ESTIMATION OF NOISE MODEL AND DENOISING OF WIND DRIVEN AMBIENT NOISE IN SHALLOW WATER USING THE LMS ALGORITHM

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Signal transmission in ocean using water as a channel is a challenging process due to the effect of attenuation, spreading, reverberation, absorption etc., apart from the contribution of acoustic signals due to ambient noises. Ambient noises in sea are of two types namely manmade (shipping, aircraft over the sea, motor on boat, etc) and natural (rain, wind, marine fishes, seismic, etc). The ambient noises contribute more effect on reducing the quality of acoustic signal. In this paper we concentrate on denoising the effect due to wind on underwater acoustic signal using the LMS algorithm. The wind speed of the collected data ranges from 2.11 m/s to 6.57 m/s. The analysis is carried out for acoustic frequencies ranging from 100 Hz to 8 kHz. It is found that a linear relationship between noise spectrum and wind speed exists over the entire frequency range. The results of the empirical data are compared with the results obtained with the aid of the noise model developed. An adaptive model exploiting the Least Mean Square (LMS) algorithm to denoise wind driven ambient noise in shallow water has been proposed. The observation shows that the Signal to Noise Ratio (SNR) is enhanced two fold and the Mean Square Error (MSE) decreases exponentially with the aid of the LMS adaptive algorithm.

INTRODUCTION

Signal transmission underwater is a challenging task. Generally, low frequency acoustic signals are used for transmission underwater as electromagnetic signals are highly attenuated. Any modulated signal transmitted in water, undergoes various losses due to attenuation, reverberation, spreading and internal waves etc apart from ambient noise due to natural and manmade sources.

The residual noise background in the absence of individual identifiable sources may be considered as the natural noise environment for hydrophone sensors. It comprises a number of components that contribute to the Noise Level (NL) in varying degrees depending on the location of measurements [1]. The sources contributing noise include geological disturbances, non-linear wave interaction, turbulent wind stress on the sea surface, shipping, distant storms, seismic prospecting, marine animals, breaking waves, spray, rain, hail impacts and turbulence [2]. The ambient noise level spectrum is summarized in [3]. Furthermore Knudsen spectra [4] show the strong dependence of spectral power level with wind speed and sea states.

Noise measurements made in the Northern Hemisphere show self-similar wind dependent noise spectra between 100 Hz and 10 kHz [3,4], but no dependency on wind speed below 100 Hz, with noise at these lower frequencies being attributable to distant shipping. Measurements made at 40 different locations in the Southern Hemisphere showed that in regions of low shipping density the effect of wind speed is dominant in the frequency band of 22 Hz to 5 kHz [5].

The ambient noise masks the signals from underwater acoustic instruments, so the detection and cancellation of background noise is essential to enhance the SNR of acoustic based underwater instruments. This can be done by a proper adaptive filter implementation [6,7]. In this paper, an LMS based adaptive algorithm to denoise the received signal is implemented.

DATA COLLECTION AND NOISE MODEL

Data collection

The data for analysis were collected using two calibrated omni-directional reson TC 4032 hydrophones mounted in a vertical array at 5 m and 15 m depths where the depth of the sea is 25.7 m. The hydrophones have a receiving sensitivity of -170 dB over a frequency range between 100 Hz and 100 kHz. The data were acquired at a rate of 50 kHz and 500 kHz, filtered and digitised with a portable data acquisition system with 12-bit resolution. The wind speed was simultaneously measured. The measurement consists of 7 sets of data. The wind speeds of collected data range from 2.11 m/s to 6.57 m/s.

Noise model

Theoretically, the relationship between the noise levels is assumed to be proportional to the logarithm of the wind speed and this can be expressed as

$$NL = B + 20n \log(U) \tag{1}$$

where NL and U represent noise level and wind speed respectively.

The constants B and n were determined by comparing the experimental data to the model at different frequencies, where n is obtained from a 1/20 slope of regression line and the ordinate intercept of the line gives B for each empirical fit. The spectral analysis was carried out in MATLAB using the Welch method of averaging periodogram. The frequency of interest for this study ranges from 500 Hz to 8 kHz, it is inferred that wind speed and the noise level is best correlated over the frequency analyzed.

DENOISING USING LMS ALGORITHM

From the PSD of the data collected, it is noted that the noise due to wind is dominating over a range of 500 Hz to 5 kHz and extends up to 6 kHz. The effect is high at lower frequencies. Above 6 kHz, the effect due to wind is low and remains constant. An adaptive filter with the LMS algorithm is developed to denoise the effect of wind on the signal. An adaptive filter is a self-designing system that relies for its operation on a recursive algorithm which makes it possible for the filter to perform satisfactorily in an environment where knowledge of the relevant statistics is not required. The algorithm starts from some predetermined set of initial conditions, representing whatever is known about the environment. In a non-stationary environment, the algorithm offers a tracking capability in which it can track time variations in the statistics of the input data provided that the variations are sufficiently slow.

Theoretical model

The most commonly used structure in implementing adaptive filters is the transversal structure shown in Fig. 1. The transversal adaptive filter can be split into two main parts, the filter part and the update part. The function of the filter part is to calculate the filter output $y(n)$, whereas the function of the update part is to adjust the set of N filter co-efficient (w_i), i = 0, 1, …, N-1 (tap weights) so that the output $y(n)$ reaches as close as possible to a desired signal $d(n)$.

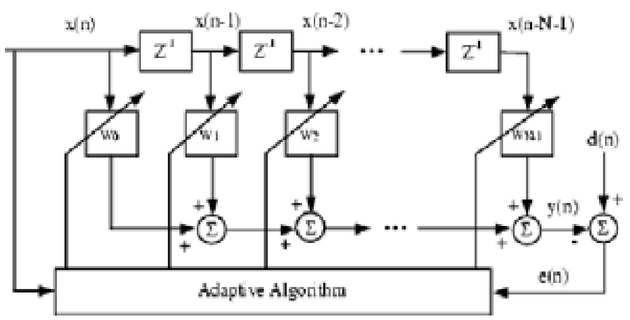


Figure 1. Structure of adaptive filter

In this paper, the filter weights are updated using the LMS algorithm which can remove the noise due to wind that gets added in the channel with the transmitted signal. Initially a test signal (training signal similar to desired signal/reference signal) is fed as input signal to the weight update of the adaptive filter for the update operation. The input to the adaptive filter will be two signals, one is noisy signal and the other is output of weight update in order to tune the filter. When the adaptive weights are tuned according to the signal fed initially, the inputs to the adaptive filter will be from the adaptive portion (update) tuned earlier and the noisy signal. The adaptive filter estimates the error due to the noisy signal. This estimated signal is compared with the reference signal and the difference between these two gives the error signal. The error signal is the exact mismatch between the reference signal and the adaptive filter estimated output. This error signal is passed to the weight update where the weight updates according to the error signal and this updated signal is now compared with the next sample of input noisy signal in the filter. This process is repeated till the error signal tends to zero which means that the weight update is perfectly tuned to the desired signal and there by the estimated output of the adaptive filter is the transmitted signal. The weight update is carried out using the LMS algorithm and the effects of non-stationary of the noise signals are eliminated.

