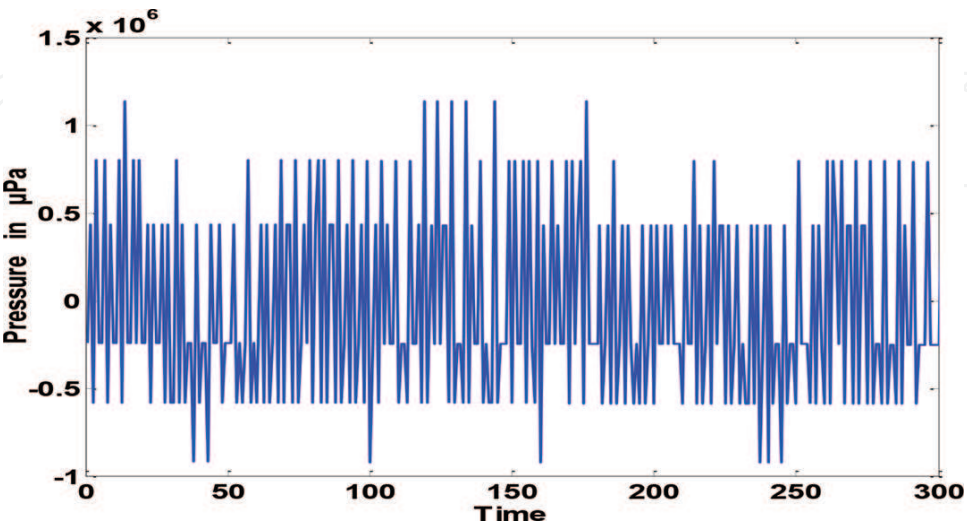
Figure 5. Wind noise signal.
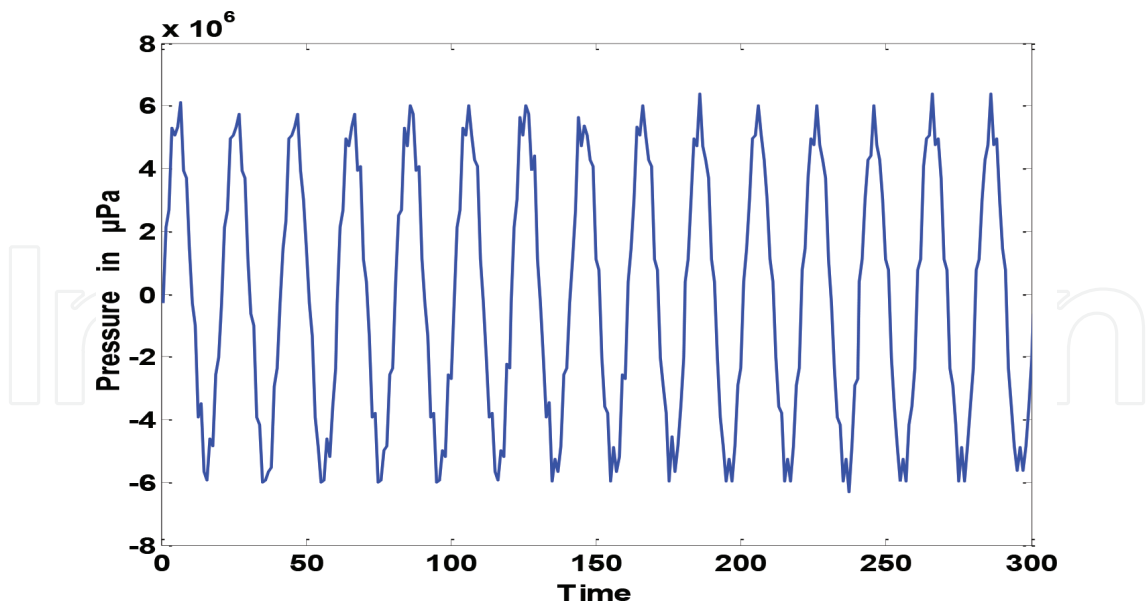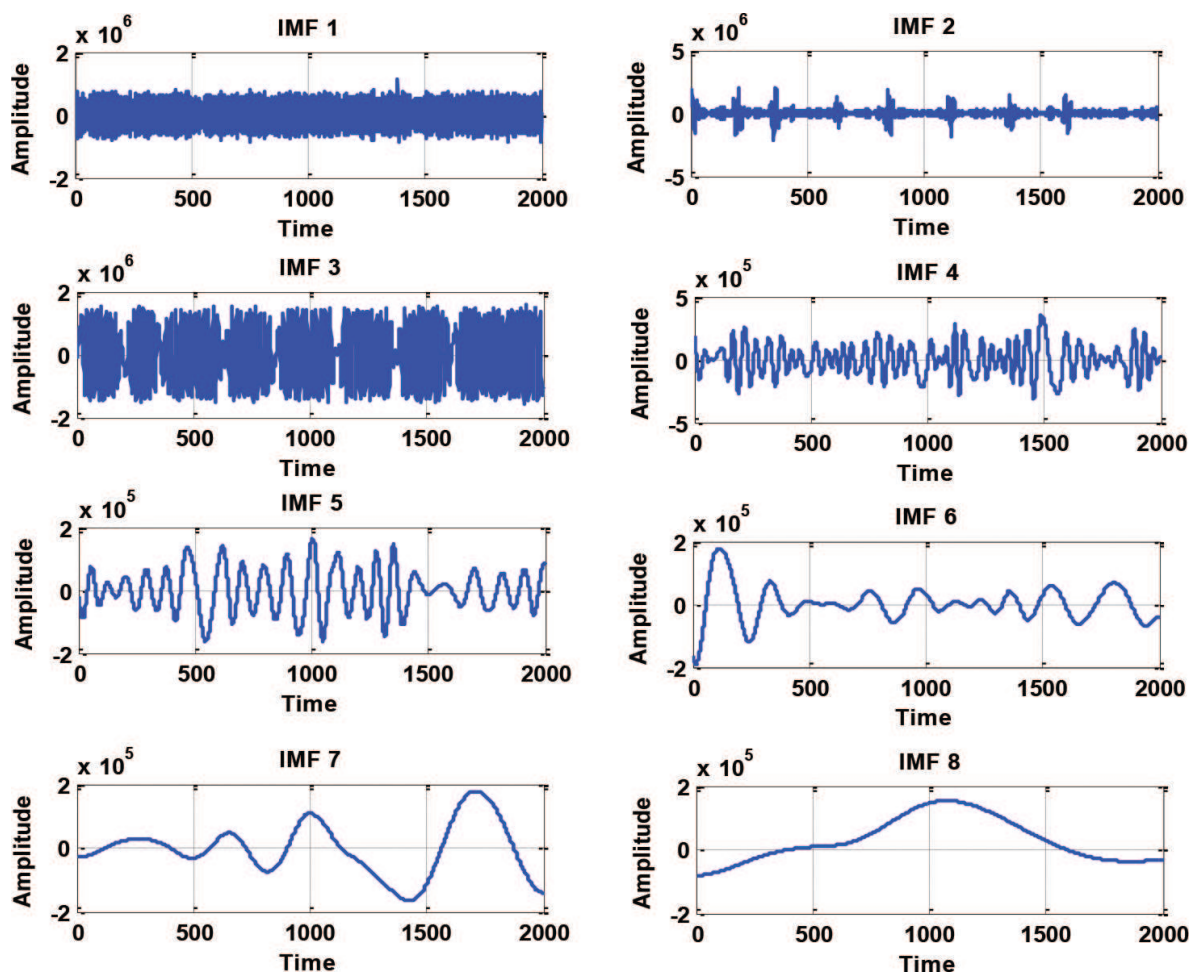
Figure 6. Noisy signal at 5.06 m/s.

