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Archives of Acoustics Vol. **48**, No. 1, pp. 39–48 (2023), doi: 10.24425/aoa.2023.144264

Research Paper

Acoustic Identification of Dolphin Whistle Types in Deep Waters of Arabian Sea Using Wavelet Threshold Denoising Approach

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(*received February 15, 2022; accepted October 7, 2022*)

In situ time series measurements of ocean ambient noise, have been made in deep waters of the Arabian Sea, using an autonomous passive acoustic monitoring system deployed as part of the Ocean Moored buoy network in the Northern Indian Ocean (OMNI) buoy mooring operated by the National Institute of Ocean Technology (NIOT), in Chennai during November 2018 to November 2019. The analysis of ambient noise records during the spring (April–June) showed the presence of dolphin whistles but contaminated by unwanted impulsive shackle noise. The frequency contours of the dolphin whistles occur in narrow band in the range 4–16 kHz. However, the unwanted impulsive shackle noise occurs in broad band with the noise level higher by ~20 dB over the dolphin signals, and it reduces the quality of dolphin whistles. A wavelet based threshold denoising technique followed by a subtraction method is implemented. Reduction of unwanted shackle noise is effectively done and different dolphin whistle types are identified. This wavelet denoising approach is demonstrated for extraction of dolphin whistles in the presence of challenging impulsive shackle noise. Furthermore, this study should be useful for identifying other cetacean species when the signal of interest is interrupted by unwanted mechanical noise.

Keywords: deep water ambient noise; Arabian Sea; wavelet threshold denoising; impulsive shackle noise; dolphin whistle types.

1. Introduction

Sounds produced by marine species are often identified using time-frequency representations for extraction of salient and distinguishing features of their vocalization. The problem of extracting the sound from the spectrogram can be compounded by low signal to noise ratio and the obstruction of acoustic files with non-stationary anthropogenic sound sources. Wavelet transforms are preferred over a conventional method using the fast Fourier transform (FFT) in identifying a predominant biological noise source using the multi-resolution denoising algorithm (Powell *et al.*, 1995; Learned, Willsky, 1995). The wavelet transform is used by Huynh *et al.* (1998) in classifying whale and porpoise sounds. A wavelet based threshold denoising technique followed by a subtraction method is implemented here that can be used for marine species identification. The algorithm is demonstrated for identification of dolphin whistles from noise data corrupted with mechanical noise.

Dolphins are mainly vocal mammalian family, and the vocal communication plays an important role in mediating social interactions (Slater, 1983). They are inhabited in all over the world's oceans and mostly distributed in warm equatorial to subpolar regions, and in coastal as well as offshore waters (Corkeron, Van Parijs, 2001). Dolphins produce mainly two primary types of sounds associated with specific behavioral contexts: non-pulse tonal frequency modulated whistles and rapid repetition of burst-pulsed click sounds (Au, 1993; Jones *et al.*, 2020). Whistles are non-pulse characteristics, longer duration with a narrow frequency band (Boisseau, 2005; Akiyama, Ohta, 2007). These whistle sounds play a crucial role in maintaining contact between dispersed individuals (Caldwell *et al.*, 1990; Janik, Slater, 1998; Sayigh *et al.*, 1999; Janik *et al.*, 2006; 2013; Rachinas-Lopes *et al.*, 2017), group cohesion with male-male alliances, vocal communication between mother and calf pairs, and also promote as a greeting signal when the groups joining each other (Smolker *et al.*, 1993; Janik, 2009; Quick, Janik, 2012; King *et al.*, 2019). The amplitude and duration of the whistles may vary, however the stereotyped frequency contour over time of the whistle seems to comprise the information for recognition (Janik *et al.*, 2006). The discrete parameters to classify whistles include: start frequency, end frequency, minimum frequency, maximum frequency, bandwidth, duration, and number of inflection points (Janik *et al.*, 1994; Esch *et al.*, 2009). However, in some instances the whistle signals are often contaminated by the mechanical noises particular to the rubbing and mooring components such as shackles and cables. It is hard to distinguish the frequency contour of the whistles once the signal of interest is corrupted with unwanted sounds. Therefore, it is important to implement the denoising method which improves the quality of signal.

