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Technical Paper

De-noising algorithm for SNR improvement of underwater acoustic signals using CWT based on Fourier Transform

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Abstract

Underwater wireless communication is a prominent research field owing to its vast range of applications such as underwater sensor networks, remotely operated vehicles (ROVs) and tsunami warning systems. The acoustic signals used in the underwater wireless systems are 10^5 times slower than light which makes it band-limited. Communication under water is affected not only by natural activities but also by shipping noises, all of which degrade the performance of underwater systems. Hence appropriate de-noising algorithms have to be developed to improve the performance of the band-limited underwater systems. The algorithm described in this paper was developed using linear frequency modulation (FM) waveform as input and using the continuous wavelet transformation (CWT) based on fast Fourier Transform (FFT) method with Morlet wavelet. The proposed algorithm provides an SNR improvement of around 12 dB when compared with the algorithm developed using the chirp signal as input and using Morlet wavelet with wavelet packet decomposition (WPD) technique.

Keywords: De-noising, signal-to-noise ratio, SNR, continuous wavelet transformation, CWT, acoustic signal

1. Introduction

Underwater wireless communication has gained traction as an important research field owing to the vast range of applications such as underwater seismic monitoring, remotely operated vehicles (ROVs) and disaster warning systems. The underwater systems are band-limited because the acoustic signals used for communication are 10^5 times slower than light.

Communication through sea water is affected by underwater ambient noise (Urick, 1984; Dahl et al., 2007; Sivakumar and Rajendran, 2010; Sadaf et al., 2015). The ambient noise may be caused by natural activities (e.g. flora and fauna, rainfall and wind) or manmade activities (e.g. fishing boats). These activities are responsible for the degradation of the band-limited underwater systems' performance. Hence algorithms need to be designed to remove ambient noise, thereby increasing the performance of the underwater systems.

Techniques like adaptive filters (Yadav and Sharma, 2015), matched phase noise reduction and frame-based time-scale filters (Ou et al., 2011) are used for removal of ambient noise from acoustic signals. However, these techniques are not effective in removing the noise. Prior information of the noise spectrum is needed for the operation of the aforementioned algorithms.

Wavelet theory, which provides multi-resolution analysis, overcomes the above drawbacks. The multi-resolution analysis provides a better understanding of the time domain signals. Wavelet theory is based on the principle of autocorrelation, where the wavelet designed similar to the original signal is correlated with the noisy signal. Thresholds are applied to the resulting wavelet coefficients to remove the coefficients pertaining to noises. The original signal is reconstructed by applying the inverse wavelet transform.

The algorithm designed with chirp signal as input using Morlet wavelet (Raj and Murali, 2013) based on the wavelet packet decomposition (WPD) (Gokhale and Khanduja, 2010; Chen and Zhang, 2011) is not verty effective and provides a signal-to-noise ratio (SNR) improvement of around 7 dB.

The proposed algorithm is developed using the linear frequency modulation (FM) waveform as the

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input and the continuous wavelet transform (CWT) based on fast Fourier Transform. Here, we explain the proposed algorithm and compare it's performance to that of other proposed solutions.

2. Literature review

The technique of memory-less noise suppressing non-linearity in the adaptive filter of an acoustic echo canceller based on normalised least mean square (LMS) was investigated by Wada and Juang (2009). They concluded that both semi-blind source separation (SBSS) based independent component analysis (ICA) and error enhancement procedure are well correlated. These methods help to distinguish the desired signal from other noises or disturbing signals.

Jarrot et al. (2005) handled the difficulty of recovering the signal from underwater ambient noise in the environment of multipath propagation of underwater signal. White noise cannot be overlooked because of the distinct spectral characteristics. Hence the classical time estimation method cannot be used here. To overcome this disadvantage, a new method was introduced using unitary warping, which converts a nonlinear signal to a commensurate linear one.

The effects of ocean mediation and disruption of underwater background ambient noise were studied by Tu and Jiang (2004). The signal exhibited random process and time-varying characteristics. Hence the de-noising procedure included wavelet transformation of the underwater acoustic signal, and a threshold of the wavelet coefficient and inverse wavelet transformation for reconstructing the received signal.