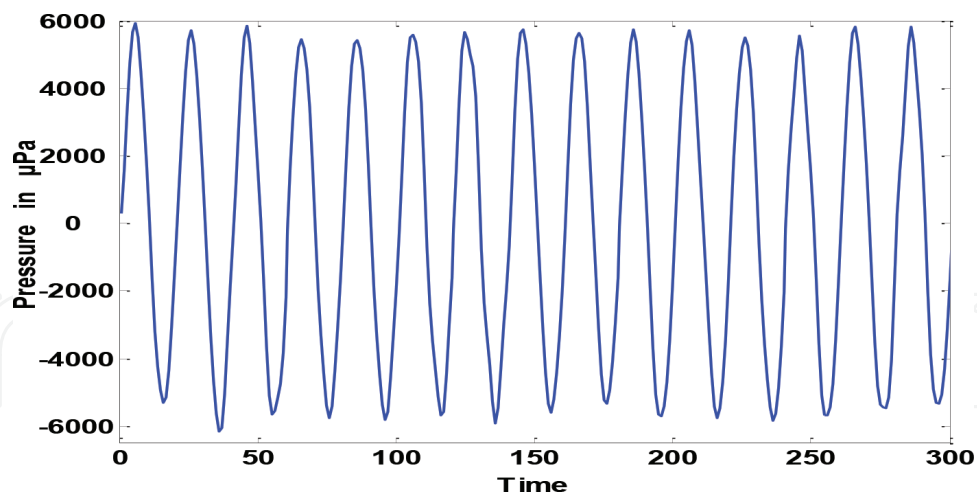**Figure 7.** IMFs obtained from the noisy signal.

Figure 8. Denoised output signal for Time domain EMD.

amplitude. It is apparent from **Figures 4** and **8** that the denoised signal amplitude is lesser than the actual input signal; even though the denoised signal is similar to the input signal, it is not an exact resemblance to the input [1].

5. Denoising using EEMD

The output is not satisfactory in the EMD-based time domain method. So to improve the performance, the same time domain thresholding is used along with ensemble empirical mode decomposition (EEMD).

Ensemble EMD is a novel noise-assisted method of data analysis that has been proposed to surpass the scale separation problem without the subjective intermittence test. According to this, the true IMF components are defined as the mean of the ensemble of trials. Here, every IMF component comprises the signal along with white noise, whose amplitude is finite. It is very much feasible to isolate the scale without any selection of advanced subjective criterion in the ensemble approach. This novel method is reaped from the recent study of statistical properties of white noise [12] (Wu and Huang, 2004). This exemplifies the fact that EMD is an efficient adaptive dyadic filter bank when it is applied to white noise. Particularly, this novel method has the inspiration from the noise added analysis started by Flandrin et al (2005) and Gledhill (2003). The results of these experiments made it clear that noise is a useful tool in the analysis of data in the empirical mode decomposition [12].

The main feature of EEMD is the addition of white noise results in populating the whole time-frequency space equally, while the constituting components of dissimilar scales are isolated by the filter bank. In this state, the bits of the signal belongs to dissimilar scales would automatically proposed onto proper scales of reference given by the white noise as the background. Mode mixing can be avoided by the addition of finite noise, and hence, EEMD has an edge over the EMD method.

EEMD method is as follows:

1.   Initially adding a series of white noise to the signal that is considered as a target.

2.   Next is extracting IMF through decomposition of noise added data.

3.   Repeating steps 1 and 2 several times, with dissimilar series of white noise every time.

4.   Final results are the extraction of ensemble of corresponding IMFs of the decomposition [1].

As a matter of fact, the amplitude of the noise that is added is tiny, and it does not necessarily introduce the change of extreme upon which the EMD is dependent. The effect of white noise becomes negligible with the increase in ensemble members.

5.1. Denoising using EEMD based on time domain approach

The denoising process using EEMD has the same input signal and noise signal, which is used in Section 4.1, and is used to get the noisy signal. The noisy signal was applied as an input to the EEMD-based denoising algorithm. The input and output of EEMD algorithm are shown in **Figure 9**. In EEMD-based denoising algorithm, the output amplitude is the same as that of the
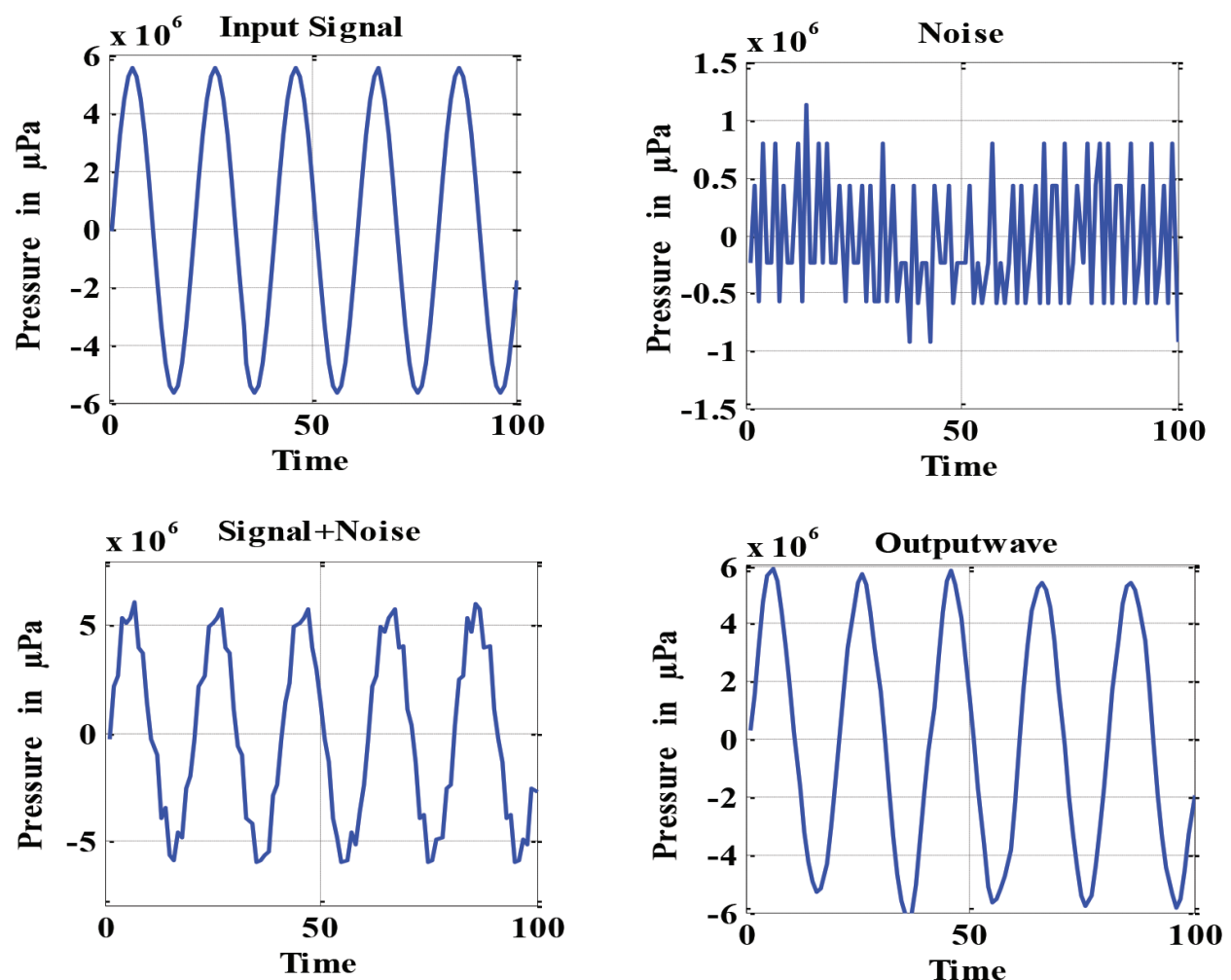