Mathematical model

The input signal $x(n)$ to the adaptive filter at the receiver side is the sum of the desired signal $d(n)$ and interfering noise $v(n)$ in the channel

$$x(n) = d(n) + v(n) \tag{2}$$

where $x(n)$ is the input signal to the adaptive filter, $d(n)$ is the desired signal and $v(n)$ is the interfering noise. The adaptive variable filter has a Finite Impulse Response (FIR) structure. For FIR structures the impulse response is equal to the filter coefficients. The coefficients for a filter of order p is defined as

$$w_n = [w_n(0), w_n(1),..., w_n(p)]^T \tag{3}$$

The error signal $e(n)$ or cost function is the difference between the desired signal $d(n)$ and the estimated signal $y(n)$.

$$e(n) = d(n) - y(n) \tag{4}$$

The variable filter estimates the desired signal by convolving the input signal with the impulse response. In vector notation this is expressed as

$$y(n) = w_n * x(n) \tag{5}$$

where

$$x(n) = [x(n), x(n-1),..., x(n-p)]^T \tag{6}$$

is the input signal vector. Moreover, the variable filter updates the filter coefficients at every time instant

$$w_{n+1} = w_n + \Delta w_n \tag{7}$$

and the adaptive algorithm generates this correction factor based on the input and error signals.

The LMS algorithm is a linear adaptive filtering algorithm, which, in general consists of two basic processes: a filtering process and an adaptive process. The LMS algorithm is built on the transversal filter concept. This component is responsible for performing the filtering process using a mechanism for performing the adaptive control process on the tap weights of the transversal filter. The LMS algorithm can be written in the form of three basic relations as

1. Adaptive filter output: $y(n) = \hat{w}^H(n)x(n)$
2. Estimation error or error signal is $e(n) = d(n) - y(n)$
3. Tap-weight adaptation is given by $\hat{w}(n + 1) = \hat{w}(n) + \mu x(n)e(n)$

where $e(n)$ is the error signal, $x(n)$ is the input signal vector, μ is the step-size parameter, $\hat{w}(n)$ is the tap-weight vector, $d(n)$ is the desired response

RESULTS AND DISCUSSION

Estimation of power spectrum of collected data

Eight sets of data with various wind speeds of 2.11, 3.32, 4.52, 5.92, 6.03, 6.06, 6.16, 6.57m/s are used for analysis. The power spectral densities using the Bartlett and Welch methods for all wind speeds over a range of 25 kHz are shown in Figs. 2(a) and 2(b), respectively. The parameters considered for estimation are shown in Table 1.

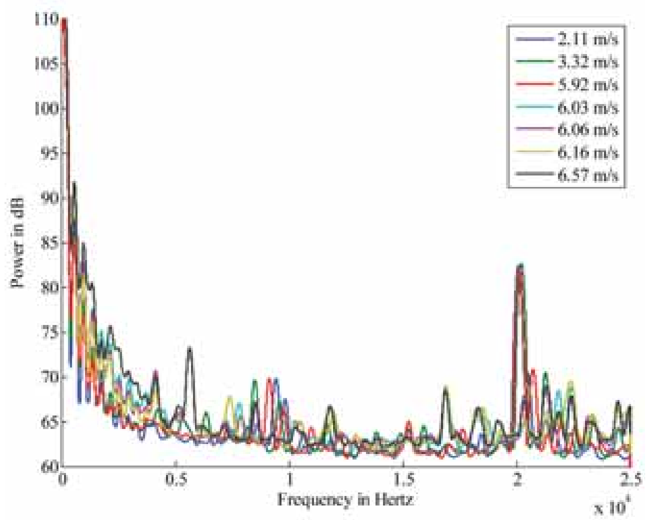


Figure 2(a). Power spectral density for various wind speeds using the Bartlett Method

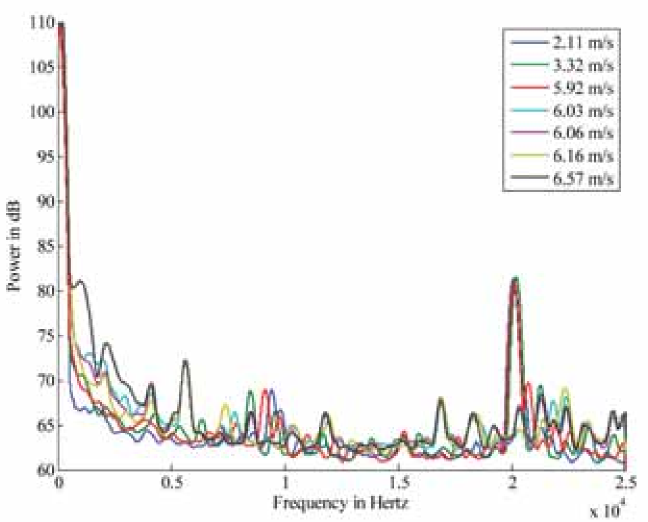


Figure 2(b). Power spectral density for various wind speeds using the Welch Method

Table 1. Parameters considered for estimation of power spectral density

Parameters	Value
Sampling frequency	50 kHz
Window type	Hanning
N-point FFT	65536
FFT window size	1024
Overlapping	50%
Hydrophone sensitivity	-170dB

For a wind speed of 2.11 m/s, the effect of wind is high at lower frequencies and it is found that the Noise Sound Level (NSL) is maximum around 76 dB for 500 Hz and decreases to 65 dB for 5 kHz. Above 5 kHz, the NSL is found to be constant. The estimation is carried out for all wind speeds mentioned above. It is inferred that as the wind speed increases the noise level also increases and the spectral level decreases with increase in frequencies. It can be noted that at 500 Hz the NSL is 76 dB for a wind speed of 2.11 m/s and it is 85 dB for a higher wind speed of 6.57 m/s. It is also evident at various frequencies that the wind speed increases the noise level. It is observed that the NSL is 73, 69, 67, 66, 65.5 and 65 dB at 500 Hz, 1 kHz, 2 kHz, 3 kHz, 4 kHz and 5 kHz respectively for a wind speed of 2.11 m/s. Similarly, the NSL is 82, 76, 73, 72.7, 68 and 66 dB for a wind speed of 6.57 m/s. The noise level of other wind speeds mentioned lies between these two levels. The analysis has been carried out to study the wind dependent ambient noise spectrum level in the frequency range between 500 Hz to 8 kHz.

Noise model analysis

The noise model has been developed and the results are presented in Fig. 3. It is noticed that there is a steep increase in the slope of the noise level as wind speed increases. It is found that above 5 kHz the NSL does not increase and remains constant, which leads to the conclusion that the effect of wind is dominating at lower frequencies.

Table 2 shows the values of *B* and *n* obtained from regression plots. The value of slope is maximun at 500 Hz and decreases as frequency increases. The values of *n* and *B* obtained from the emperical fitting are used for validation with measured noise level.

Figure 4 shows the comparison of predicted noise levels in dB using the noise model and measured noise levels for wind speed of 2.11 m/s, 3.32 m/s, 5.92 m/s and 6.57 m/s. It is observed that the predicted noise levels are as good as with the measured noise levels. As the wind speed increases the predicted noise model deviates slightly from the measured noise level.

