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Enhanced LOFAR Detection Processing for Passive SONAR

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ABSTRACT

This study surveys methods for improvements in the processing and visualization of Low Frequency Analysis and Recording (LOFAR) in sonar systems. The surveyed method employs a weighted Fast Fourier Transform (FFT) technique to compute LOFAR (Low Frequency Analysis and Recording) spectrum, with the weighting function inversely proportional to the variance of phase estimates for each frequency bin. The approach leverages the observation that stable line spectra display lower variance in phase estimates when compared to broadband signals and ambient noise. Simulation results substantiate the effectiveness of the proposed technique. The technique is applied to the DeepShip underwater dataset available in the public domain, and the performance of the proposed algorithm is recorded.

Keywords: LOFAR analysis; Deepship dataset; Stable line spectrum; Variance of phase

1. INTRODUCTION

Low frequency tonal detection plays a crucial role in underwater passive sonar for early warning due to the fact that low frequency signals travel long distances in the sea. This technique is vital for detecting and classifying underwater targets early.

Underwater acoustic target detection involves identifying the presence of a target and extracting its features through the analysis of acoustic signals. Passive sonar is utilized to detect, track, localize, and identify targets by their own emissions, making it the preferred mode of covert surveillance[1-6]. The acoustic radiation from vessels comprises a continuous spectrum and narrowband discrete components, primarily caused by mechanical vibration and propulsion machinery. The machinery noise and propeller modulation are observed in the low-frequency region. These narrowband discrete components, known as the tonal line spectrum, exhibit higher power than other radiated components[5]. The tonal component conveys information about the type of machinery and propulsion of the target, making it crucial for target detection and recognition. Additionally, low-frequency tonal signals can propagate over longer distances since they are attenuated less compared to higher frequency components. In this context, low frequency tonal detection embedded in wide-band background noise plays a vital role in early detection of underwater targets[2].

However, challenges exist for tonal detection. First, advancements in noise reduction techniques have rendered targets of interest quieter, thereby weakening the tonal line spectrum, especially over long distances. Second, passive sonar is susceptible to time-varying noise from the marine environment, which can easily overshadow the tonal line spectrum. Third, the number of tonal line spectra, as well as their emergence and disappearance, remains unknown and varies for each target during the observation period. This variability arises from potential changes in the target's operational regime, where different machinery may be activated or deactivated.

A survey of related literature reveals that Zheng[7]*, et al.* proposed a line spectrum detection algorithm based on the phase feature of target radiated noise. Park and Jung[8] proposed a convolutional neural network to identify tonal frequencies in a LOFARGRAM. Empirical mode decomposition and Hilbert Huang transform methods[9] are used to reveal the time varying characteristics in underwater acoustic signals. Analysis looks into the problem of robust underwater tone detection, which takes care of scalloping loss or the picket fence effect in DFT[10]. Van, Goh & Chee[11] analysed statistical properties of optimum tonal detectors and derived a maximum likelihood detector for tonal detection. Kim[12]*, et al.* look at tonal signal detection in passive sonar using atomic norm minimization. In[14], an algorithm utilising long-time coherent integration is introduced to enhance the robustness of tonal signal detection, particularly in scenarios affected by Doppler frequency shifts. To capture the line spectral characteristics of underwater acoustic targets[15], introduces a methodology that integrates image processing and a deep autoencoder network (DAE). The proposed approach aims to amplify the low-frequency faint line spectrum of underwater targets within an exceptionally low signal-to-noise ratio environment, leveraging measured data from sizable underwater vehicles.

A new signal-processing technique for machine performance monitoring[16], where the proposed technique exploits fluctuations in phase angles of machine rotational

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frequency signals to determine their dynamic temporal coherence. Based on the observation that the radiated noise of the passive target contains highly intensive and stable line spectrum, the paper[17] puts forward the Conventional Beamforming Variance-of-Frequency Detector, which weighs the bearing spectrum using the variance of the peak frequency of each azimuth.