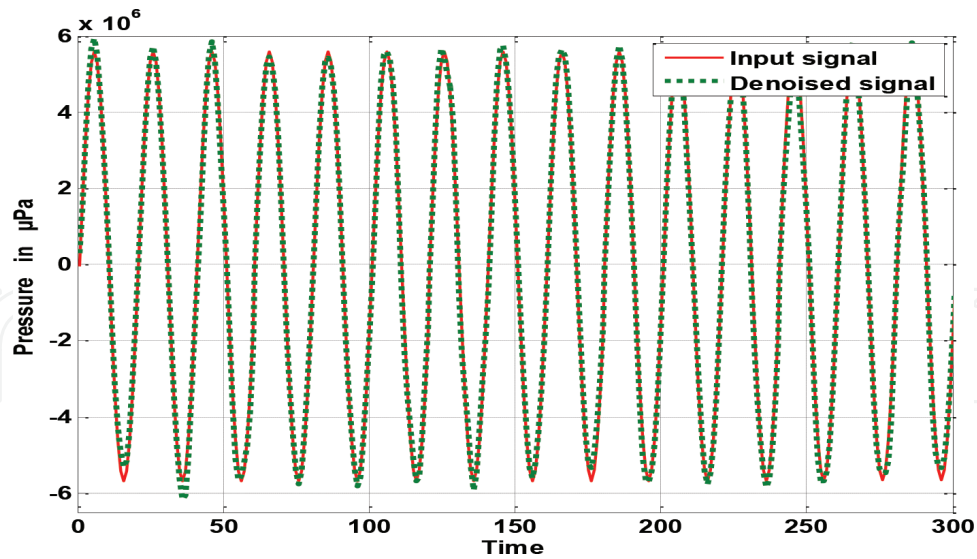**Figure 9.** Input and output signals of EEMD algorithm.

Figure 10. Input and denoised output signals comparison graph (EEMD method).

input signal amplitude, when compared to EMD-based denoising algorithm output. Even though the denoised signal amplitude is quite satisfactory, the output signal does not resemble the input signal exactly.

Comparison, between the input and denoised signal, which is obtained by EEMD, based time domain denoising algorithm, is presented in **Figure 10**. This algorithm produces better output compared to the output of EMD algorithm. But this algorithm takes more time to produce output, and also the output signal needs improvement.

6. Proposed denoising method using EMD based on frequency domain approach

In this proposed algorithm, EMD is used as a denoising tool. Earlier EMD-based denoising methods had been done using time domain thresholding.

The proposed algorithm is based on frequency domain thresholding, and the algorithm is shown in **Figure 11**. The proposed algorithm is simple, and it capable of producing better results than the existing algorithms. As the value of threshold depends on the noise signal, this algorithm performs well for different wind noise signals, i.e., noise collected for various wind speeds. From the results, it is concluded that the algorithm works well even if the signal amplitude and the noise amplitude are same. The signal shown in **Figure 12** is considered as an input signal. **Figure 13** shows the real-time wind-driven underwater ambient noise signal, which is measured at the wind speed of 5.06 m/s. The input signal is added with the noise signal.