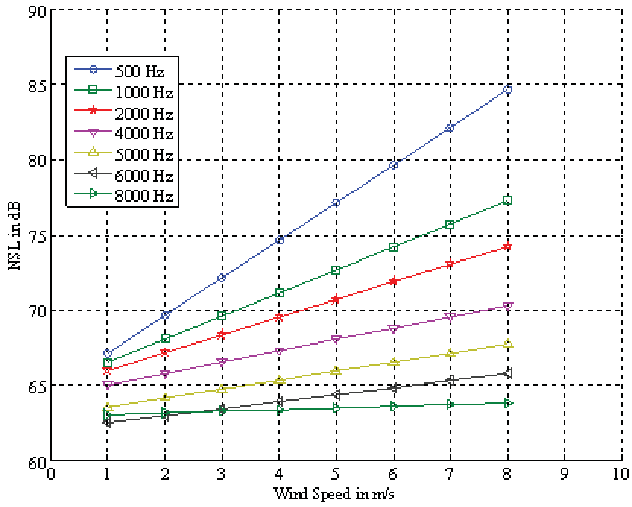
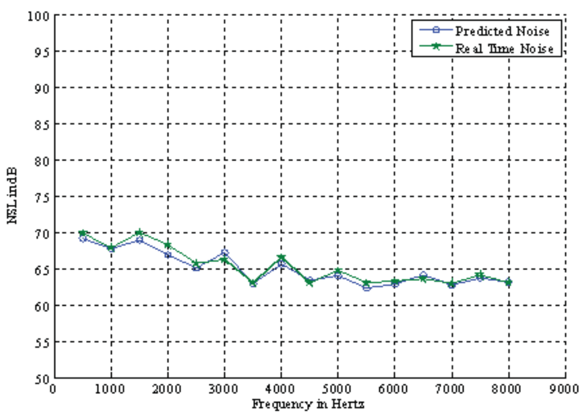


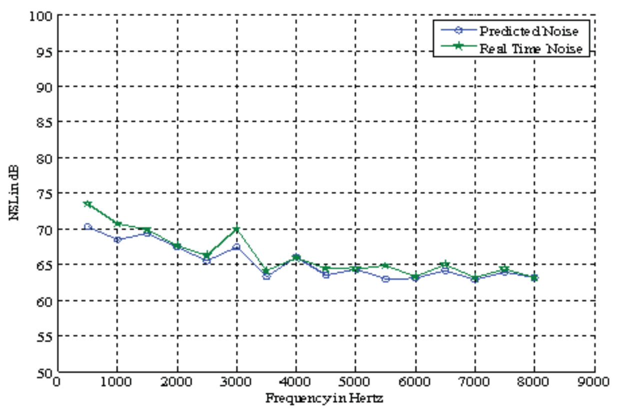
Figure 3. Effect of NSL at different wind speeds for different frequencies

Table 2. Values of *B* and *n* from regression plots

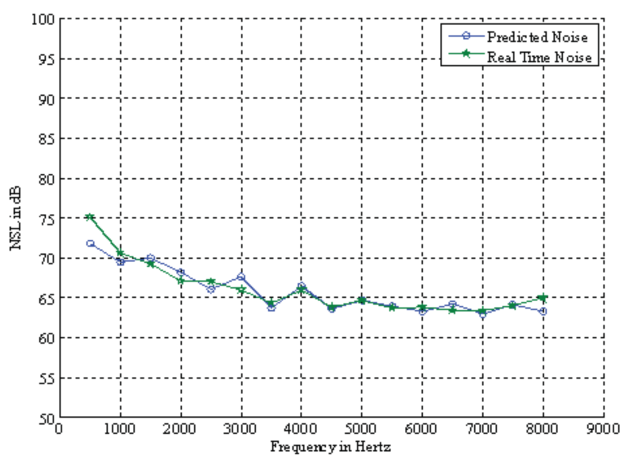
Frequency (Hz)	*B*	*n*
500	67.14	0.13
1000	66.57	0.08
1500	68.16	0.05
2000	65.98	0.06
2500	64.28	0.05
3000	66.93	0.02
3500	62.29	0.04
4000	65.04	0.04
4500	63.19	0.01
5000	63.56	0.03
5500	61.04	0.08
6000	62.5	0.02
6500	64.06	0.003
7000	62.56	0.01
7500	63.41	0.02
8000	63.04	0.006



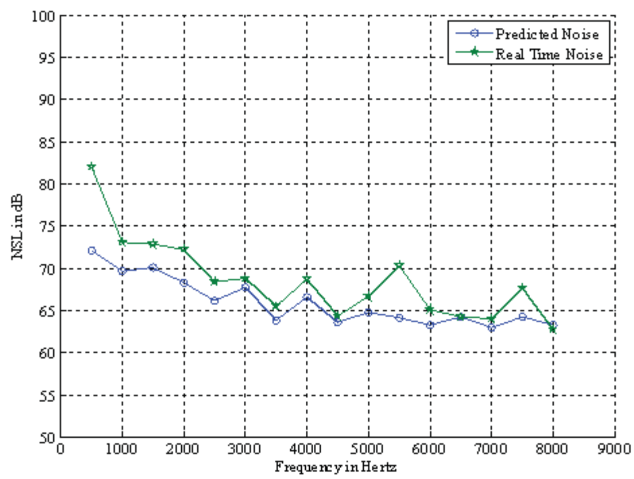
For wind speed of 2.11 m/s



For wind speed of 3.32 m/s



For wind speed of 6.92 m/s



For wind speed of 6.57 m/s

Figure 4. Comparison of predicted and measured noise levels for various wind speeds

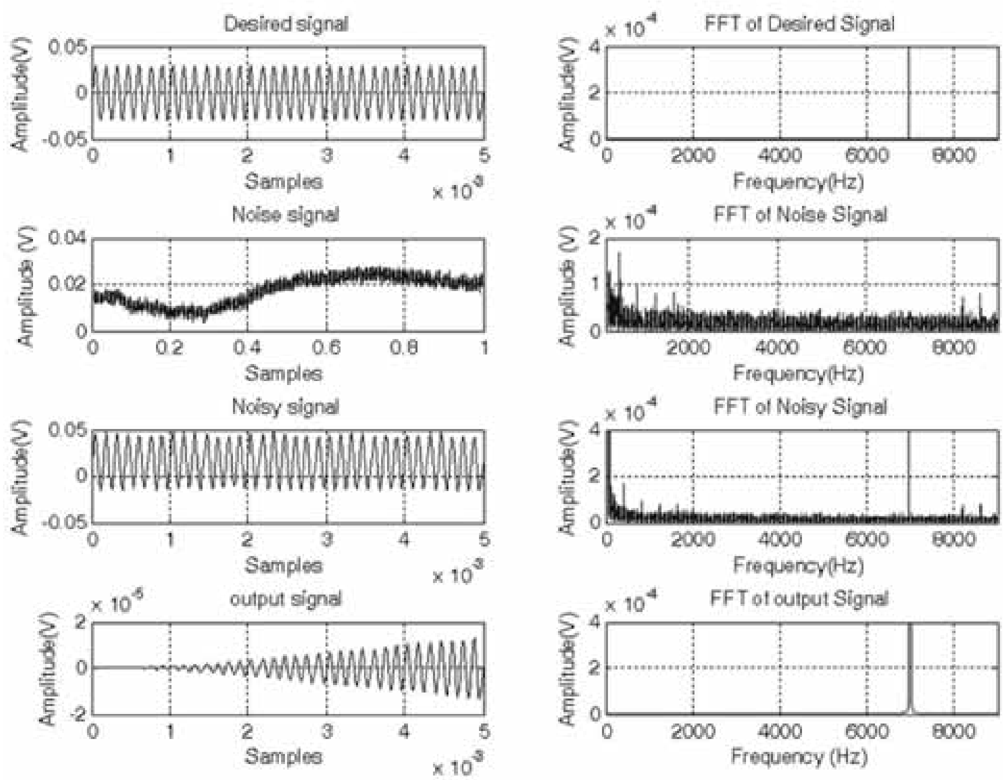


Figure 5(a). Time and FFT representation of desired signal, noise data due to wind, noisy signal 2 (desired signal plus noise) and reconstructed signal by LMS algorithm for a lower wind speed of 2.11 m/s