Our study aims to improve the efficacy of low-frequency tonal detection algorithms in sonar applications. The proposed technique harnesses both the phase and magnitude information of the stable line spectrum. This paper is organised as follows: Section 2 delve into comprehensive explanations of passive sonar and the Low Frequency Analysis and Recording (LOFAR) processing in sonar. The system model is meticulously outlined in Section 3, while the architectural intricacies of the conventional LOFAR processor and enhanced LOFAR processor are explained in Sections 4 and 5 respectively. The performance analysis of the proposed method is shown in Section 6. Section 7 presents the simulation results, including an in-depth examination utilizing the DeepShip ocean dataset[13]. To the best of our knowledge, our work is the first attempt to utilize LOFAR algorithm validation using DeepShip ocean dataset and the proposed method exhibits performance improvement in terms of output Spectral Level Ratio (SLR) which is better than the results reported[7].

Although subspace decomposition methods like Principal Component Analysis (PCA) and Multiple Signal Classification techniques (MUSIC) are reported in the literature for line frequency estimation, these techniques rely on subspace decomposition techniques which are computationally complex. Compared to it our proposed technique is computationally simpler and can be readily absorbed in the existing LOFAR processor without much computational overhead. Subspace methods depend on the relative magnitude of the Eigenvalues which are dependent on the energy of the constituent signals. This can lead to situations in which a high-energy signal may mask the resolvability of a low-level signal using such methods. In the proposed technique the variation of phase through the first derivative helps even a relatively low SNR signal to be given a good weightage even in the presence of high SNR components which would have limited the detection in a conventional LOFAR processing or subspace-based methods.

2. PASSIVE SONAR

In passive sonar, sensor signals received from the array are digitized after necessary signal conditioning, and the resultant data is processed by the beamformer which forms beams steered at different look directions. At the beamformer output (Fig. 1), the different beam time series are subjected to broad spectrum shape analysis, Low frequency Analysis and Recording (LOFAR) and Detection of Envelope Modulation on Noise (DEMON) analysis. These detection processes aim to differentiate the target signal from background noise by utilizing the time-dependent characteristics of the signal. In a controlled laboratory setting, the system undergoes testing by introducing digital signals from a Signal Noise Simulator (SNS). This testing environment ensures a comprehensive evaluation of the passive sonar system's performance in detecting, localising, and classifying target signals in varying signal to noise ratio (SNR) conditions. The LOFAR technique plays a crucial role in detecting stable line spectra in current passive sonar systems. The LOFAR detection subsystem provides operators with a panoramic narrow-band spectral view.

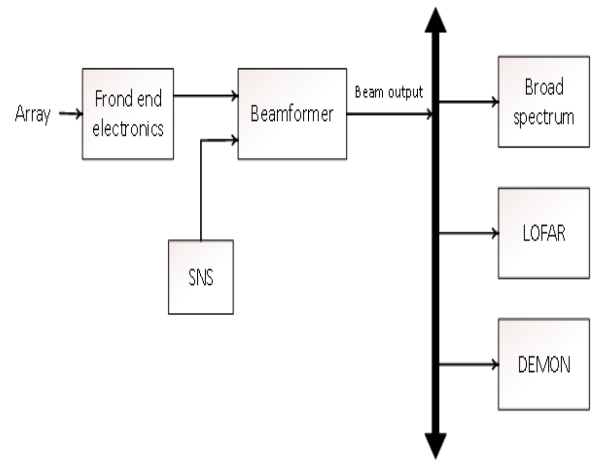


Figure 1. LOFAR processor in SONAR context.