Wang et al. (2009) studied several de-noising techniques, such as wavelet shrinkage threshold (WST), genetic matching pursuit (GAMP) and general matching pursuit (GMP). The WST method held back white noise for low frequency signals, with a narrow frequency bandwidth attributed to the dyadic frequency partition of discrete wavelet transform (DWT). The de-noising process in GMP and GAMP are similar, with time consumption being the only difference. It is essential to maintain the high frequency component for high frequency signals in de-noising the broad bandwidth signals, which was best suited for the GAMP based method. It is theoretically proven that the GMP method had better accuracy in maximum cases. The GMP method, requires very high speed computers with large memories, for complex calculations, which increases the time consumption of GMP. GAMP based de-noising techniques are still difficult in real time for sound signals with high sampling rate.

Hou et al.'s (2008) research on signals with low signal-to-noise ratio shows that the recovery of suppressed signal in ambient noise is very important in the detection and identification process of such signals. They proposed using pangas (a type of fishing boat) for de-noising ship produced noise. In doing so, they achieved a proper estimation of signals using dual-tree CWT. The proposed model was analysed with both ship radiated noise and ambient noise, and proved through experimental measurement.

Aggarwal et al. (2011) proposed DWT algorithm-based voice signal de-noising for both hard and soft thresholding. This analysis was performed on voice signal corrupted by babble noise at several SNR levels. The SNR and means square error (MSE) were calculated and compared using two type of thresholding methods. It was observed that hard thresholding is less efficient than soft thresholding.

3. Methodology

The proposed method develops a de-noising algorithm using CWT based on FFT (Komorowski and Pietraszek, 2016). The input is the linear FM waveform generated using the 'phased linear FM waveform' command in MATLAB. The generated linear FM signal was contaminated using real-time ambient noise data collected from the shallow waters of Bay of Bengal along the Chennai coast. Ambient noise data were removed using the de-noising algorithms developed through CWT and FFT. The effectiveness of the proposed algorithm was evaluated using SNR as the performance metric.

3.1. Collection of ambient noise data

Ambient data were collected using a reasonably equipped boat in the shallow waters of Bay of Bengal at a depth of 25 m below sea level. Calibrated omnidirectional hydrophones with a receiving sensitivity of 170 dB and frequency ranging from 0.1 Hz to 25 kHz were used to measure the acoustic pressure of ambient noise. The data collection setup is shown in Fig 1. The data acquisition system (DAS), including computers, hydrophones and a power supply, was secured on a boat. The hydrophones were fixed on a mounted L-shaped setup that was then immersed into the shallow water. The hydrophones, were balanced by weights as shown in Fig 1.

The hydrophones measured ambient noise that occurred in the sea coming from various sources, such as fish, sea animals, sea traffic and ships, and the DAS received and stored the data. The specification of the omnidirectional hydrophones made of piezo-resistive material is: 12–24 operating voltage; –2°C to 55°C operating temperature;

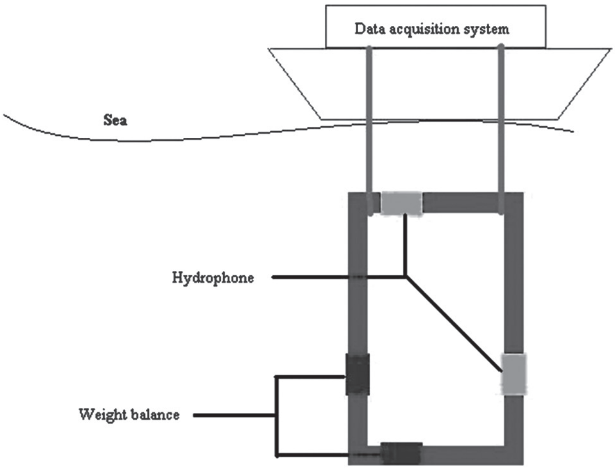

Fig 1: Data collection setup

600 m operating depth; 700 m survival depth; up to 25 kHz operating frequency; and up to –170 dB sensitivity.

3.2. De-noising algorithm

The CWT is generally expressed as the correlation of the analysed noisy signal *x(t)* and the wavelet function $\psi(t)$, and is defined by the following equation:

$$C_w(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \tag{1}$$

where a represents the scaling or dilation, b indicates the time-shifting or translation parameter and $C_w(a,b)$ corresponds to the wavelet coefficients.