Denoising is the process of extracting an original signal from the noise (Bey, 2006). In general, the signal is corrupted by noise during its transmission, acquisition, reception, and processing (Isabona, Azi, 2012). Many researchers studied different denoising techniques, such as median filtering, mean filtering, the Fourier transform, and Wiener filtering which are a linear approach and suitable for stationary signals (Chen *et al.*, 2006; Lukac *et al.*, 2007; Zhang, Xiong, 2009). However, the ambient noise in the ocean is non-stationary because of the combination of many oceanic sources including unwanted impulsive mechanical mooring noises which are difficult to extract using a linear approach. Therefore, it is significant to implement the non-linear wavelet threshold denoising approach (Khan *et al.*, 2015). Various non-stationary signal extraction methods have emerged in recent years, and the algorithms are wavelet decomposition, empirical mode decomposition, the Hilbert-Huang transform, and variational mode decomposition (Dragomiretskiy, Zosso, 2013; Ukte *et al.*, 2014; Xiang, Wang, 2015). However, to work these approaches, certain conditions must be met such as decomposition levels, modal number, and termination thresholds. Among these, the wavelet decomposition method is designed for non-stationary signals, which combines both the time and frequency domain. Mallat (1989) describes the theoretical and mathematical approach for understanding wavelet decomposition on signal denoising. The key advantage of wavelet denoising is to split the data into different frequency components and study the noise spikes in each frequency component at different resolution (Chang *et al.*, 2000). The wavelet denoising is an emerging advance technique in signal processing that used in a various applications particularly image processing, data compression, impulsive events characterization, pattern recognition signal extraction and denoising (Yu *et al.*, 2007; Li, Zhou, 2008). This type of technique will be useful for removing impact noise produced in the mooring, when acoustic recorders are incorporated in multisuite ocean moorings. Also data acquisition during rough seas creates more platform noise which is unavoidable. Metal chains and shackles in mooring cause clonking noise in the same frequency range 100 Hz to a few kHz (Marley *et al.*, 2017). So the algorithm described in this paper should be useful for the above mentioned types of noise.

In this paper, the study area is located in the South of Lakshadweep Islands with the close proximity to the Maldives which presents itself a highly varying bathymetric and oceanographic environments so, the area affords a wide variety of cetaceans (Prakash *et al.*, 2015). It shows as different habitat types particularly the coral reefs, seagrass beds, rocky and sandy shores, deep water canyons and trenches that offer a vast marine biodiversity for cetaceans (Pillai, Jasmine, 1989; Mallik, 2017). To identify the cetacean species, visual observation was the commonly used method in which observers can identify the species in a limited sighting conditions (weather, seastate, and daylight). Basing on the visual surveys along with anecdotal evidence, 14 species of cetaceans have been documented in this area (Panicker *et al.*, 2020). Among them, the most commonly sited species are dolphins and studies on acoustic identification is very scarce.

The signal denoising methods would be adequate to eliminate the noise if the unwanted noise levels are lower as compared to the source signals. However, noise removal will be a challenge when the unwanted noise level is higher than the source signals. In this study, the unwanted impulsive shackle noise is higher as compared to that of dolphin whistle signals, and both are non-stationary with transient and vary quickly. However, the frequency contours of the dolphin whistle signals are different from that of unwanted impulsive shackle noise which enables the wavelet denoising technique effective for implementation.

This study is mainly on identification of whistle signals produced by dolphins from the passive acoustic measurements by implementing the wavelet threshold denoising technique along with the subtraction method to remove the unwanted impulsive shackle noise of the mooring system. This study addresses how to tackle the contaminated acoustic data due to impulsive mechanical noise and identify species in a marine based biological ecosystem which would provide the baseline information regarding cetaceans.

2. Materials and methods

2.1. Acoustic measurements

The deep ocean ambient noise measurement system combined with the Ocean Moored buoy network for the Northern Indian Ocean (OMNI) buoy was deployed at the south of Lakshadweep (AD9) in the South Eastern Arabian Sea at the ocean depth of ~2100 m during November 2018 to October 2019 (Fig. 1). The system firmly holds a glass sphere along with hydrophone (bandwidth 10 Hz to 100 kHz), data acquisition system, and power pack. The noise data were acquired at a sampling rate of 32 kHz for a duration of 12 min for every half an hour. The hydrophone-sensed acoustic pressure fluctuation caused by different sources of noise, which translates into electrical signals and converts to units of micropascal [μPa] by applying the receiving sensitivity (−165 dB re 1 V/μPa) of the hydrophone.