3. SYSTEM MODEL

At the beamformer output (Fig.1), the beam output time series are processed to obtain broad spectrum, LOFAR and DEMON output. The time series of each beam output can be modelled as:

$$x(t) = \sum_{n=1}^{N} A_n \cos(2\pi f_n t + \varphi_n) + b_s(t) + n(t) \tag{1}$$

where, A_n represents the amplitude of each line spectrum, f_n is the frequency of line spectrum, φ_n is the random phase of line spectrum, t denotes time, and N is the number of tonal frequencies. The $b_s(t)$ represents the band-limited broadband signal which includes cavitation noise and propeller modulation and has a characteristic continuous spectral shape. $b_s(t)$ is Gaussian-distributed with mean 0 and variance σ_b^2. φ_n and $b_s(t)$ are independent and φ_n follows a uniform distribution in $U[-\pi,+\pi]$. $n(t)$ represents the ambient noise which is Gaussian distributed with mean 0 and variance σ_n^2. The spectrum level ratio (SLR) between the n^{th} line spectrum and continuous spectrum of $b_s(t)$ is given by [2],

$$\begin{aligned}(SLR)_{fn_{b_s}} &= \frac{\frac{A_n^2}{4}}{\frac{\sigma_b^2}{2B}} = \frac{BA_n^2}{2\sigma_b^2} \\ &\approx 10 - 25\,dB\end{aligned} \tag{2}$$

where, B is the bandwidth of the broadband signal emanating from the target. The SLR between the broadband signal and the background noise is given by:

$$(SLR)_{b_{s_n}} = \frac{\sigma_b^2}{2B}\Big/\frac{\sigma_n^2}{2B} = \frac{\sigma_b^2}{\sigma_n^2} \tag{3}$$

The SLR between the line spectrum at f_n and background noise $n(t)$ is given by:

$$(SLR)_{fn_n} = \frac{\frac{A_n^2}{4}}{\frac{\sigma_n^2}{2B}} = \frac{BA_n^2}{2\sigma_n^2} \tag{4}$$

From Eqn. (2) and Eqn. (3), we get,

$$(SLR)_{fn_n} = (SLR)_{fn_{b_s}} \times (SLR)_{b_{s_n}} \tag{5}$$

The SLR between the line spectrum at f_n and background noise $n(t)$ in dB is given by:

$$(SLR)_{fn_n} dB = (SLR)_{fn_{b_s}} dB + (SLR)_{b_{s_n}} dB \tag{6}$$

From Eqn. (6), it is evident that the spectrum level of the line spectrum of the target is 10-25 dB above the spectrum level of the broadband signal emanating from the target as shown in Fig. 2. This observation motivates the use of line spectrum detection for long-range target detection.

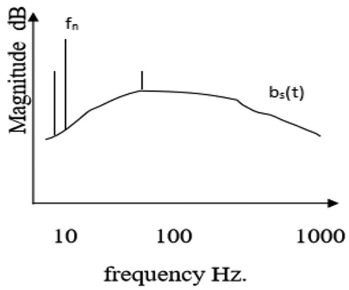


Figure 2. Broadband signal and line spectrum.

4. LOFAR PROCESSOR

In the LOFAR processor, the beamformer output is analysed in the frequency domain to extract the tonal line spectrum radiated by the target. The beam output is low-pass filtered to limit the frequency in the band of interest. The output of the low-pass filter is then subjected to high-resolution FFT analysis is shown in Fig. 3. The spectral lines are integrated, normalized, and quantized before being transferred to the amplitude and waterfall displays.

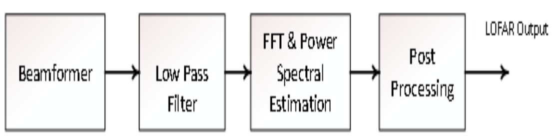


Figure 3. LOFAR processor.

5. ENHANCED LOFAR PROCESSOR

In the enhanced LOFAR technique, a weight vector is derived from the variance of the derivative of the phase of the FFT output. The weighting of the magnitude of the FFT output with this weight vector significantly improves the line detection performance when compared to the conventional approach of power spectral estimation from the FFT output. The algorithm is explained below.