The CWT requires considerable time for the calculation of the wavelet series. Hence, methods to accelerate the calculation of the CWT efficient algorithms were developed. One such algorithm is using FFT to calculate CWT. Equation 1 can be rewritten in the form of convolution as follows:

$$C_w(a,b) = \int_{-\infty}^{\infty} x(t)\psi^*{}_a(b-t)dt \tag{2}$$

It can be observed that equation 2 represents the CWT obtained by the convolution of the chosen wavelet and the signal to be analysed, which is the linear FM signal contaminated using ambient noise data.

CWT can also be expressed in terms of inverse Fourier transform, as shown in equation 3. Equation 4 represents FFT of wavelet function $\psi(t)$ and equation 5 represents the FFT of the analysed signal $x(t)$. ω indicates the frequency of the signal $x(t)$. This makes CWT a simple convolution of the wavelet and signal at different locations.

$$C_w(a,b) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \widehat{X}(w)\widehat{\psi}^*_{a,b}(w)dw \tag{3}$$

where

$$\widehat{\psi}^*_{a,b}(w) = \sqrt{a\widehat{\psi}^*}(aw)e^{jwb} \tag{4}$$

$$\hat{x}(w) = \int_{-\infty}^{\infty} x(t)e^{-jwt}\,dt \tag{5}$$

The coefficients obtained using CWT using FFT were then filtered based on a threshold computed by using the characteristics of the noise data. The signal was then reconstructed. In this work, the derivative of Gaussian (DOG) wavelet and Mortlet wavelet were used to understand the de-noising capabilities.

4. Results and discussion

The linear FM signal, which is the general characteristic of the pulses transmitted under water, is generated as shown in Fig 2. Fig 3 presents the frequency spectrum of the generated linear FM signal.

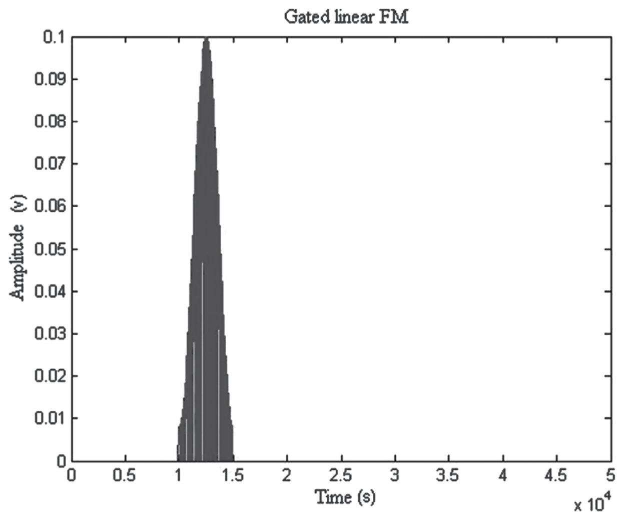

Fig 2: Gated linear FM

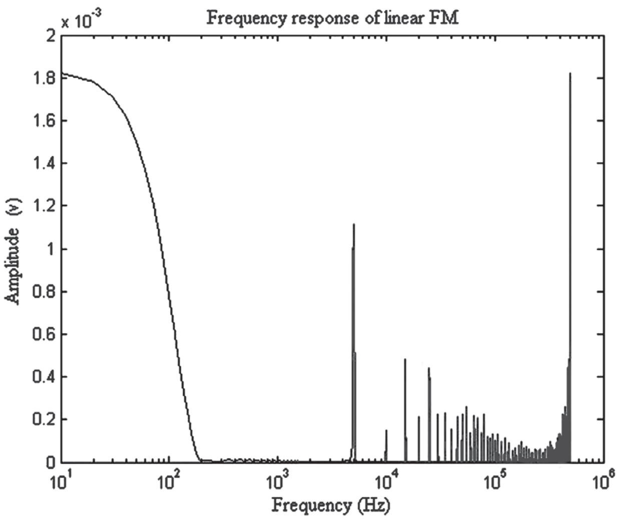

Fig 3: Spectrum of gated linear FM

The linear FM signal transmitted in the ocean is contaminated by the ambient noise caused by multiple artefacts in the ocean. Fig 4 represents the ambient noise collected in the shallow waters of Bay of Bengal. This ambient noise signal was then added to the linear FM signal, and the resultant signal is as shown in Fig 5.

The CWT using FFT was performed on the noisy linear FM signal using Paul, DOG and Mortlet wavelets. Thresholding was performed on the wavelet coefficients after which the inverse wavelet transform was applied to reconstruct the signal. Fig 6 represents the signal decomposition, and Fig 6(b) is similar in frequency and shape to the linear FM signal. Similarly, Figs 7 and 8 indicate the signal decomposition using DOG and Mortlet wavelets, respectively.