The noisy signal is shown in **Figure 14**, which is noisier compared to the signal which are applied in the previous algorithms.
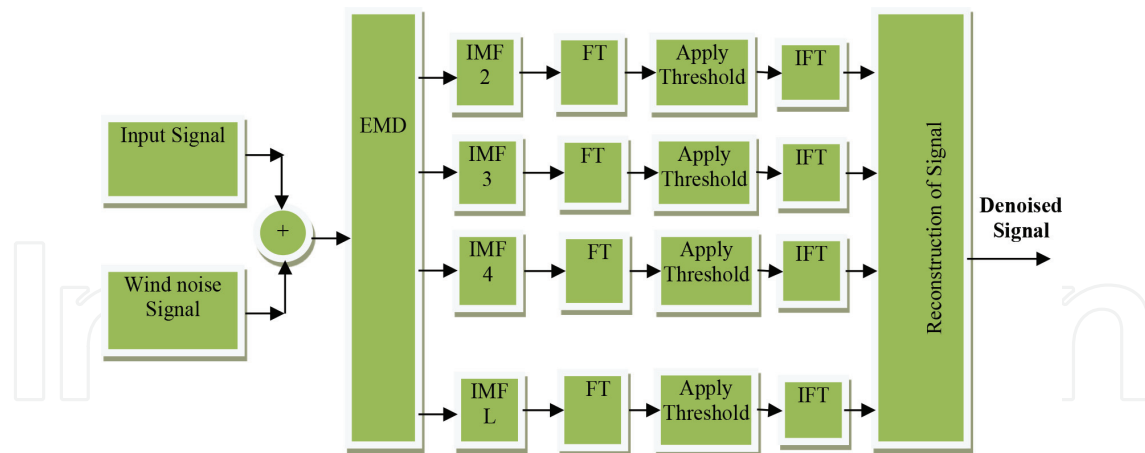
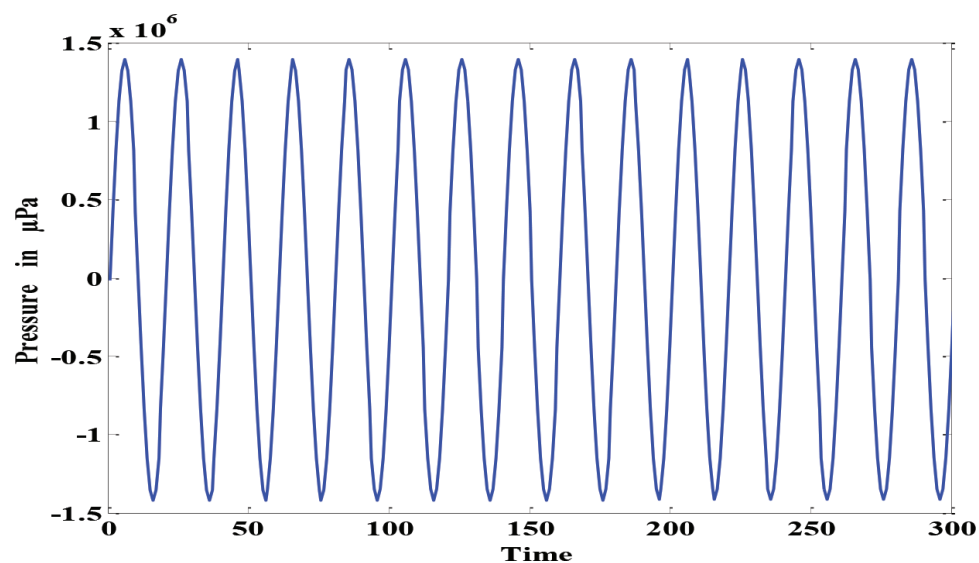**Figure 11.** Proposed denoising algorithm based on EMD.

Figure 12. Input signal (0.0053 = 5 mv).

The noisy signal is decomposed into a set of IMFs by using EMD function. The IMFs are shown in **Figure 15**.

From the figure, it is clear that the IMF1 contains more noise. So we have eliminated IMF1. Then, we have applied FFT to other IMFs, which is shown in **Figure 16**.

From the figure, it is clear that IMF 2–4 have more noise components and IMF 5–8 have more signal components. Different threshold values have been used and better outputs are obtained, when the threshold value is set as 70–90% of maximum FFT amplitude, i.e., in each IMF, the coefficients of IMF signal, which have FFT amplitude below the threshold value, were assigned zero. After applying threshold, IFFT was taken to each IMF, and then, all the thresholded IMFs were added to get the denoised signal. The denoised signal is shown in **Figure 17** for different threshold values. The output was good for the threshold values of 70% and above. At 90% threshold, the output resembles the input signal very well. Compared to the existing time
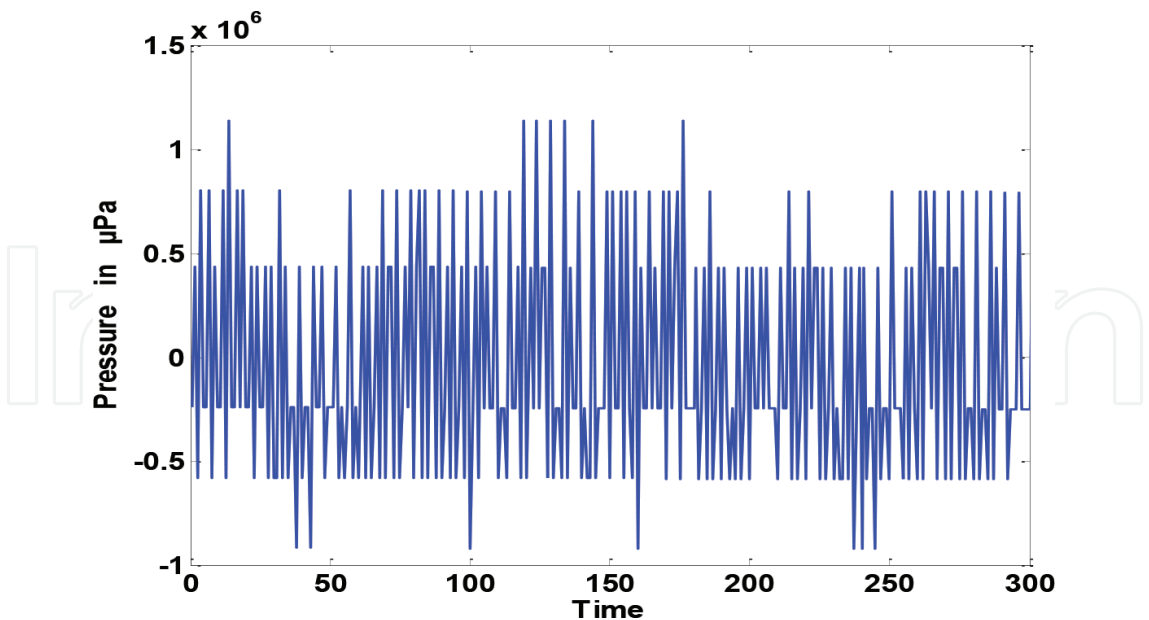
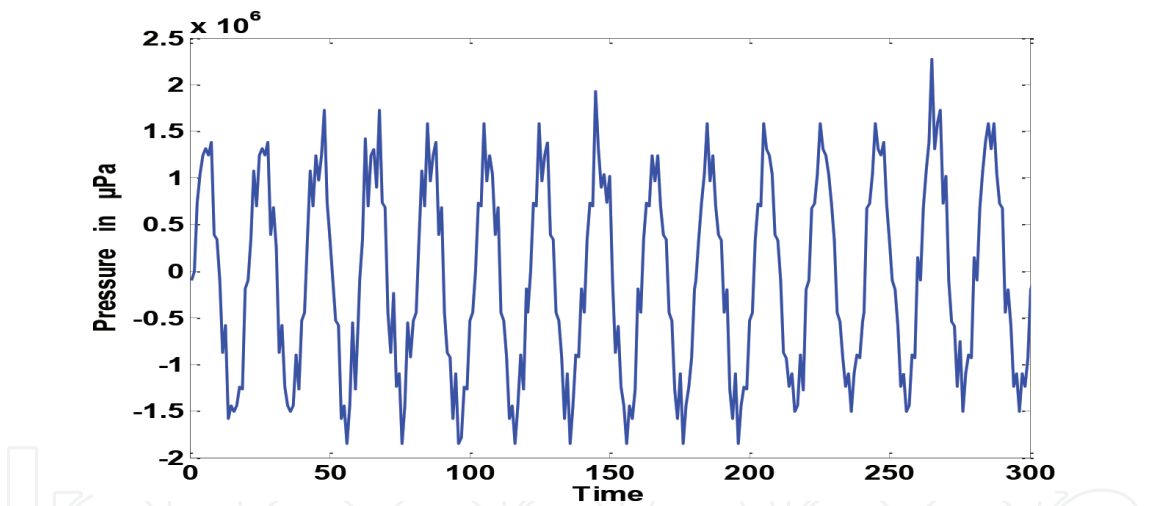**Figure 13.** Noise signal.