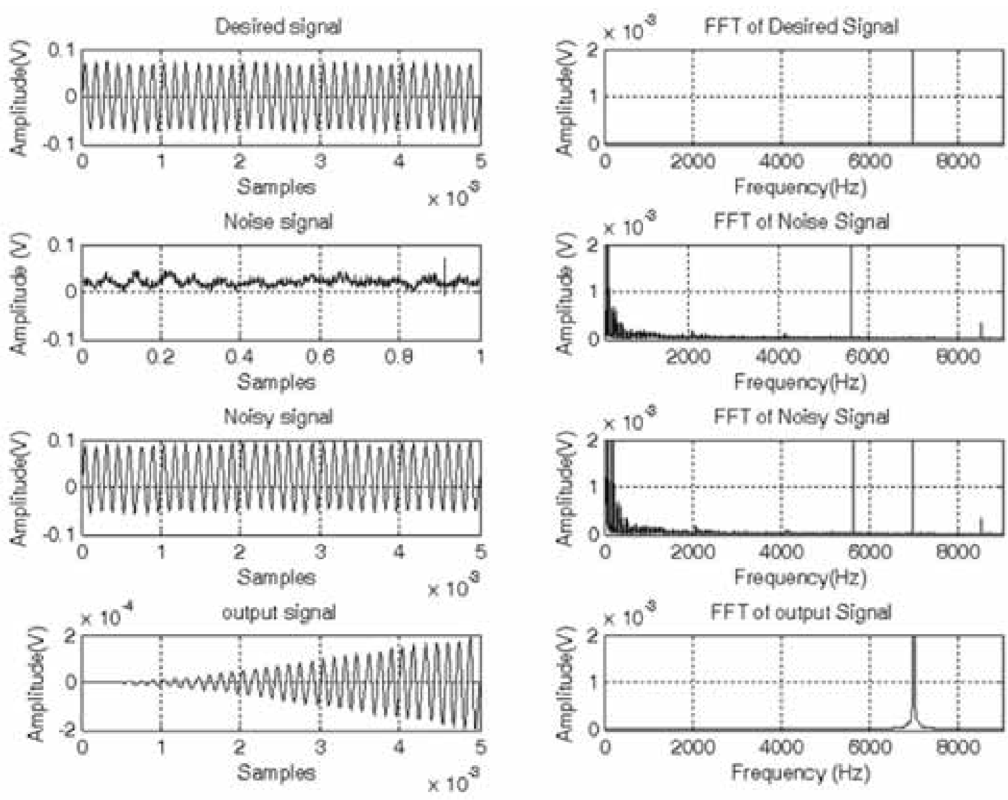


Figure 5(b). Time and FFT representation of desired signal, noise data due to wind, noisy signal 3 (desired signal plus noise) and reconstructed signal by LMS algorithm for a high wind speed of 6.16 m/s

Adaptive filter output

The data collected at 5 m depth for a wind speed of 2.11 m/s is considered as a noise signal. A desired signal $d(n)$ of 7 kHz is passed through the underwater channel where interference signal $v(n)$ with a wind speed of 2.11 m/s gets combined and forms a noisy signal $x(n)$. It can be noted that the amplitude of $d(n)$ is highly affected by $v(n)$. The $x(n)$ is the input to the adaptive filter which uses the LMS algorithm. The adaptive filter adapts to the $d(n)$ by changing the weight update equation $w(n+1)$ from the error signal obtained by comparing $x(n)$ and $d(n)$. The noise due to wind effect gets cancelled and thereby the reconstruction of $d(n)$ of 7 kHz is effectively measured. The same process is carried out for all wind speeds. The time domain and FFT of the $d(n)$, $v(n)$, $x(n)$ and reconstructed signal is obtained by using an LMS based adaptive filter for a minimum wind speed of 2.11 m/s and a highest wind speed of 6.59 m/s are shown in Fig. 5(a) and 5(b). The SNR and MSE of the adaptive filter using LMS algorithm is calculated. It is found that the output SNR of the filter is doubled when compared to the input SNR. The MSE is also reduced. The performance of the LMS based adaptive algorithm is determined for all wind speeds mentioned above and the results are represented in the form of spectrograms.

Spectrogram representation

Here, the spectrogram is a three dimensional representation based on the LMS adaptive algorithm in denoising the wind driven ambient noise. In spectrogram figures, the y axis represents the data collection time-period in seconds and the x axis represents the frequency (Hz) available at the corresponding time. The intensity of the signal available for the total time-period of the experiment carried out is represented by distinct grey patches. Figure 6(a) shows the spectrogram for wind speed of 2.11m/s with $d(n)$ of 7 kHz, $v(n)$ over a range of 100 Hz to 10 kHz, $x(n)$ and the reconstructed signal over the same ranges. The presence of noise signals are represented in dark patches whose intensity varies from 60 to 80 dB as shown in PSD plot. The hydrophone used to collect the data has a capacity to receive signals ranging from 100 Hz to 10 kHz. The high intensity at 0 to 100 Hz in the noise and noisy signals are due to turbulence. This turbulence generated noise signal is also eliminated by the filter.

Similarly the spectrogram is evaluated for all wind speeds ranging from 3.32 to 6.57 m/s and the results on the performance of the LMS adaptive algorithm are shown in Fig. 6(a) to 6(h). In Fig. 6(g) and 6(h), the noise due to marine species at 6 kHz is clearly visible. It is inferred that the adaptive LMS algorithm developed also eliminates the effect due to marine species. Hence it is found that the LMS algorithm eliminates all undesired signals in the range considered and reconstructs the required desired signal against all sources of ambient noise