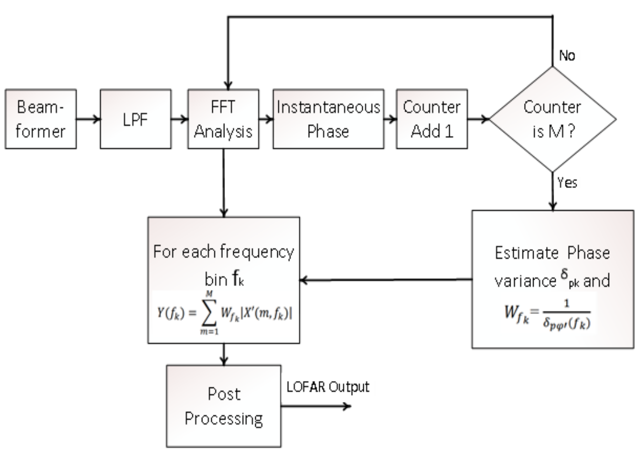


Figure 4. Enhanced LOFAR processor.

Algorithm

1. Take the FFT of the time sequence $x(n)$. The sequence $x(n)$ is the discrete data obtained at the output of the beamformer. The FFT output X_k for each frequency bin is given by:

$$X(m, f_k) = \frac{1}{N}\sum_{n=0}^{N-1} x(n) e^{\frac{-j2\pi kn}{N}}, \quad k = 1,2,.........,K, \quad m = 1,2,.........,M \tag{7}$$

where, n denotes the sample number, N denotes the FFT length, f_k denotes the k^{th} frequency bin, and m denotes the block number.

2. Pass the FFT output to an α-β filter such that

$$X'(m, f_k) = \alpha X(m-1, f_k) + \beta X(m, f_k) \tag{8}$$

where

$\alpha \in [0,1], \beta = (1-\alpha)$ and $X(0, f_k) = 0$

3. Extract the phase information $(\varphi(m, f_k))$ of each frequency bin f_k

$$\varphi(m, f_k) = \arctan\left\{\frac{\mathrm{Im}(X'(m, f_k))}{\mathrm{Re}(X'(m, f_k))}\right\} \quad 1 \le k \le K \text{ and } 1 \le m \le M \tag{9}$$

4. Repeat step 1 and step 2 for each block such that $(\varphi(m, f_k)$ is obtained for M blocks and K frequency bins.
5. Calculate the difference in phase for each frequency bin across adjacent blocks/time instant. This is equivalent to finding the first-order derivative of the phase for each frequency bin. Denote the derivative of the phase $\varphi(m, f_k)$ as $\varphi'(m, f_k)$.
6. Calculate the variance of the phase estimates, denoted as $\delta_{p\varphi'}(f_k)$. The unbiased estimator of variance is used for the variance estimation.
7. Compute a weighting function for each frequency bin f_k as:

$$W_{f_k} = \frac{1}{\delta_{p\varphi'}(f_k)} \tag{10}$$

8. Obtain the final spectral output $Y(f_k)$ after applying the weighting function to the FFT magnitude computed for each frequency bins f_k, as per the Eqn. 11,

$$Y(f_k) = \sum_{m=1}^{M} W_{f_k} \left|X'(m, f_k)\right| \tag{11}$$

6. PERFORMANCE ANALYSIS

The proposed method relies on the fact that the phase estimates of the stable line spectrum have a lesser variance compared to the phase spectrum of broadband signals and noise, whose phase spectrum fluctuates randomly. Therefore, a weighting function inversely proportional to the variance of the phase can be used to enhance the line spectrum estimate.

Assume that the variance of the phase estimate $\varphi'(m, f_k)$ is δ_n and δ_s in the case of noise and signal, respectively. The phase estimate of signal and noise frequency follows a uniform distribution in $[-\pi,+\pi]$ with M number statistic.