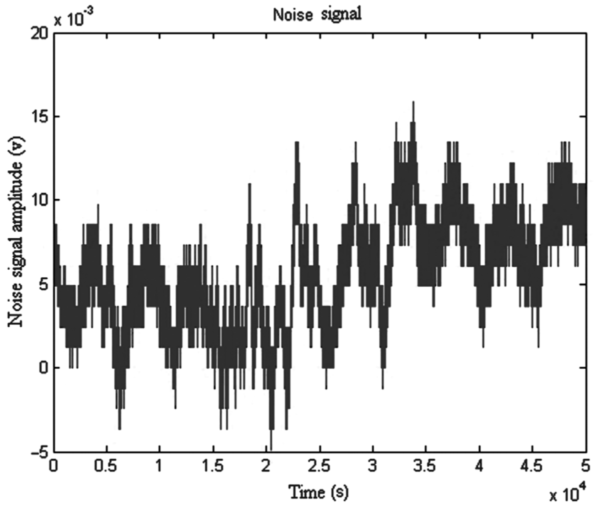

Fig 4: Noise signal

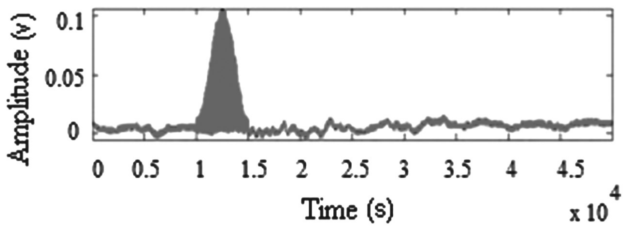

Fig 5: The gated linear FM signal with additive ambient noise

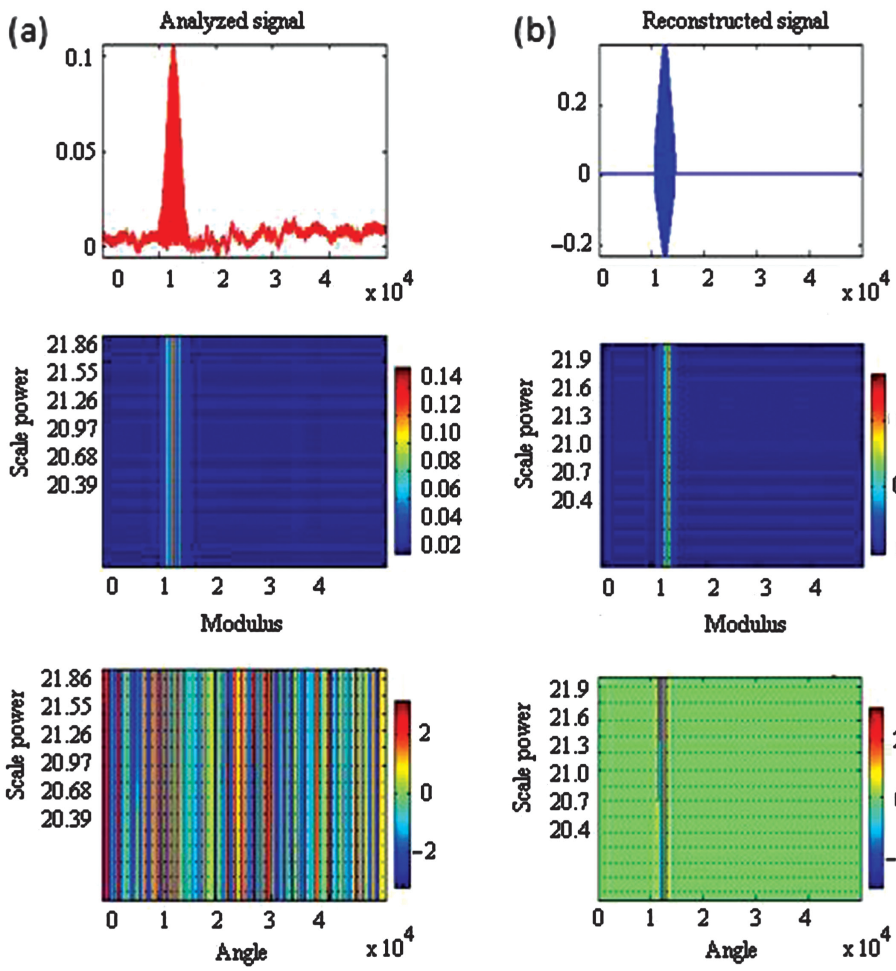

Fig 6: (a) CWT performed on the noisy linear FM signal using Paul wavelet; and (b) signal reconstructed using Paul wavelet