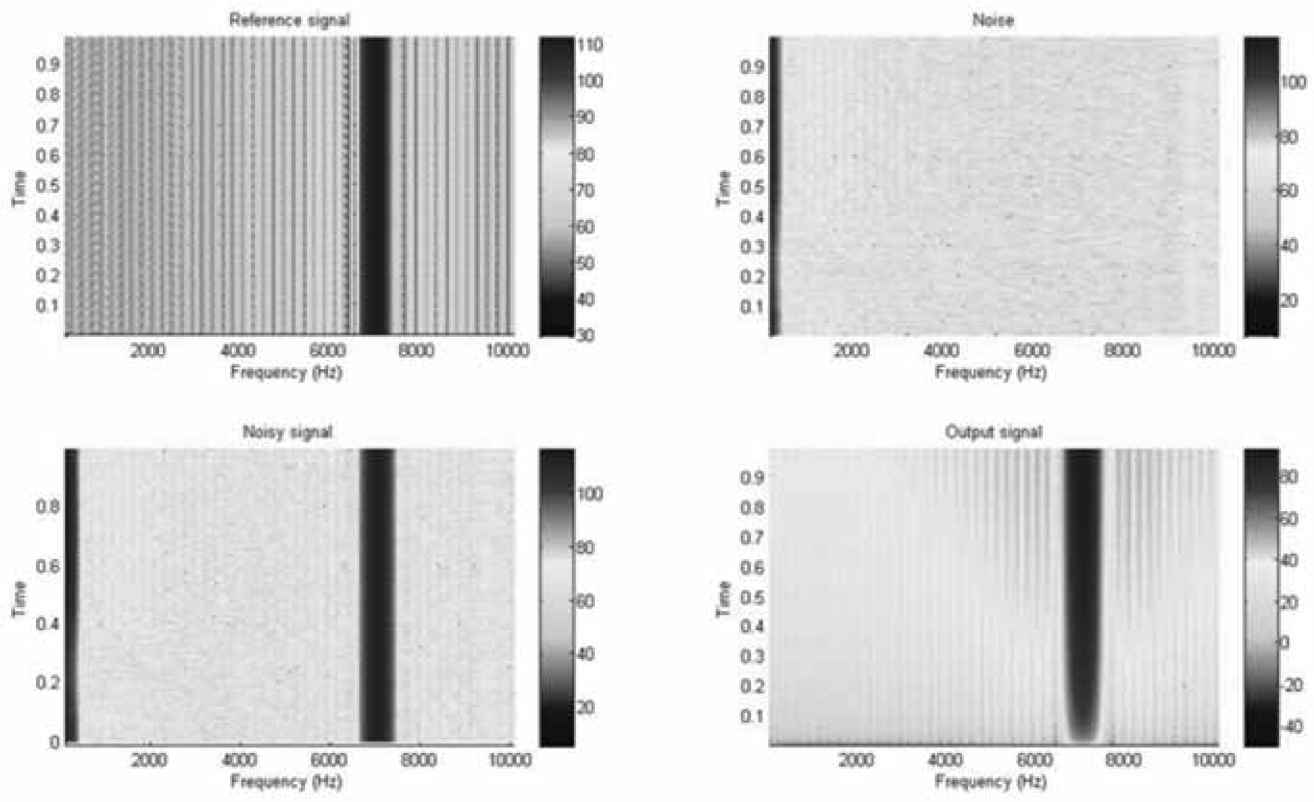


Figure 6(a). Denoising output of wind driven ambient noise by LMS algorithm (2.11 m/s)

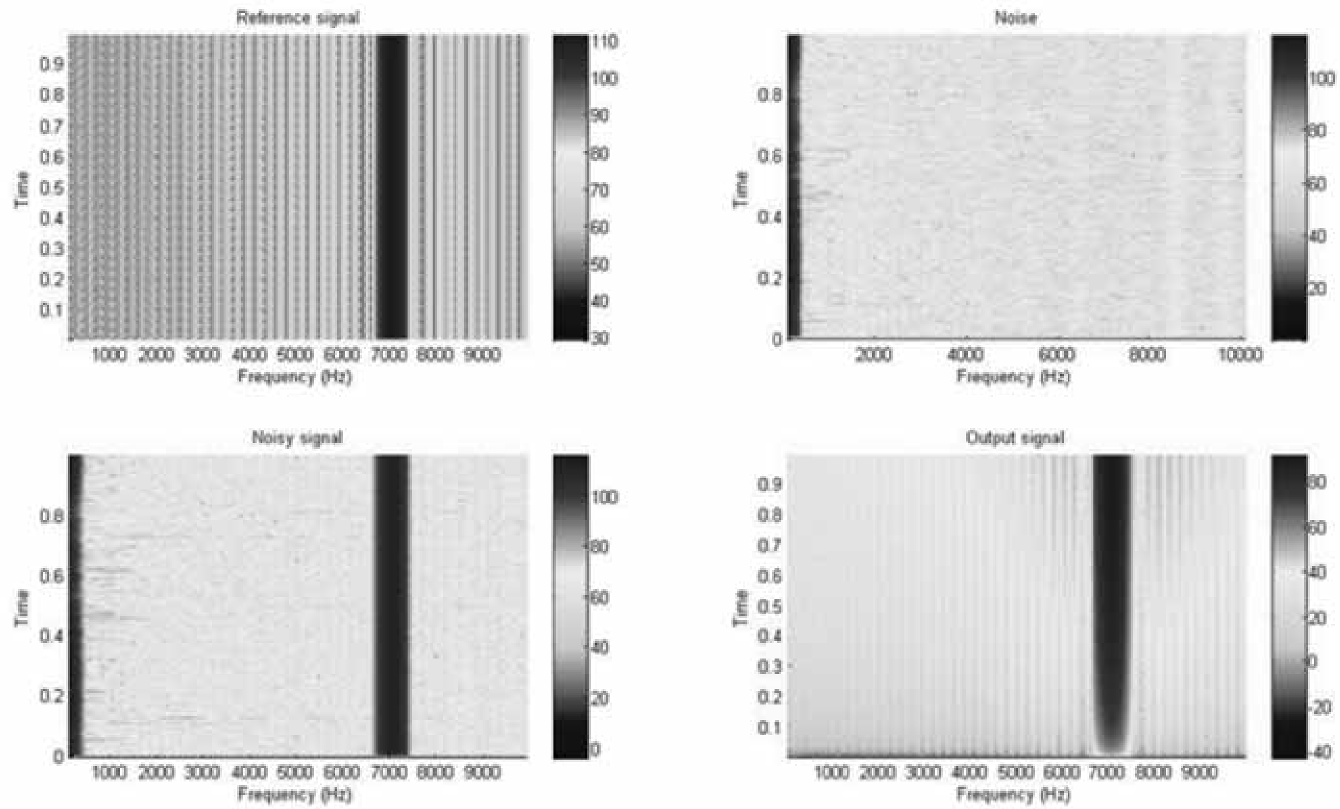


Figure 6(b). Denoising output of wind driven ambient noise by LMS algorithm (3.32 m/s)