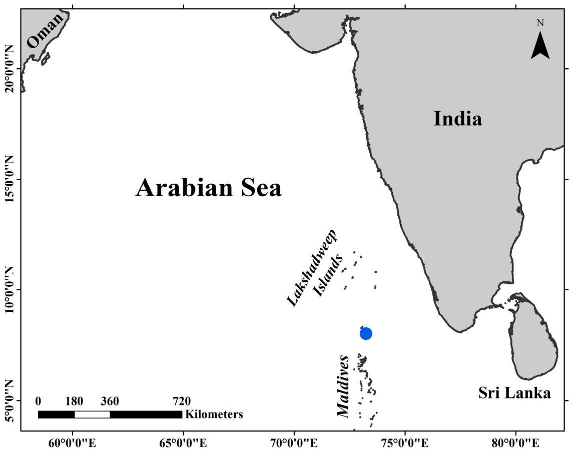

Fig. 1. Deployment location of OMNI buoy in the Arabian Sea (AD9) is indicated in blue filled dot.

The oscillogram, spectrograms, and Welch's averaged power spectral density (dB re 1 $\mu\text{Pa}^2/\text{Hz}$) were analyzed using MATLAB (MATLAB R2021a). Multiple spectra were obtained by segmenting the data into smaller portions using a Hamming window and 2048 point FFT with 50% overlap. The resulting spectra were then averaged to obtain the final spectrum. The frequency resolution of each power spectrum is 15.6 Hz, which is determined by the sampling frequency and the number of points in the FFTs in each power spectrum.

2.2. Wavelet threshold denoising

The wavelet threshold denoising technique contains three steps: signal decomposition, thresholding, and signal reconstruction (Donoho, Johnstone, 1994). In this method, the signal is decomposed into approximation and detail coefficients at each level. The approximations are high-scale and low frequency components, and the details are low-scale and high frequency components of the signal (Tikkanen, 1999). The threshold value is very important parameter in the wavelet threshold denoising technique. There are four threshold selection methods particularly the universal threshold, rigorous Stein's Unbiased Risk Estimate (SURE), heuristic SURE, and minimax (Donoho, Johnstone, 1994). In this study, the rigorous SURE threshold estimation is adopted. The threshold (T) is defined by:

$$T = \sqrt{2\log_e\left(N\log_2\left(N\right)\right)}, \tag{1}$$

where N is the number of samples in the input signal. Once the value of threshold is estimated using this method, a hard or soft thresholding function is needed to filter the wavelet coefficients which contain unwanted noise (Donoho, Johnstone, 1995). For the hard threshold, the absolute values of wavelet coefficients below the threshold level are set to zero, and the values above the threshold are kept unchanged. In soft threshold, the wavelet coefficients whose values are lower than the zero threshold, and the coefficients above the threshold level are also modified (Donoho, Johnstone, 1995). In this study, the soft threshold method is considered because the wavelet coefficients become more stable and smoothening as compared to the hard threshold. Finally, the in situ signal is denoised and reconstructed using modified level coefficients.

In this study, the in situ time series data of ambient noise is the combination of unwanted impulsive shackle noise along with dolphins whistle signals. The noise level of the impulsive shackle dominates the whistles of dolphin which is difficult to identify from frequency contours. Therefore, the wavelet threshold denoising technique is implemented using the MATLAB function wden:

$$\text{signal}_{\text{denoised}} = \text{wden (input data, rigrsure, s,} \\ \text{mln, level, wname),} \tag{2}$$

where $\text{signal}_{\text{denoised}}$ is the denoised signal, input data is the original in situ data, rigrsure specifies the adaptive threshold selection using the principle of SURE. The term s denotes soft thresholding, mln indicates multi-threshold re-scaling at level coefficients, the level determines the decomposition of the signal using the syntax level = wmaxlev (N, wname), where N is the number of samples in the input signal. The wname is a wavelet family and the function wden performs wavelet denoise of the input signal. In this study, we chose the wavelet function Daubechies [db5] (Daubechies, 1992; Rowe, Abbott, 1995), and estimated the decomposition level at 20 using the above syntax.

After implementing the wavelet threshold denoising technique, the unwanted impulsive shackle noise exists and suppresses the resulted wanted signal because the value of noise is higher as compared to the signal. Hence a subtraction method is implemented followed by the wavelet threshold denoising technique. A flowchart on the threshold denoising algorithm described in this work is shown in Fig. 2.