Consider the Weighted FFT output $Y(f_k)$ in the case of signal and noise scenario.

$$Y(f_k) = \sum_{m=1}^{M} W_{f_k} \left|X(m,f_k)\right| = \sum_{m=1}^{M} \left|X(m,f_k)\right| \left(\frac{1}{\delta_n}+\frac{1}{\delta_s}\right) \tag{12}$$

The spectral level ratio between the signal component $X_s(m,f_k)$ and noise component $X_n(m,f_k)$ of the $Y(f_k)$ is given by

$$SLR_{output2} = \frac{Var\left(\sum_{m=1}^{M}\left|X_s(m,f_k)\right|.\frac{1}{\delta_s}\right)}{Var\left(\sum_{m=1}^{M}\left|X_n(m,f_k)\right|.\frac{1}{\delta_n}\right)} = \left(\frac{\delta_n^2}{\delta_s^2}\right)\frac{Var\left(\sum_{m=1}^{M}\left|X_s(m,f_k)\right|\right)}{Var\left(\sum_{m=1}^{M}\left|X_n(m,f_k)\right|\right)} \tag{13}$$

where, Var is the variance operator.

From Eqn. (13), it is evident that,

$$SLR_{output2}(dB) = 10\log 10\left(\frac{\delta_n^2}{\delta_s^2}\right) + SLR_{output1}(dB) \tag{14}$$

where

$$SLR_{output1}(dB) = 10\log 10\left(\frac{Var\left(\sum_{m=1}^{M}\left|X_s(m,f_k)\right|\right)}{Var\left(\sum_{m=1}^{M}\left|X_n(m,f_k)\right|\right)}\right)$$

is the *SLR* of the conventional LOFAR output. Therefore, when $\delta_s^2 << \delta_n^2$ we get an additional gain corresponding to the factor $\left(\frac{\delta_n^2}{\delta_s^2}\right)$ in this proposed scheme. In the next section, the simulation results of the proposed method will be discussed in detail.

7. SIMULATION RESULTS

The radiated noise of an underwater acoustic target consists of a mixture of continuous spectrum and superimposed line components. Various field measurements have been conducted and reported in standard literature[2]. According to these reports, the line components are typically 10 to 25 dB above the broadband component.

In the simulation, a target radiated signal is utilized, encompassing a broadband continuous spectrum and two stable line spectra. The line spectra have a Spectrum Level Ratio (SLR) of 15 dB above the broadband signal. This is taken due to the fact that the line spectra resulting from machinery vibrations typically have a positive SLR compared to the broadband continuous signal emitted by the target. The line spectrum is simulated at 312.5 Hz and 1000 Hz respectively. The SLR between the broadband continuous spectrum and the simulated ambient noise is set at -5 dB. Both the continuous spectrum and ambient noise are band-limited within the 0-4 kHz band. The simulation is carried out with a sampling frequency of 32 kHz. The 1024-point FFT is taken with each frequency bin having a resolution of 31.25 Hz.

The reason for choosing 312.5 Hz and 1000 Hz is due to the fact that line spectral components are frequently seen in