Figure 14. Noisy signal.

domain thresholding algorithm, the proposed frequency domain thresholding algorithm fetches better results.

In the existing algorithm, the signal amplitude is considered to be 20 mv, and in the proposed algorithm, the signal amplitude is considered to be 5 mv. In the existing algorithm, the denoised signal amplitude is much lesser than the actual input signal, and also, the output does not exactly resemble the input signal. But in the proposed algorithm, the amplitude of denoised signal (at 90% threshold) is same as that of the input signal, which is shown in **Figure 18**. Also, here, the denoised signal resemblance of the input signal is good. In all the results, the signal amplitude is represented in micropascal, i.e., volt is converted into
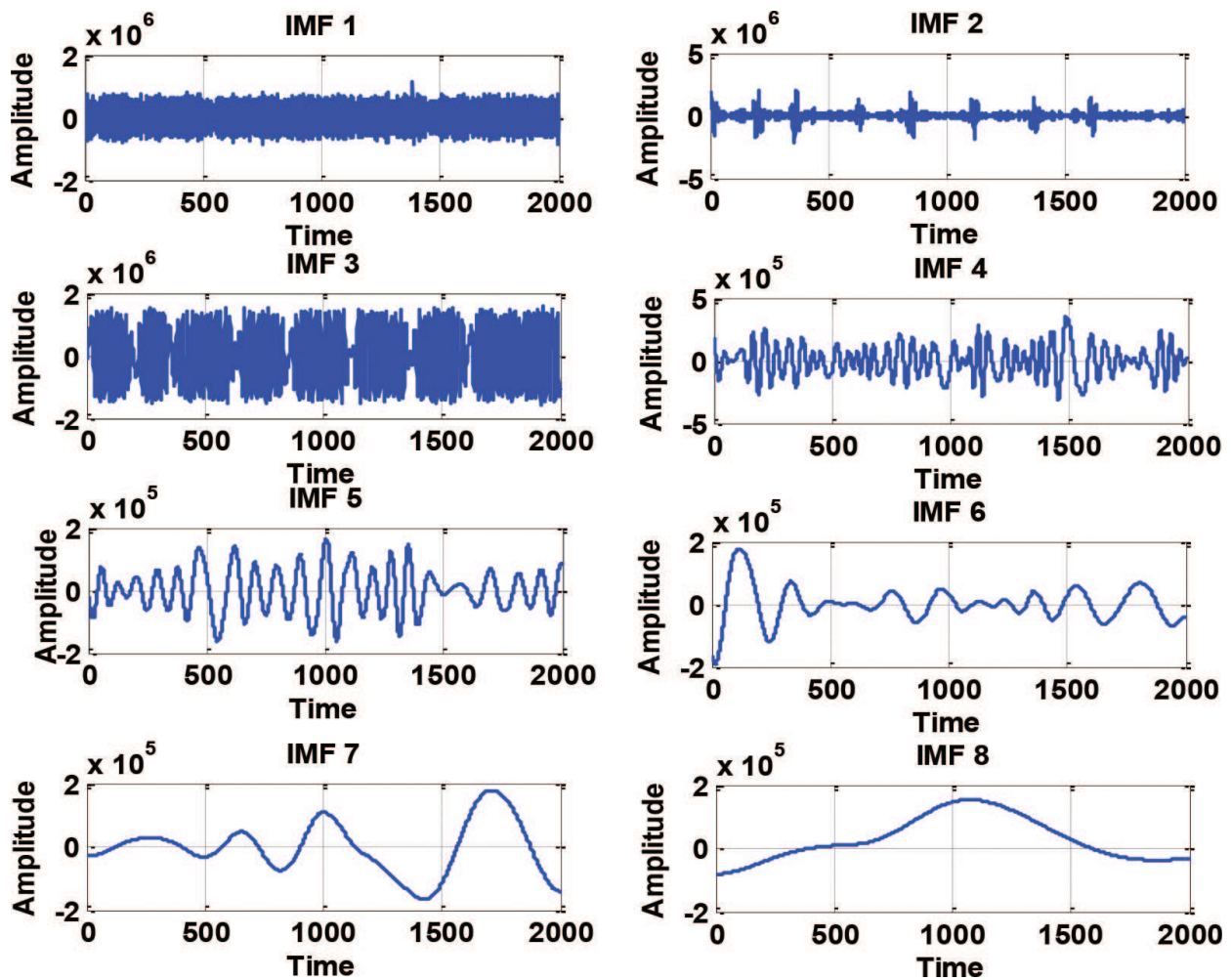
Figure 15. IMFs of noisy signal.

micropascal-based on the sensitivity of the microphone. This result again reveals the reliability of the algorithm for different wind noise signals.

This algorithm is tested even for chirp input signal. **Figure 19** shows the chirp input signal, noise, and noisy output signal of the proposed algorithm. **Figure 20** presents the IMFs of the noisy signal, which is produced by adding the chirp input with the wind noise signal (5.06 m/s). This IMF is different from one, which is shown in **Figure 15**. The comparison between the input and denoised signal is presented in **Figure 21**. From this figure, it is clear that the proposed algorithm performs well even for chirp input signal.

In order to validate the algorithm, the mean square error (MSE) is calculated using the following equation.

$$\text{Mean square error (MSE)} = \frac{1}{N} \sum_{n=1}^{N} (Z(n) - \hat{Z}(n))^2 \tag{9}$$