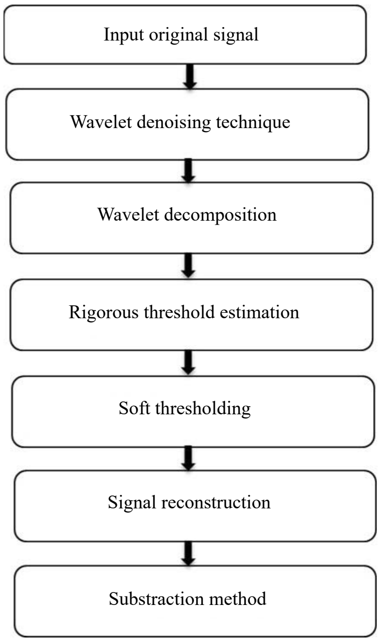

Fig. 2. Block diagram of wavelet based threshold denoising algorithm.

In this method, a residual signal is estimated by subtracting the denoised signal from the original in situ data (Math Works, n.d). The unwanted impulsive shackle noise is isolated by subtracting the residual signal from the denoised signal, and the wanted signal (dolphin whistle signals) is obtained by subtracting the unwanted impulsive shackle noise from the original in situ data.

3. Results

In situ time series measurements of deep water ambient noise in the spring period were considered for analysis, i.e., April–June, 2019. The in situ time series data have been recorded as audio files during the measurement, and analyzed using time-frequency spectrogram. During the study period, 12 data sets of recorded audio files resembled dolphin whistles, which are mostly contaminated by unwanted impulsive shackle noise. Among these, Fig. 3a represents the oscillogram of an in situ data recorded on 31/05/2019 at 11:58 hr. The spectrogram in Fig. 3b shows the mixing of unwanted background noise, impulsive shackle noise as well as the dolphin whistle sounds. The sounds produced by impulsive shackle noise in the frequency range of 0–16 kHz contaminates the dolphin whistle signals.

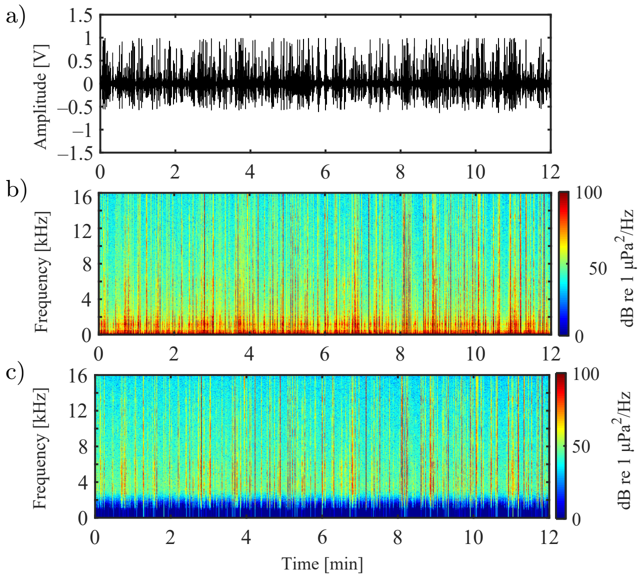

Fig. 3. a) Oscillogram; b) spectrogram of the original signal; c) spectrogram of the original signal using butterworth high pass filter up to 3 kHz. The vertical striplines in spectrogram are shown as impulsive shackle noise.

A butterworth high pass filter with 3 kHz cut-off is employed to the in situ data in order to suppress the unwanted low frequency background noise which is falling below the dolphin whistles (Fig. 3c). The spectrograms in Fig. 4 show the whistles of dolphin which are subsequently extracted from the original spectrogram of Fig. 3c. The results shown here are from in situ data recorded on 31/05/2019 at 11:58 hr with duration of 12 minutes. The whistles produced by dolphins are narrow band with the spectral peak in the frequency range of 4–16 kHz (Fig. 4). However, it is difficult to identify the frequency contour of different whistle types because the signals are indistinguishable due to the impact of impulsive shackle noise. It is analysed that the averaged noise level is about ~82 dB due to impulsive shackle noise whereas it is about ~62 dB produced by dolphins whistle signal (Fig. 4a). When compared the noise levels of impulsive shackle noise to that of the dolphin signal, it is observed that the unwanted impulsive shackle noise is higher by ~20 dB as compared to that of dolphin signals. It means that the noise level of dolphins whistle signals are significantly lower and buried under the impulsive shackle noise, which is difficult to retrieve.

Therefore, to retrieve the dolphin whistle signals, the wavelet threshold denoising approach has been implemented along with the commonly used subtraction method. The oscillogram and spectrogram of the proposed wavelet denoising approach is shown in Figs. 5a and 5b.