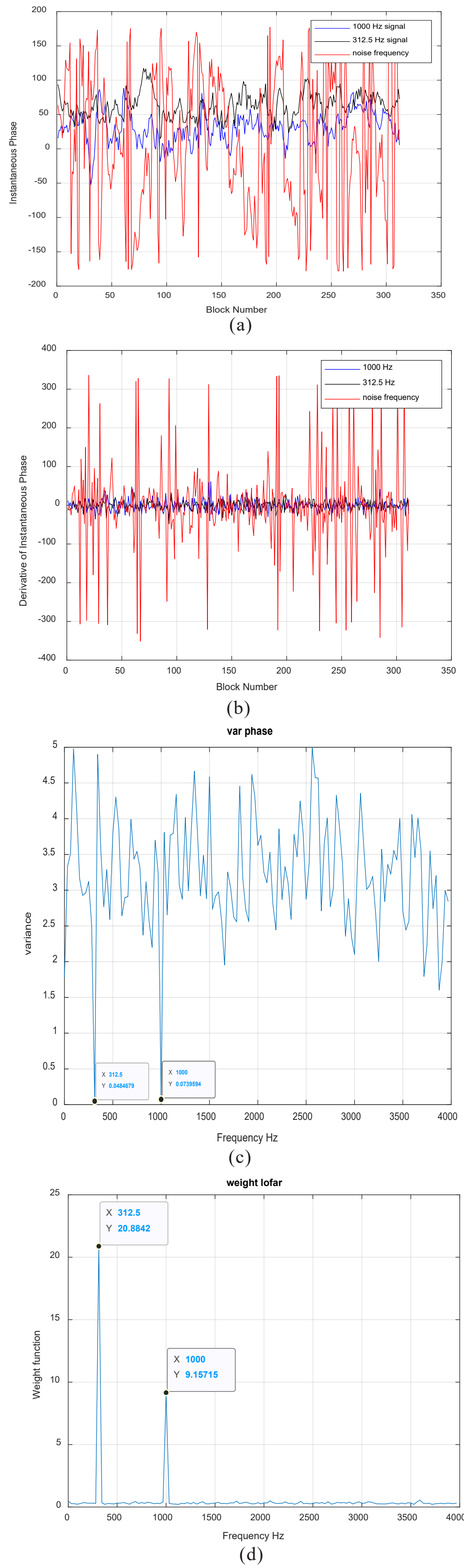


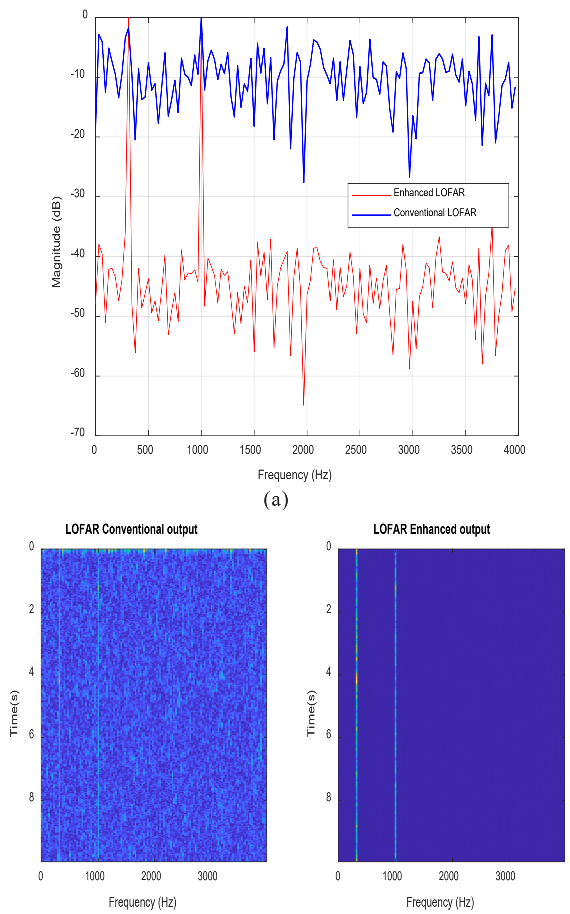
Figure 5. (a) Instantaneous phase for different frequency; (b) Derivative of instantaneous phase; (c) Variance of phase estimates for different frequencies; and (d) Weight vector for each frequency bin.

the lower frequency region, typically below 1 kHz, whereas the passive sonar band of interest for this study extends up to 12 kHz band. The sampling frequency of 32 kHz was chosen because it is approximately 2.5 times the highest passband frequency.

Fig. 5(a) illustrates the phase estimate values of the line spectrum and background noise computed according to step 3 of Section 5.a. The derivative of instantaneous phase calculated as per step 5 of Section 5.a. is depicted in Fig. 5(b). The Fig 5(c) showcases the variance of phase estimates $\delta_{p\dot{\varphi}}(f_k)$ for different frequency bins. The weight vector computed as per Eqn. (10) is plotted in the Fig. 5(d).