where N is the length of data, $Z(n)$ is the actual input signal, and $\hat{Z}(n)$ is the denoised signal.
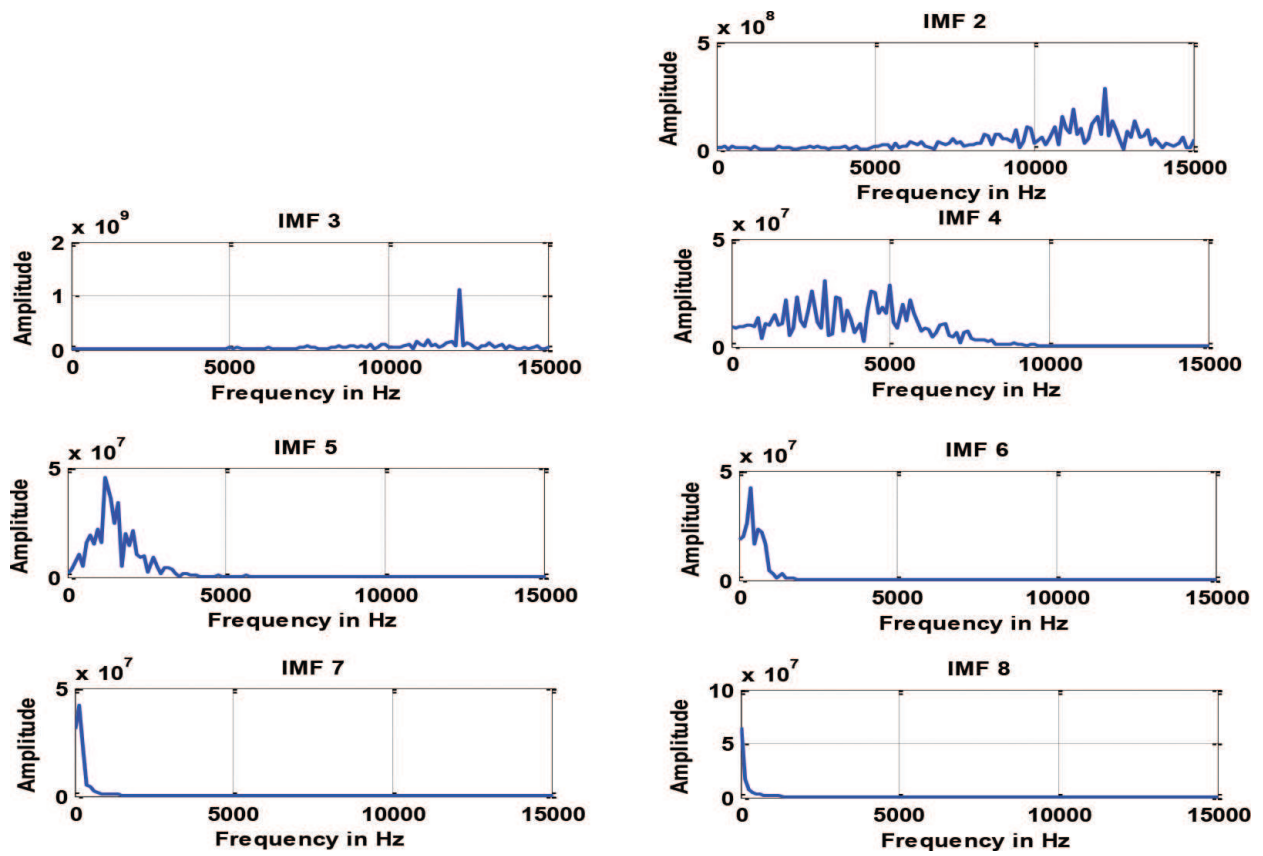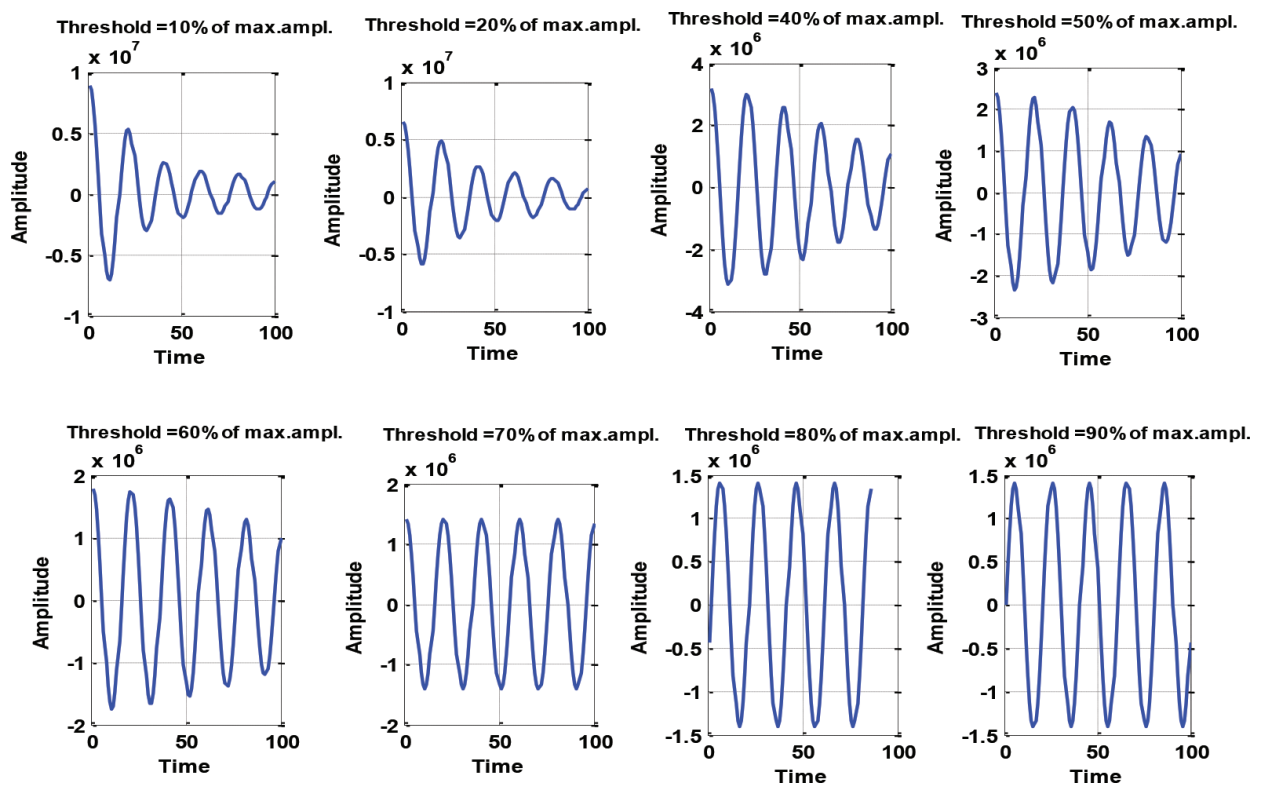
Figure 16. FFT of IMFs.