The denoised version of the spectrogram (Fig. 5b) shows the dominance of impulsive shackle noise, since the noise levels of impulsive shackle are higher than the noise level of dolphin whistle signals. The residual sig-

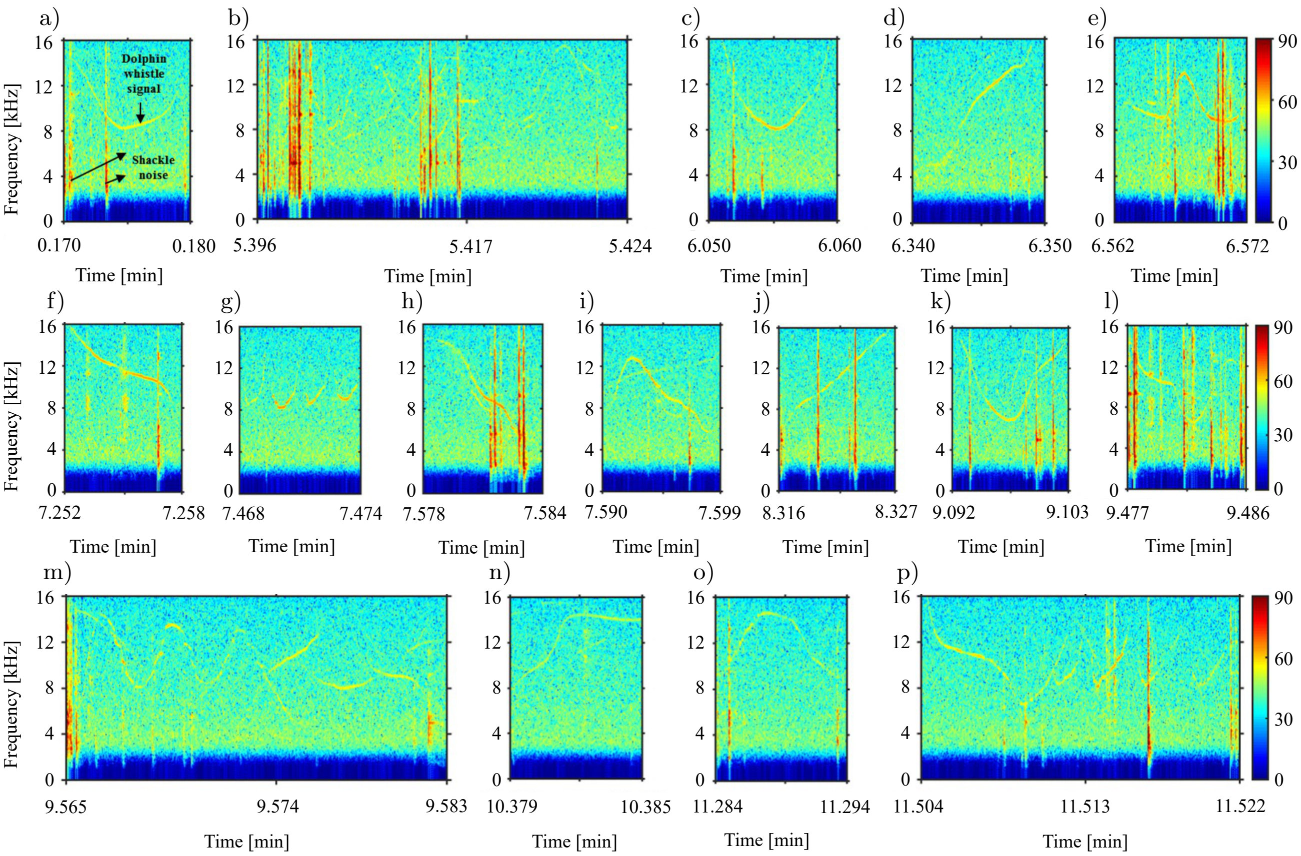

Fig. 4. Spectrograms of dolphin whistle signals (a–p) along with unwanted impulsive shackle noise which are extracted from Fig. 3c. The time axis represents Time in minutes from the start of the recording till the 12th minute reading from top panel.