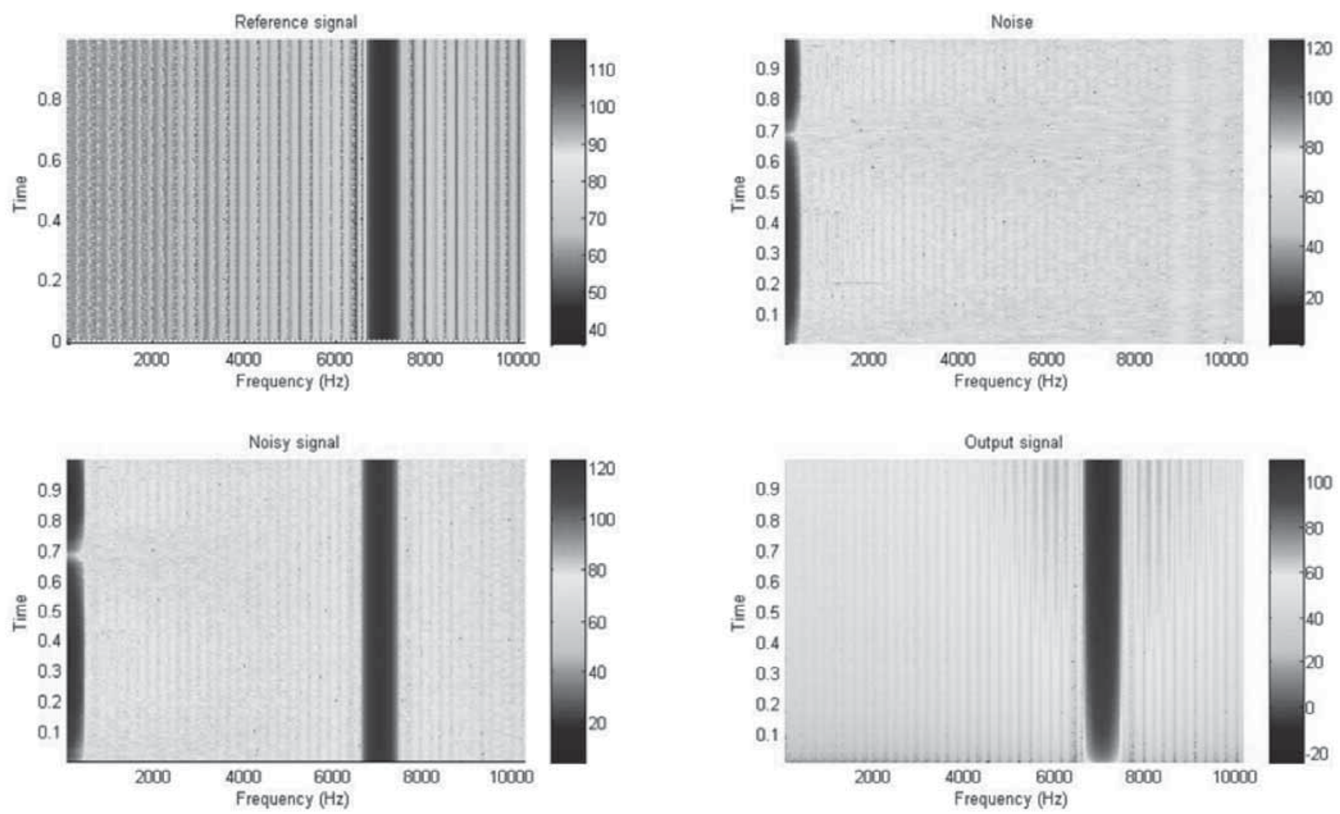


Figure 6(c). Denoising output of wind driven ambient noise by LMS algorithm (4.52 m/s)

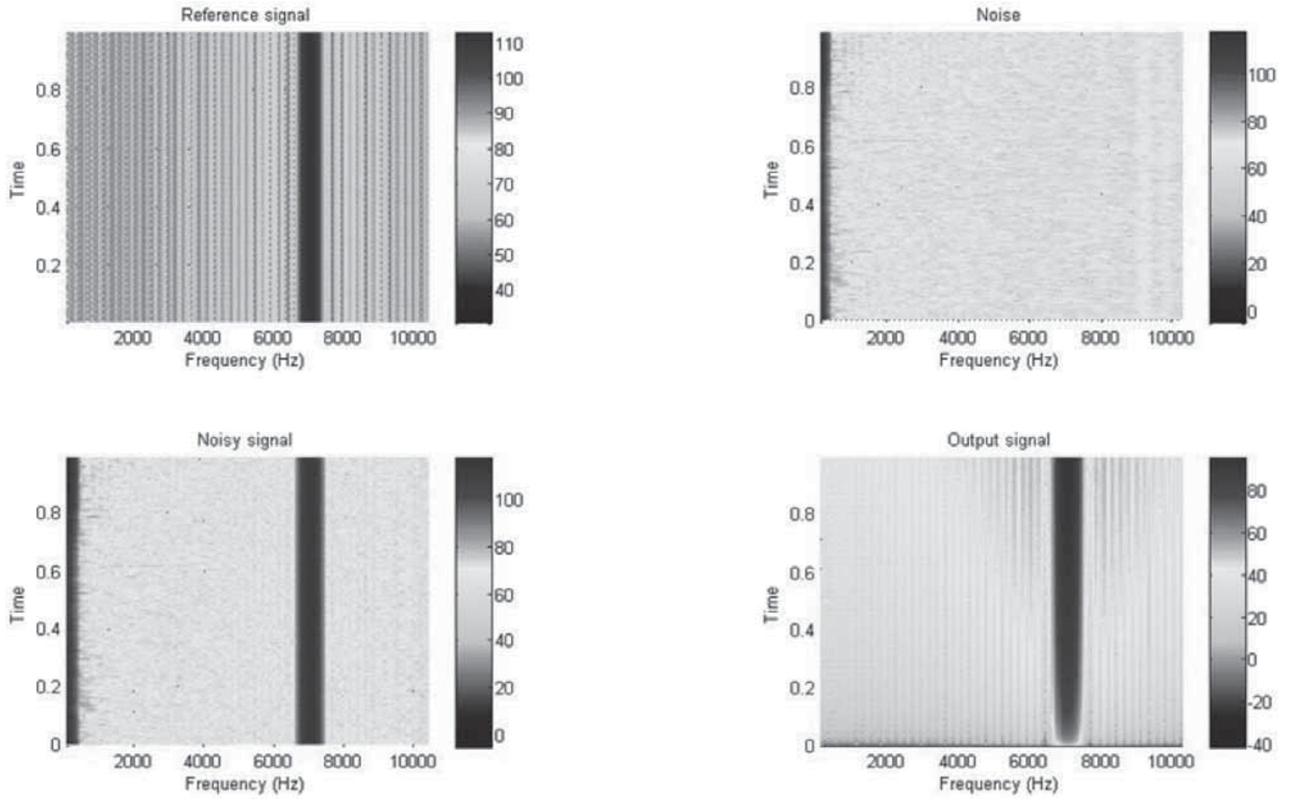


Figure 6(d). Denoising output of wind driven ambient noise by LMS algorithm (5.92 m/s)