A comparison of outputs obtained from the conventional method and the proposed method is presented in the figure below. Fig. 6(a) demonstrates that Enhanced LOFAR exhibits an SNR difference of 40 dB between the line spectrum and back ground noise.

The waterfall display provides a time history of the LOFAR output. The waterfall display of the LOFAR output from one beam is depicted in Fig. 6(b), with the conventional technique plotted on the left and the waterfall of enhanced LOFAR shown on the right.



(a)

(b)

Figure 6. (a) Enhanced LOFAR vs conventional LOFAR; and (b) Waterfall display comparison of conventional technique and the proposed technique.

7.1 Performance Gain Analysis

In this section, the performance of the algorithm under different Signal to Noise Ratio (SNR) conditions is analysed. SNR is measured as the ratio of the variance of the broadband signal and the line spectrum to the variance of back ground noise. The standard deviation of the phase estimate for different SNR conditions for signal and noise is plotted in Fig. 7. From the figure it is evident that the phase variance of signal components reduces with increasing SNR, whereas the variance of the noise phase estimate does not vary with respect to SNR.

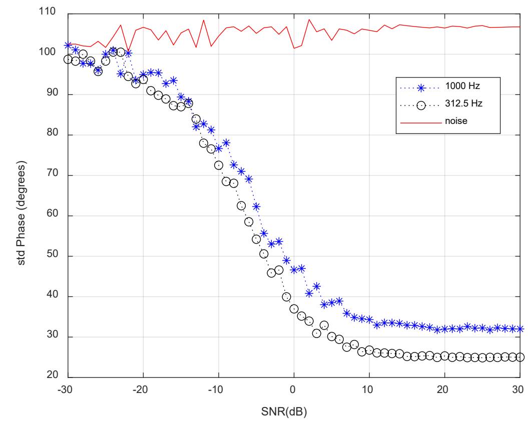


Figure 7. Phase standard deviation vs SNR.

The output Spectral Line Ratio (*SLR*) between signal spectrum and noise in the two methods for different SNR conditions is plotted in the figure below. The Fig. 8 shows that from -20 dB onwards the proposed method exhibits performance improvement in terms of output SLR. Consider SNR of -10 dB, this technique is giving a performance improvement in detection by 5 dB which is better than the results[7]. This concludes to longer detection ranges for a fixed SNR with this proposed technique.

From Fig. 8, it is evident that the output SLR between the line spectrum and the background noise of this proposed method is larger than that of the conventional FFT method, when the input SNR is larger than −20 dB. The reason is that the proposed method first computes derivative of phase variance for each frequency unit and uses the weighting function to obtain the final spectrum. From Eqn. (14), the output SLR between the line spectrum and the background noise of this proposed method is increased by a factor of $\left(\frac{\delta_n^2}{\delta_s^2}\right)$.

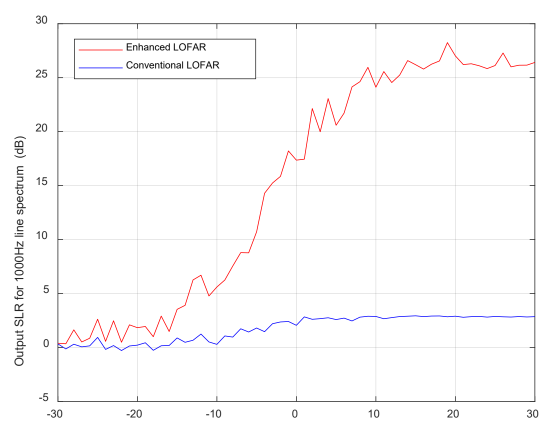


Figure 8. Output SLR between 1000 Hz and background noise under different input SNR.

7.2 Performance Analysis on Ocean Data

To conduct research in the area of underwater acoustics, an acoustic dataset named DeepShip[13] is available in public domain which can be used to benchmark the performance of newly developed algorithms. This data set contains underwater recordings of 256 different ships belonging to four classes. The performance of the proposed algorithm is verified using this data set.