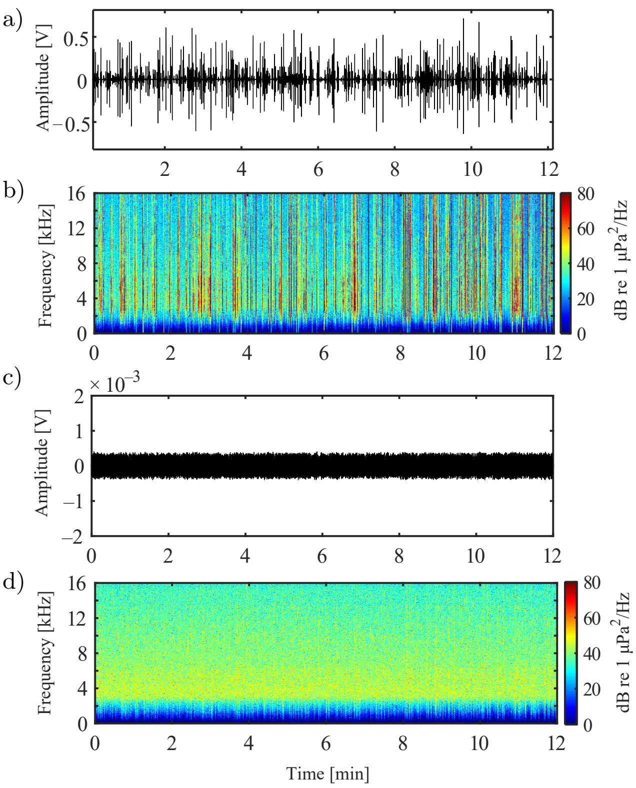

Fig. 5. a) Oscillogram and b) spectrogram of denoised signal; c) oscillogram and d) spectrogram of residual signal.

nal is obtained by taking the difference between the original signal and the denoised signal (Figs. 5c and 5d). In residual output, it contains the combination of whistle signals along with white Gaussian noise other than the impulsive shackle noise. However, denoised signal contains higher values of impulsive shackle noise and lower values of the whistle signals. Hence, only shackle noise can be estimated by subtracting the residual signal from the denoised signal, which is shown in Fig. 6. Finally, the wanted signal of dolphin whistles can be extracted by subtracting only shackle noise from the original signal (Fig. 7).

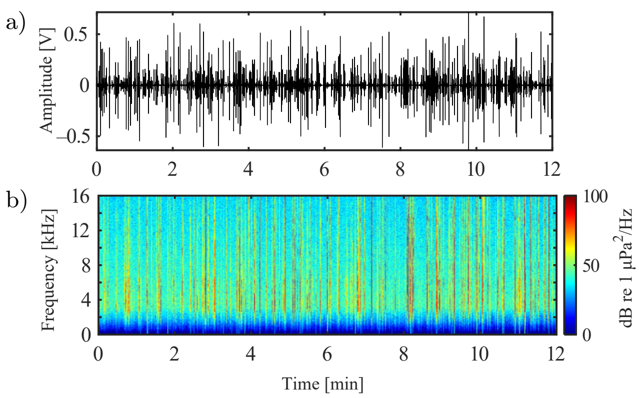

Fig. 6. a) Oscillogram and b) spectrogram of shackle noise.

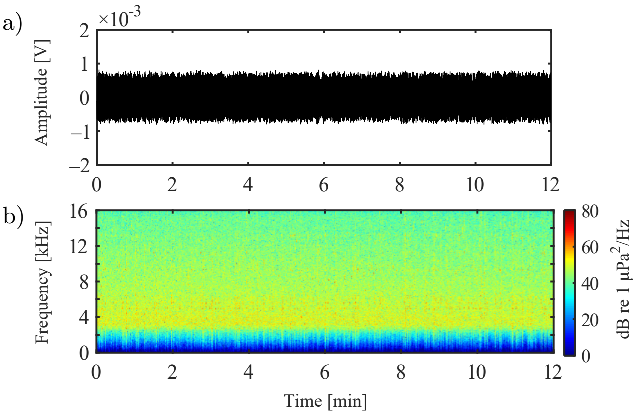

Fig. 7. a) Oscillogram and b) spectrogram of wanted dolphin whistle signals.

The segmented spectrograms of Fig. 8 are extracted from the Fig. 7b, which illustrates the removal of impulsive shackle noise and significant improvement of dolphin whistle signals. It is easy to detect the frequency contour and whistle types after the implementation of wavelet threshold denoising technique followed by the subtraction method. The frequency of dolphin whistles are ranged from ~4 to ~16 kHz with the duration ranges from ~0.4 to ~1.08 s. Based on the frequency contours, whistles are classified as different types such as concave, convex, upsweep, downsweep, sine, and multi-looped. Table 1 gives a detailed description of acoustic parameters for each of the dolphin whistle types. Majority of the whistle types are concave (Figs. 8a, 8c, 8k, and 8l) and convex (Figs. 8e, 8i,

Table 1. Acoustic parameters of the dolphin whistle types in deep water of Arabian Sea from in situ data recorded on 31/05/2019 at 11:58 hr. These metrics are calculated from time-frequency spectrograms of a single data considering 2048 FFT points.