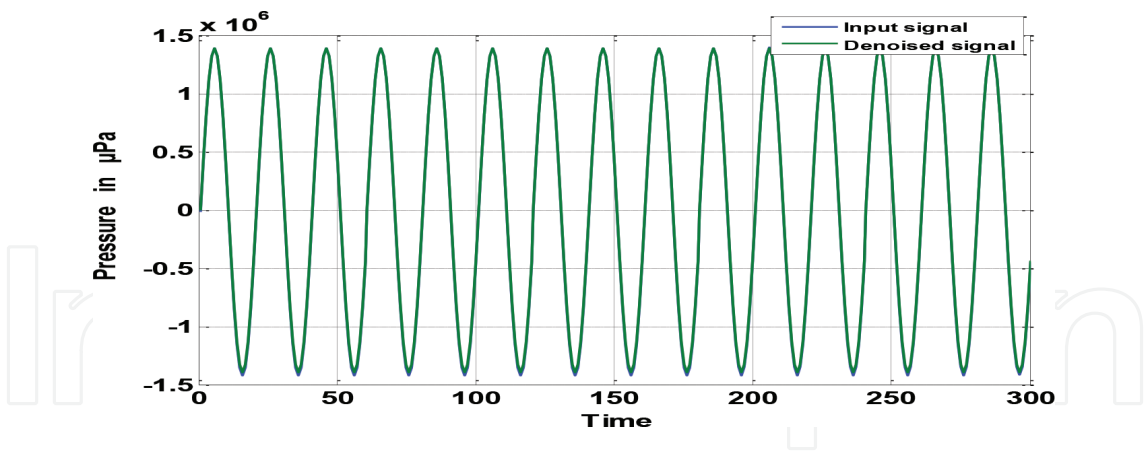**Figure 17.** Denoised signal at different threshold.

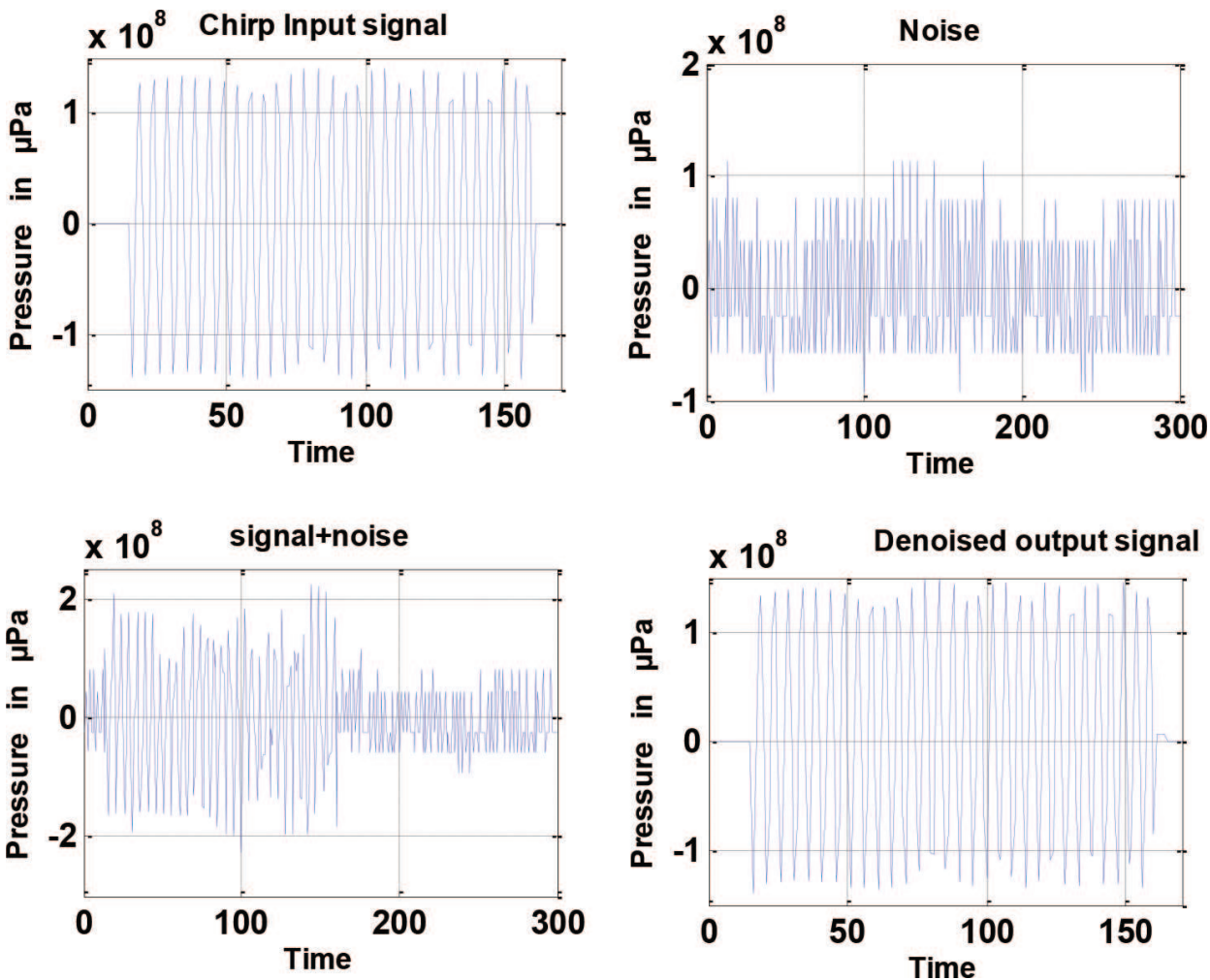**Figure 18.** Input and denoised output signal comparison graph (EMD method).

Figure 19. Output of proposed algorithm for chirp input signal.