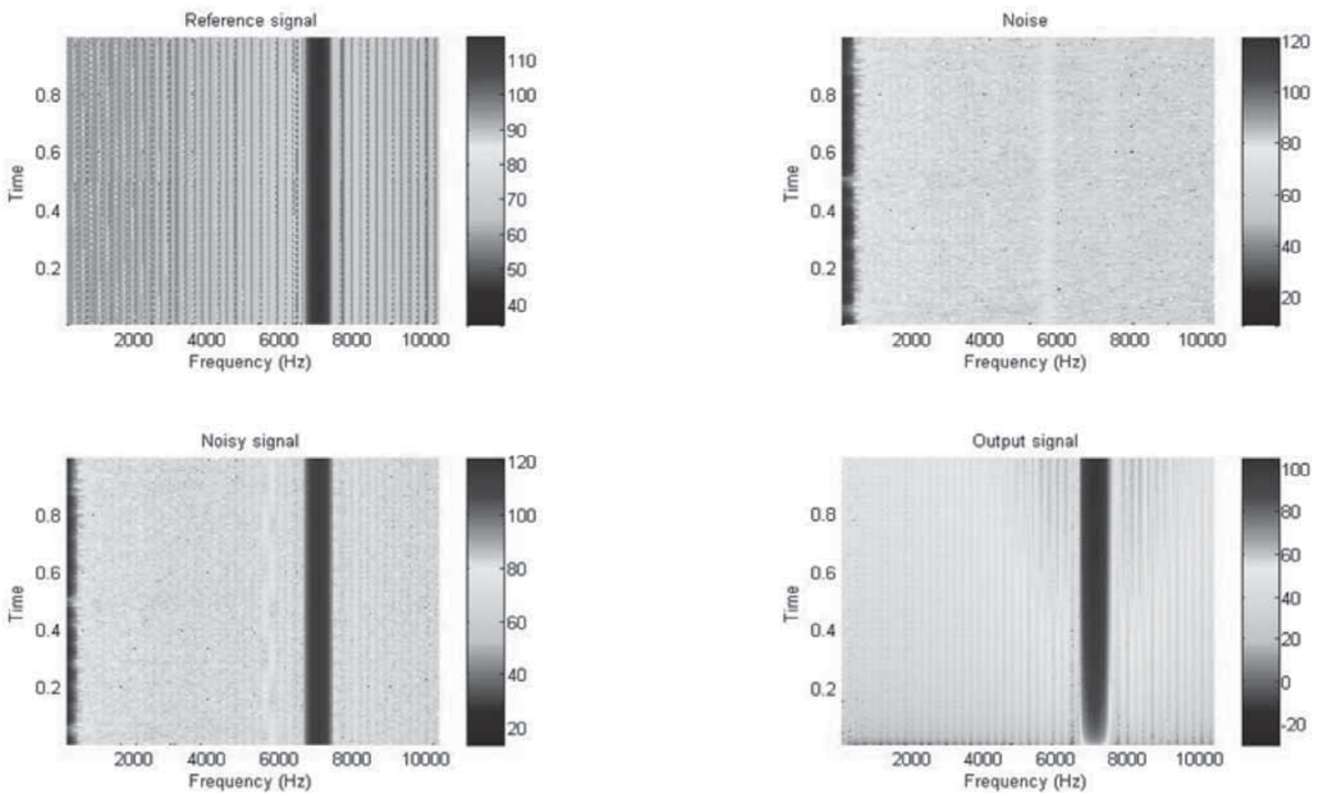


Figure 6(e). Denoising output of wind driven ambient noise by LMS algorithm (6.03 m/s)

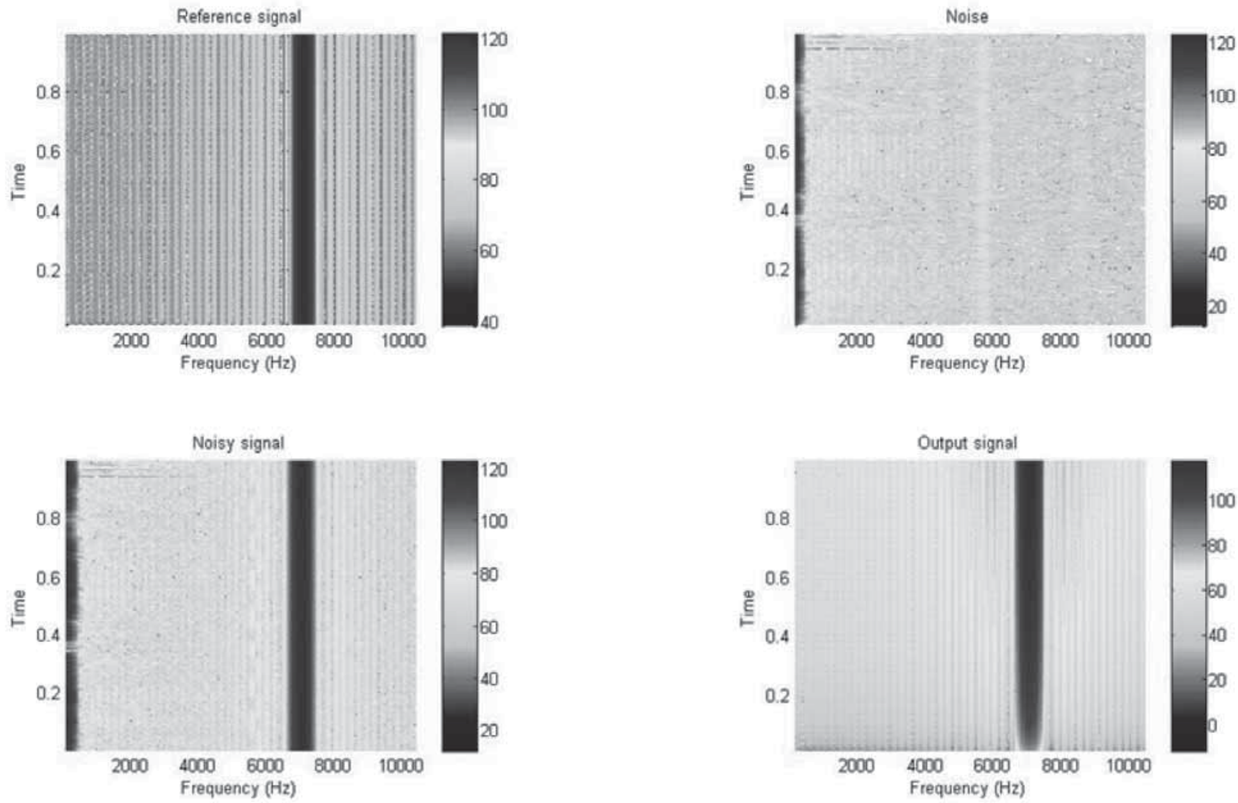


Figure 6(f). Denoising output of wind driven ambient noise by LMS algorithm (6.06 m/s)