Whistle types	Start frequency [kHz]	End frequency [kHz]	Maximum frequency [kHz]	Minimum frequency [kHz]	Duration [s]
Concave	15.90	15.25	15.90	8.21	0.6
Convex	8.25	14.25	14.62	8.25	0.6
Upsweep	4.98	15.39	15.39	4.93	0.6
Downsweep	15.60	8.92	15.60	8.92	0.4
Sine	15.25	4.15	15.25	4.15	0.9
Multi-looped	15.85	11.35	15.85	6.25	1.08

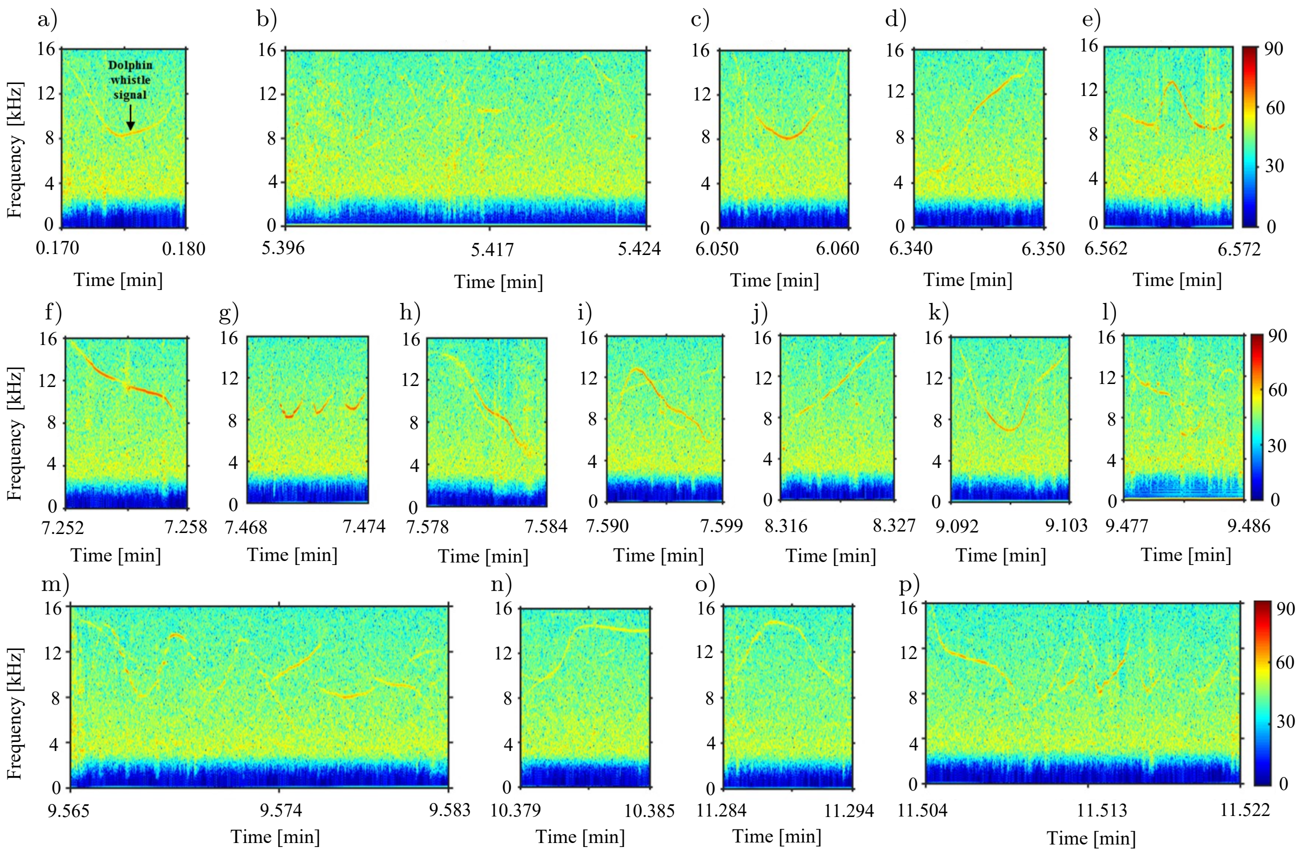

Fig. 8. Spectrograms of dolphin whistle signals (a–p) which are extracted from the Fig. 7b.

and 8o) followed by upsweep (Figs. 8d and 8j), downsweep (Figs. 8f and 8h), multi-looped (Figs. 8g and 8p), and sine (Fig. 8m).