In order to compare the performance of different algorithm, the RMSE value is calculated for different algorithm and various wind speed. It is presented in **Tables 2–5**. The RMSE value of the proposed algorithm is given in **Table 5** for different threshold values. From the table, it is
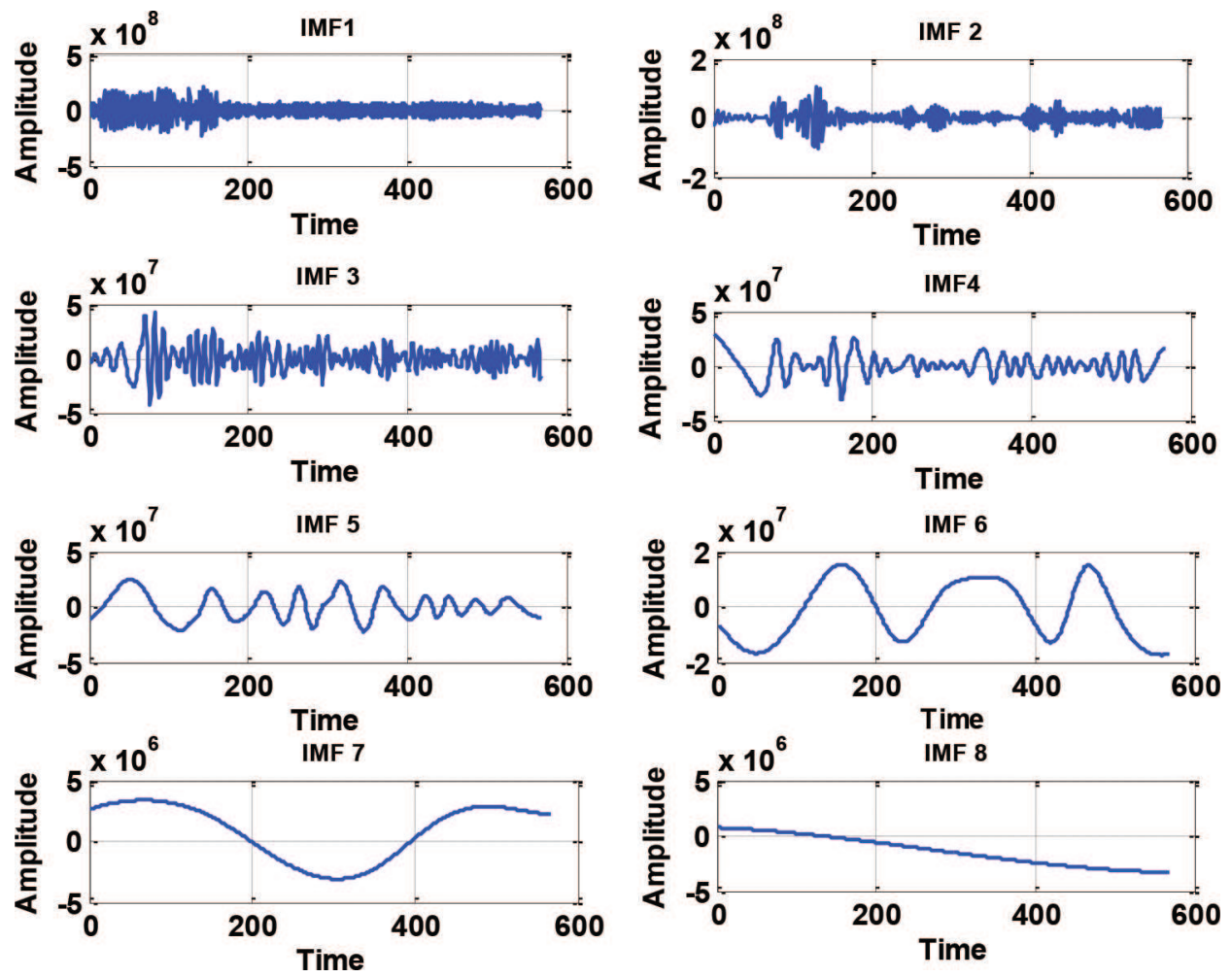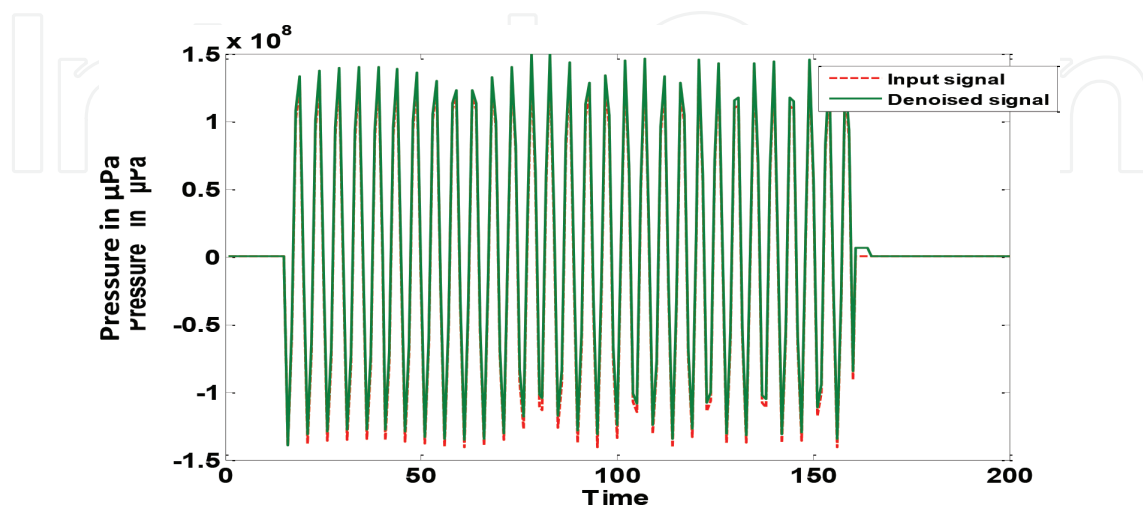
Figure 20. IMFs for chirp input signal.

Figure 21. Input and denoised output signal comparison graph (for chirp input).

RMSE value at 2.61 m/s	RMSE value at 3.52	RMSE value at 5.06	RMSE value at 6.93 m/s
0.0029	0.00061	0.00088	0.0010

Table 2. RMSE in wavelet (signal amplitude = 0.01 mv).

RMSE value at 2.61 m/s	RMSE value at 3.52	RMSE value at 5.06	RMSE value at 6.93 m/s
0.0118	0.00141	0.0071	0.00821

Table 3. RMSE in time domain EMD (signal amplitude = 0.01 mv).

RMSE value at 2.61 m/s	RMSE value at 3.52	RMSE value at 5.06	RMSE value at 6.93 m/s
0.00060	0.00044	0.00063	0.00079

Table 4. RMSE in time domain using EEMD (signal amplitude = 0.01 mv).

Threshold value in %	RMSE value at 2.61 m/s	RMSE value at 3.52 m/s	RMSE value at 5.06 m/s	RMSE value at 6.93 m/s
20	0.002991	0.004051	0.002968	0.005838
40	0.000051	0.002512	0.002343	0.002191
50	0.000051	0.001906	0.001448	0.000780
60	0.000051	0.000919	0.001062	0.000780
70	0.000051	0.000045	0.001062	0.000064
80	0.000051	0.000045	0.000055	0.000064
90	0.0001675	0.000045	0.000055	0.000064

Table 5. RMSE in frequency domain EMD (signal amplitude = 0.005 mv).

clear that the RMSE value decreases as the threshold value increases, and there is no change in the RMSE value for the threshold above 80%.

7. Summary

The proposed frequency domain-based EMD algorithm outperforms all other existing algorithms. **Table 6** shows the RMSE, which is calculated for the wind noise signal of 5.06 m/s,

RMSE value for different denoising methods for wind noise signal of 5.06 m/s			
Wavelet	EMD time domain algorithm	EEMD time domain algorithm	Proposed frequency domain based on EMD
0.00088	0.0071	0.00063	0.000055

Table 6. RMSE value comparison for different denoising algorithm.

value for different denoising methods. The RMSE value in the proposed frequency domain algorithm is less compared to the other existing algorithms. The RMSE value is calculated for various wind speeds, and it consistently performs well in the proposed frequency domain approach. It is concluded that the proposed algorithm produces better results compared to the existing algorithm. "This algorithm has been developed and duly got tested for the wind noise and as such could be further extended to include the other constituents of the ambient noise, as well."

Acknowledgements

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