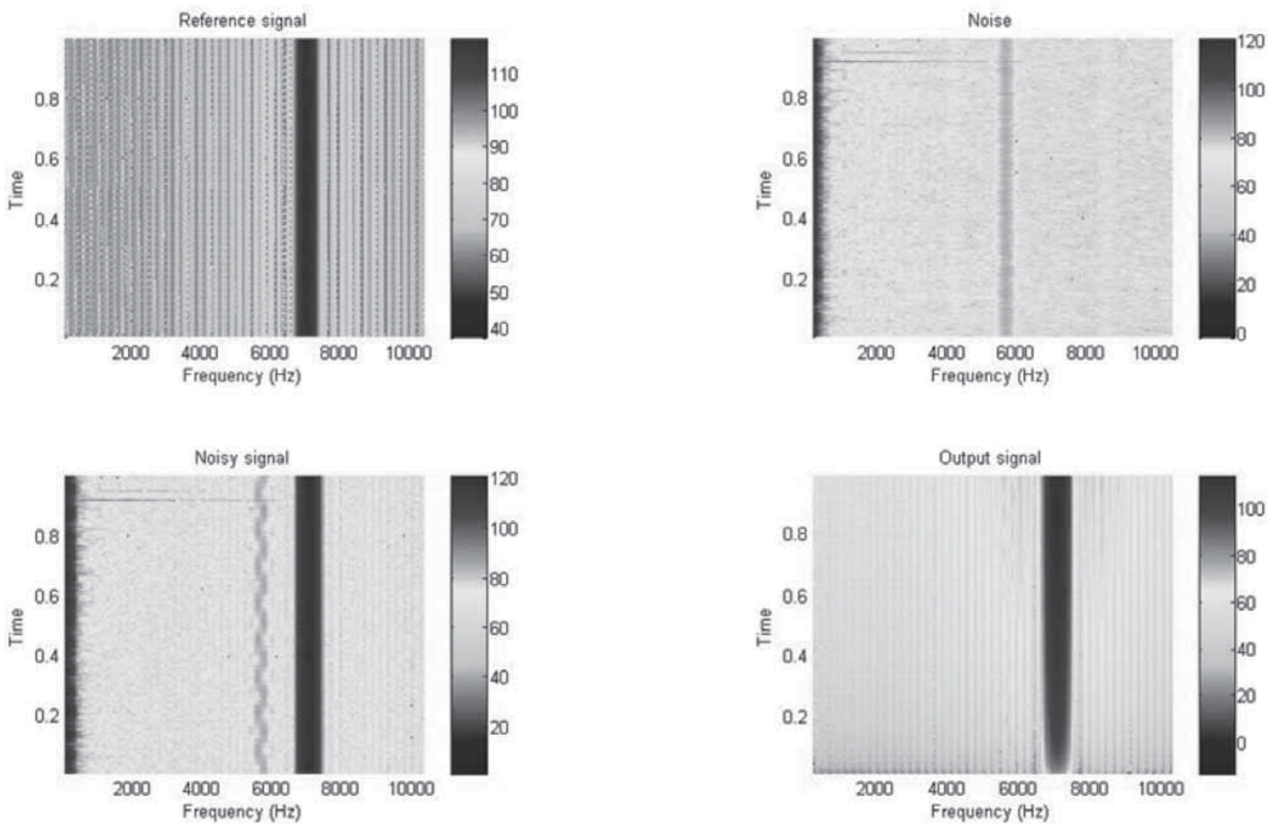


Figure 6(g). Denoising output of wind driven ambient noise by LMS algorithm (6.16 m/s)

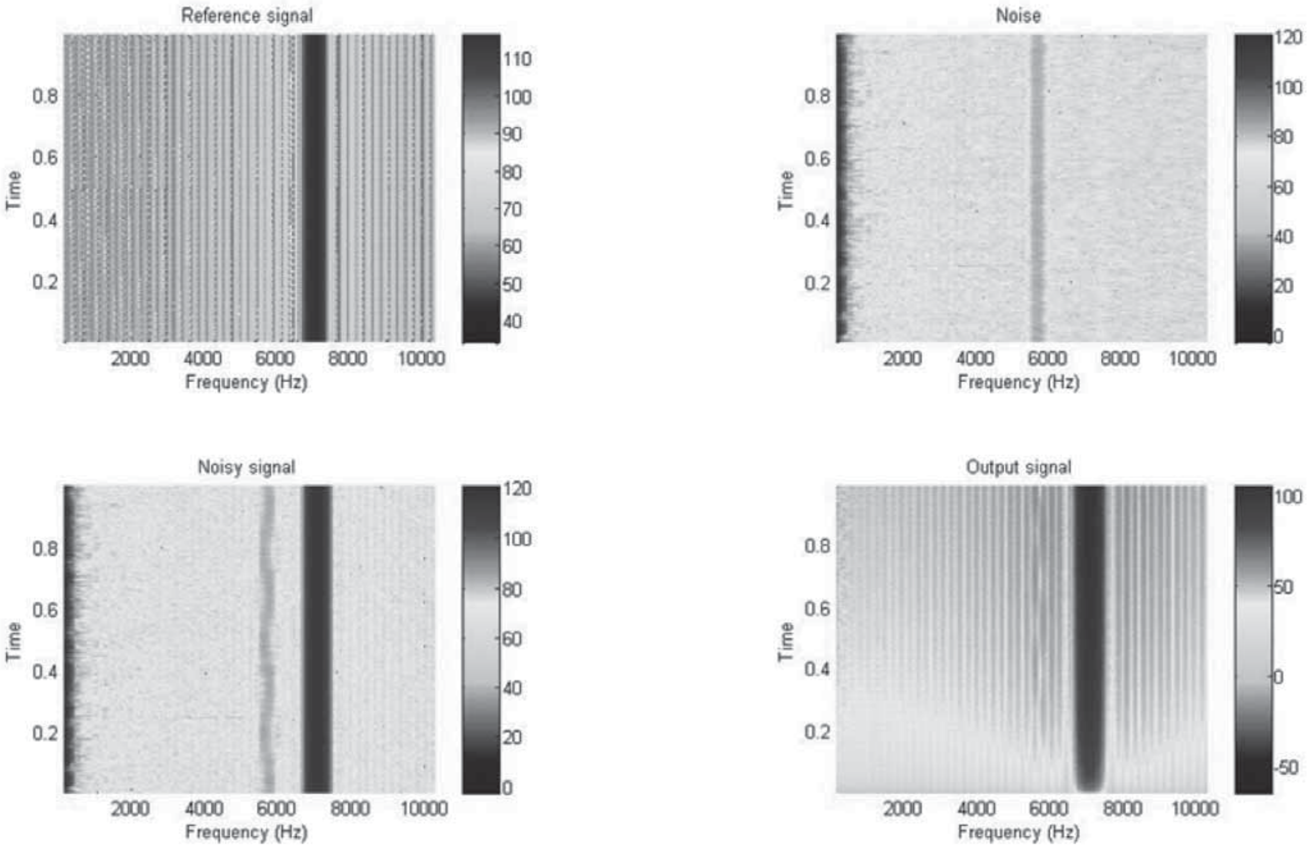


Figure 6(h). Denoising output of wind driven ambient noise by LMS algorithm (6.57 m/s)

SNR and MSE calculation

The SNR and the MSE calculated for all wind speeds considered are shown in Table 3. Using the LMS algorithm the output SNR achieved is around 53 dB for the minimum input SNR of 22 dB to a maximum of 33 dB. Hence, it is clear that there is an improvement in the SNR which ranges from 20 dB to 31 dB with an average of 25.4 dB for all wind speeds considered. Similarly the MSE is reduced from 1.8017 to 0.0195 for 2.11m/s, and similarly for all other wind speeds.

Table 3. SNR Improvement and MSE reduction using LMS algorithm for various wind speeds

Algorithm	SNR (dB) for various wind speeds							
	2.11m/s	3.32m/s	4.52m/s	5.92m/s	6.03m/s	6.06m/s	6.16m/s	6.57m/s
Input SNR	26.76	29.33	22.72	29.91	29.08	28.79	33.20	23.38
LMS	53.26	53.20	53.25	53.30	53.21	53.28	53.23	53.29
Increase in SNR	26.5	23.87	30.53	23.39	24.13	24.49	20.03	29.91

Algorithm	Mean Square Error (No unit) for various wind speeds							
	2.11m/s	3.32m/s	4.52m/s	5.92m/s	6.03m/s	6.06m/s	6.16m/s	6.57m/s
Input MSE	1.8017	1.7377	1.7511	1.7261	0.2165	0.2242	0.1437	0.3842
LMS	0.0195	0.0196	0.0195	0.0194	0.0195	0.0194	0.0195	0.0194

CONCLUSIONS

In this paper, the estimation of power spectral density for ambient noise due to wind at various speeds ranging from 2.11 m/s to 6.59 m/s is analysed and inferred that the effect of wind is dominating at frequencies from 100 Hz to 5 kHz. A noise model for estimating the effect of wind at different wind speeds for various frequencies is developed and found that it suits well with the practical data. The analysis shows that noise level increases as wind speed increases.

An adaptive LMS algorithm is developed to denoise the effect due to wind on any desired signal. The LMS algorithm implemented improves the SNR by 25.4 dB on an average for all wind speeds considered and the MSE is also reduced to an appreciable level. The spectrogram plot is presented for better understanding of the denoising effect due to wind on the signal transmitted in the shallow water region.

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