4. Discussion

In this study, it is observed that the in situ time series data of acoustic noise have been contaminated by unwanted impulsive shackle noise, which conceals the dolphin whistle signals. The results show that the unwanted impulsive shackle noise is non-stationary, with the noise levels higher by ~20 dB as compared to that of dolphin whistle signals. The wavelet threshold denoising approach followed by the subtraction method is implemented successfully, and the impulsive shackle noise is removed which are overlapped on dolphin whistle contours. The study suggests that the optimum conditions of denoising are mainly considered by Daubechies [db5] along with 20 multilevel wavelet decomposition and the rigrsure soft threshold method. The satisfactory results of wavelet denoising for dolphin whistle types are obtained and shown in the spectrogram of Fig. 8.

Seramani *et al.* (2006) implemented the wavelet denoising along with the independent component analysis to separate dolphin whistles in the underwater noise environment. Lopez-Otero *et al.* (2018) used the discrete wavelet transform to model dolphin whistle contours for species classification. An earlier study has also demonstrated the extraction of time-frequency dolphin contours based on the automated denoising method (Mallawaarachchi *et al.*, 2008). However, there is no research paper on the wavelet denoising of dolphin whistle contours in the presence of impulsive shackle noise. In the present study, the use of the wavelet denoising threshold approach to identify the dolphin whistle signal has proved to be fruitful to remove impulsive shackle noise present in the in situ time series recording. This is because the impulsive shackle noise has the different temporal and frequency structure as compared to that of dolphin whistle contours.

Many previous studies on dolphin whistle types have been reported worldwide (Janik, Slater, 1998; Wang *et al.*, 1995; Acevedo-Gutiérrez, Stienessen, 2004; Azevedo *et al.*, 2007; Kriesell *et al.*, 2004; Heiler *et al.*, 2016). Some researchers have studied the acoustic detection along with visual observation of cetacean species in the offshore waters of the Maldives and Sri Lanka (Clark *et al.*, 2012; de Vos *et al.*, 2012). However, no detailed identification of dolphin whistle types have been studied in shallow and deep waters of the Arabian Sea. The recent study has described the acoustic identification of dolphin whistle types in deep water of Lakshadweep in the Arabian Sea, and analyzed their acoustic parameters which confirms the six major whistle types in the frequency range approximately from ~4 to ~16 kHz with the whistle duration ranges from ~0.4 to ~1.08 s (Fig. 8, Table 1).

As from the recent study, it has been revealed that the wavelet threshold denoising approach has been taken under consideration for removing the non-stationary impulsive shackle noise, and effectively identify the dolphin whistle contours. The ability to detect and characterize the different whistle contours that provides significant information on dolphin communication and behavioral signals. This method of a wavelet threshold denoising approach identifies the dolphin whistle sounds, and could be used for future studies on other cetacean whistle signals which would be effected by anthropogenic as well as unwanted mechanical noise sources.

5. Conclusion

This study details a technique primarily based on the wavelet threshold approach followed by subtraction for denoising the dolphin whistle contours. The time series recordings of noise data are made in deep waters, where the dolphin whistle signals are contaminated by impulsive shackle noise. The results show that the optimal conditions for denoising are mainly based on Daubechies [db5] along with 20 multilevel wavelet decomposition and the rigrsure soft threshold method. Finally, the contaminated impulsive shackle noise is removed from the dolphin signals by using a wavelet approach. Based on the frequency contours, whistle types are identified as concave, convex, upsweep, downsweep, sine, and multi-looped. Hence, it is proven that, this method is found suitable to extract other species vocalization particularly the non-impulsive signals from passive acoustic recordings.

Acknowledgments

The authors express their sincere thanks to the Director of the National Institute of Ocean Technology, the Ministry of Earth Sciences, for encouragement to the team to do this work. The authors gratefully acknowledge the funding support from the Ministry of Earth Sciences, Government of India. The authors are very thankful to the team of the Ocean Observation System (OOS), NIOT for their support in this work. The authors sincerely thank A. Malarkodi, G. Raguraman, A. Thirunavukkarasu, P.S.S.R. Sridhar, V. Preyenga, and C. Dhanaraj of the Ocean Acoustics Group for their help in calibration of the hydrophones.

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