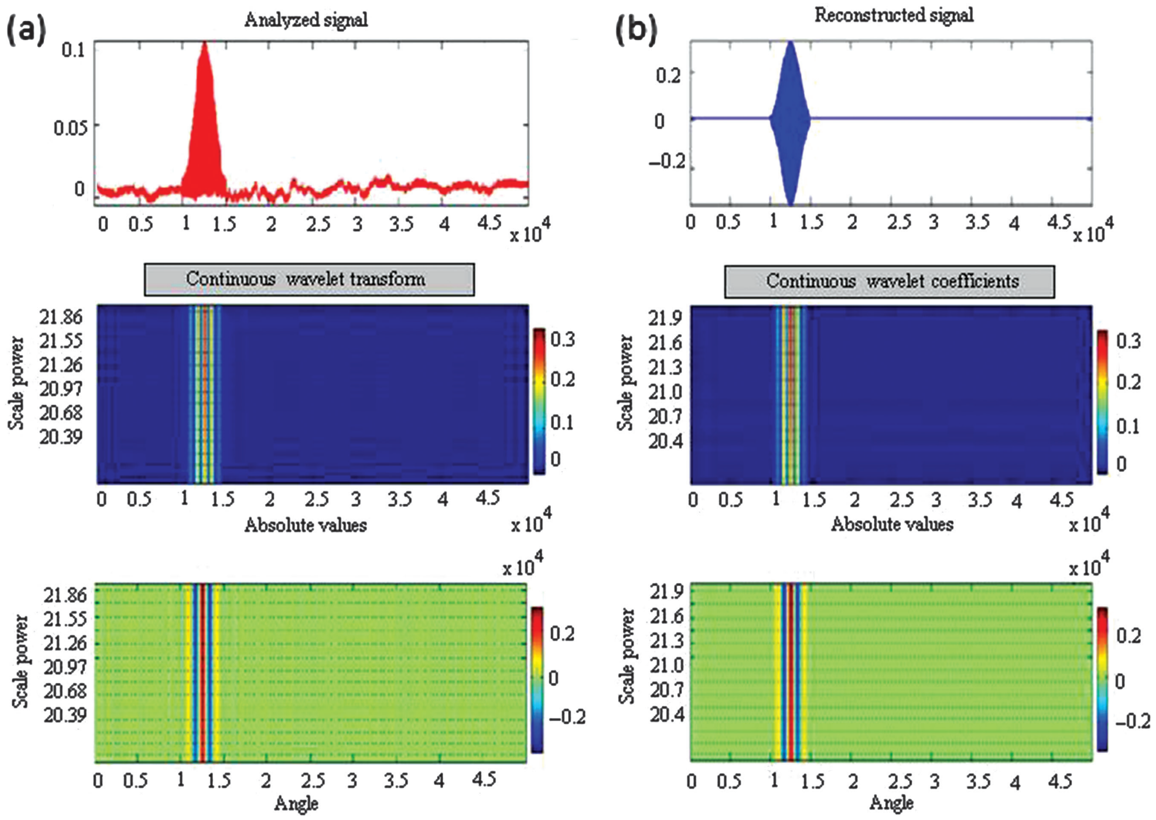

Fig 7: (a) CWT performed on the noisy linear FM signal using DOG wavelet; and (b) signal reconstructed using DOG wavelet

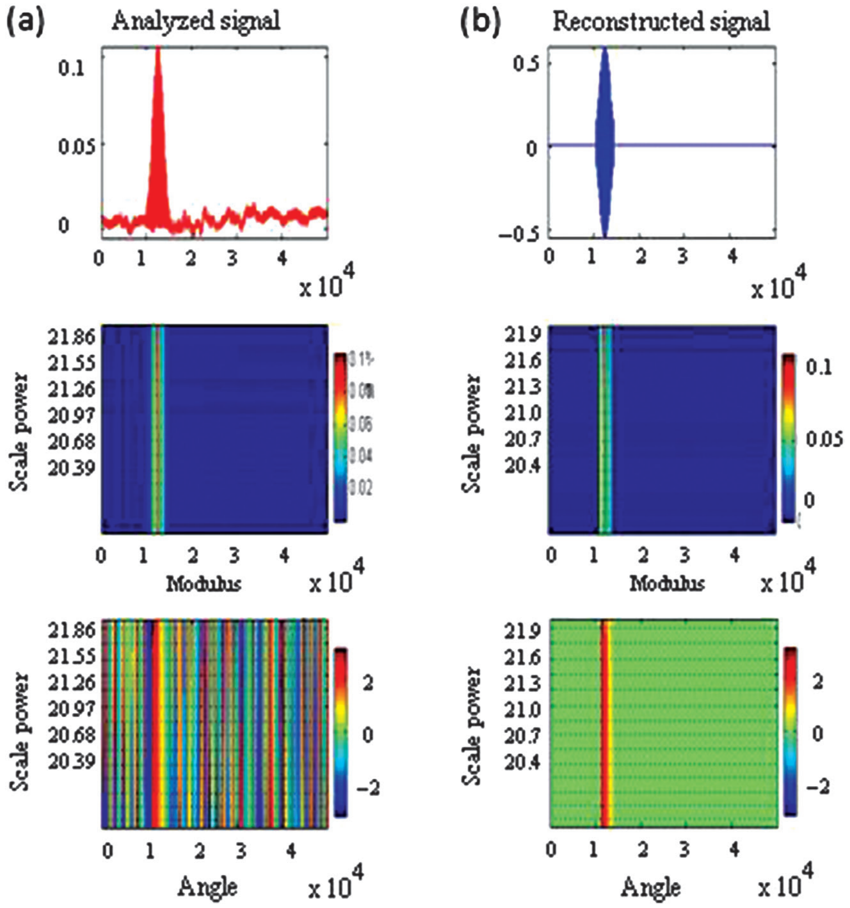

Fig 8: (a) CWT performed on the noisy linear FM signal using Mortlet Wavelet; and (b) signal reconstructed using Mortlet wavelet

The frequency spectrum of the de-noised signal is shown in Fig 9. It can be seen that the spectrum is similar to that of Fig 3, indicating that both the signals are similar in frequency. The SNR was used as the performance metric for evaluating the effectiveness of the proposed algorithm. Previous research using chirp signal as the input and based on Morlet wavelet using WPD and other de-noising techniques were able to provide an SNR improvement of 8 dB (Kalpana et al., 2014). Tables 1 to 3 present the input SNR, output SNR and the improvement in SNR obtained at the various scales for Paul, DOG and Mortlet wavelets, respectively.

As these tables show and in Fig 10, the Mortlet wavelet has the best improvement in SNR of 12 dB among the three wavelet types. Paul wavelet has an improvement of 5 dB, whereas the improvement in SNR for the DOG wavelet is the least among the three types.

Though the Mortlet wavelet provides a better SNR of 12 dB, the number of scales is 18, indicating the computational complexity and cost is high. Similarly, Paul wavelet also shows improvement on scale 12, which is again computationally high. A trade-off needs to made between the improvement in SNR and computational cost involved.

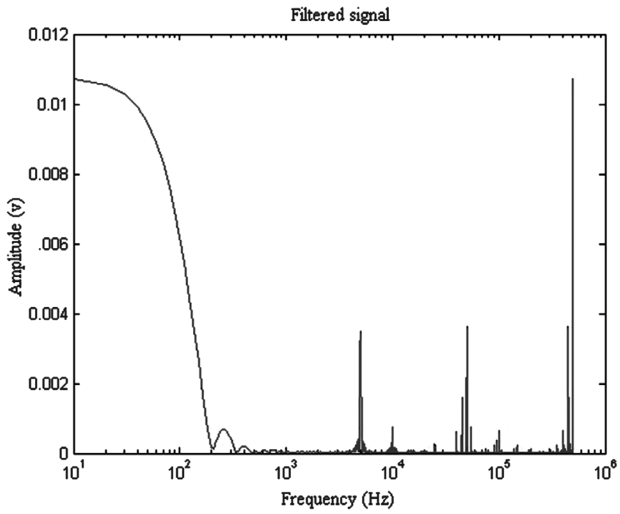

Fig 9: Frequency spectrum the de-noised linear FM signal

Table 1: SNR calculation using Paul wavelet

Scale	Spacing	No. of scales	Input SNR	Output SNR	Improvement in SNR
4	0.02	15	–16.4805	–24.12535	–7.644896684
5	0.02	15	–16.4805	–23.33733	–6.856876461
6	0.02	15	–16.4805	–21.84423	–5.36377399
7	0.02	15	–16.4805	–18.0039	–1.523440317
8	0.02	15	–16.4805	–15.28191	1.198544562
9	0.02	15	–16.4805	–13.44578	3.034672202
10	0.02	15	–16.4805	–12.12281	4.357646403
11	0.02	15	–16.4805	–11.36741	5.113042
12	0.02	15	–16.4805	–11.04461	5.435847513
13	0.02	15	–16.4805	–11.0629	5.417555089
14	0.02	15	–16.4805	–11.28844	5.192019899
15	0.02	15	–16.4805	–11.69507	4.785380766
16	0.02	15	–16.4805	–12.17331	4.30714355
17	0.02	15	–16.4805	–12.76235	3.718106129
18	0.02	15	–16.4805	–13.41826	3.062195235
19	0.02	15	–16.4805	–14.21983	2.260624364
20	0.02	15	–16.4805	–15.18508	1.295378659
21	0.02	15	–16.4805	–16.2597	0.220754701

Table 2: SNR calculation using DOG wavelet

Scale	Spacing	No. of scales	Input SNR	Output SNR	Improvement in SNR
2	0.02	15	–16.480456	–23.008565	–6.528109319
4	0.02	15	–16.480456	–15.623564	0.856891362
6	0.02	15	–16.480456	–18.751397	–2.270941745
8	0.02	15	–16.480456	–20.490776	–4.010320161
10	0.02	15	–16.480456	–22.201144	–5.720688497
12	0.02	15	–16.480456	–23.278806	–6.798350106
14	0.02	15	–16.480456	–22.938005	–6.457549435
16	0.02	15	–16.480456	–21.657182	–5.176726342
18	0.02	15	–16.480456	–20.18	–3.699544254
20	0.02	15	–16.480456	–19.097802	–2.617346682

Table 3: SNR calculation using Mortlet wavelet

Scale	Spacing	No. of scales	Input SNR	Output SNR	Improvement in SNR
4	0.02	15	–16.4805	–22.771723	–6.291267577
5	0.02	15	–16.4805	–24.558999	–8.078543287
6	0.02	15	–16.4805	–27.556428	–11.07597261
7	0.02	15	–16.4805	–22.841202	–6.360746654
8	0.02	15	–16.4805	–19.883483	–3.403027769
9	0.02	15	–16.4805	–18.453052	–1.972596841
10	0.02	15	–16.4805	–20.418402	–3.937946646
11	0.02	15	–16.4805	–19.99408	–3.513624809
12	0.02	15	–16.4805	–17.083497	–0.603041036
13	0.02	15	–16.4805	–14.432071	2.048384375
14	0.02	15	–16.4805	–10.770859	5.709596165
15	0.02	15	–16.4805	–7.3956727	9.084782793
16	0.02	15	–16.4805	–5.4517256	11.02872998
17	0.02	15	–16.4805	–4.4733611	12.00709443
18	0.02	15	–16.4805	–4.3765719	12.1038836
19	0.02	15	–16.4805	–5.0520875	11.42836807
20	0.02	15	–16.4805	–6.7259066	9.754548934
21	0.02	15	–16.4805	–9.603629	6.876826504

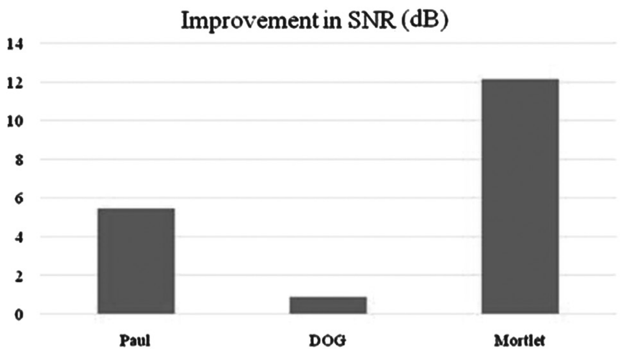

Fig 10: Comparison of the maximum improvement in SNR of the different wavelets

5. Conclusion

This paper shows that the acoustic signals used for underwater communication are affected by fishing activities, flora and fauna, thereby degrading the performance of band-limited underwater systems. The proposed algorithm using the CWT using FFT is analysed using the linear FM signal as input and the real-time noise data collected at Bay of Bengal, Chennai. The simulated results are compared with the algorithm developed using the chirp signal as input with Morlet wavelet, and also with the available wavelets in the CWT using FFT. By comparing the simulation results of the other wavelets with the proposed algorithm, the Morlet wavelet provided a better SNR improvement of 12 dB.

References

Aggarwal R, Singh JK, Gupta VK, Rathore S, Tiwari M and Khare A. (2011). Noise reduction of speech signal using wavelet transform with modified universal threshold. *International Journal of Computer Applications* **20:**14–19.

Chen S and Zhang H. (2011). Detection of underwater acoustic signal from ship noise based on WPT method. In: Proceedings of the Fourth International Workshop on Chaos-Fractals Theories and Applications (IWCFTA), 19–22 October, Hangzhou, China.

Dahl PH, Miller JH, Cato DH and Andrew RK. (2007). Underwater ambient noise. *Acoustics Today*: 23–33.

Gokhale MY and Khanduja DK. (2010). Time domain signal analysis using wavelet packet decomposition approach. *International Journal of Communications, Network and System Sciences* **3**: 321–329.

Jarrot A, Ioana C and Quinquis A. (2005). Denoising underwater signals propagating through multi-path channels. In: Proccedings of Oceans 2005 – Europe, 20–23 June, Brest, France, 501–506.

Kalpana G, Rajendran V and Sakthivel Murugan S. (2014). Study of denoising techniques for SNR improvement fort underwater acoustic communication, *Journal of Marine Engineering and Technology* **13**: 29–36.

Komorowski D and Pietraszek S. (2016). The use of continuous Wavelet Transform based on the Fast Fourier Transform in the analysis of multi-channel electrogastrography recordings. *Journal of Medical Systems* **40**: 1–10.

Kumar PS, Kish Kumar PC, Jerritta S and Rajendran V. (2017). Analysis of wind speed distributions for weekly data. *ARPN Journal of Engineering and Applied Sciences* **12**: 2419–2422.

Ou H, Allen JS and Symos VL. (2011). Frame-based time-scale filters for underwater acoustic noise reduction. *IEEE Journal of Ocean Engineering* **36**: 285–297.

Raj AS and Murali N. (2013). Morlet Wavelet UDWT Denoising and EMD based Bearing Fault Diagnosis. *Electronics* **17**: 1–8.

Sadaf S, Yashaswini P, Halagur S, Khan F and Rangaswamy S. (2015). A literature survey on ambient noise analysis for underwater acoustic signals. *International Journal for Computer Engineering and Sciences* **1**: 1–9.

Sivakumar VG and Rajendran V. (2010). Analyze the coherence of ambient noise in the bay of Bengal ocean region. In: Proceedings of Recent Advances in Space Technology Services and Climate Change, 13–15 November, Chennai, India, 433–436.

Tieshuang H, Jinglin X, Peng H and Jie S. (2008). Research of s-radiated signal denoising based on the CWT statistical wavelet mode. In: Proceedings of the 9th International Conference on Signal Processing (ICSP), 26–29 October, Beijing, China, 2851–2854.

Tu CK and Jiang YY. (2004), Development of noise reduction algorithm for underwater signals. IN: Proceedings of the 2004 International Symposium on Underwater Technology, 20–23 April, Taipei, Taiwan, 175–179.

Urick RJ. (1984). *Ambient Noise in the Sea*. Washington, DC: Undersea Warfare Technology Office, Naval Sea systems Command, Dept. of the Navy, 194 pp.

Wada TS and Juang BH. (2009). Acoustic echo cancellation based on independent component analysis and integrated residual echo enhancement. In: Proceedings of IEEE workshop on applications of Signal Processing to Audio and Acoustics, 18–21 October, NewPaltz, New York.

Wang S, He H and Chen XW. (2009). Comparison and application of signal denoising techniques based on time-frequency algorithms. In: Proceedings of the IEEE Intelligent Vehicles Symposium, 3–5 June, Xi'an, China.

Yadav R and Sharma D. (2015). De-noising of speech signal using adaptive filter algorithms, *International Journal of Technology Enhancements and Emerging Engineering Research* **3**: 24–28.