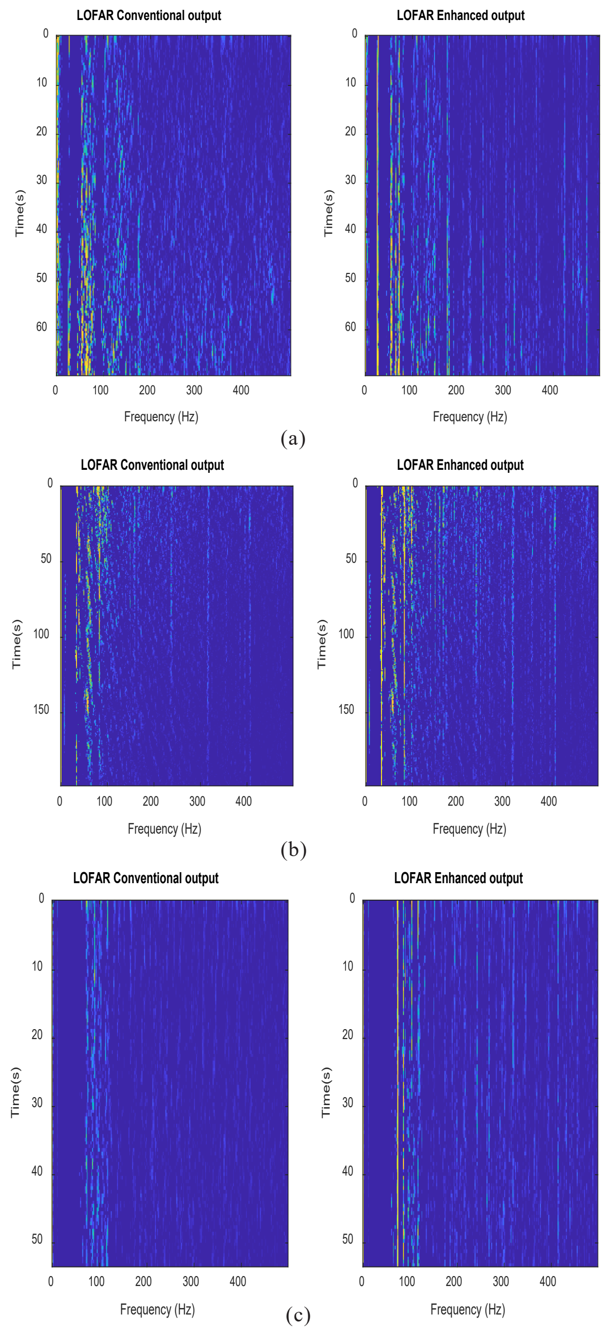


Figure 9. Conventional LOFAR vs Enhanced LOFAR for DeepShip database, (a) tanker/38.wav; (b) cargo/103.wav; and (c) passenger ship/32.wav.

The application of Enhanced LOFAR analysis on the DeepShip dataset provides compelling evidence that the line spectrum not observed in conventional LOFAR is becoming prominent in enhanced LOFAR. The results obtained from this analysis contribute to the validation and refinement of the Enhanced LOFAR methodology, showcasing its practical utility in real-world scenarios.

8. CONCLUSIONS

The focus of this paper is on evaluating the performance of the modified LOFAR processor in the context of sonar applications. A novel technique for LOFAR processing is introduced in the paper, centered around the utilisation of the variance of phase estimates to enhance the detection of weak line spectra within the LOFAR system. The proposed algorithm is subjected to a thorough analysis, combining both analytical scrutiny and simulation experiments.

The objective of this paper is to critically analyse the proposed algorithm, elucidating the underlying principles and implementation details. Additionally, comprehensive simulation results are presented to provide a practical and empirical understanding of the algorithm's performance. The findings of the analysis, both analytical and empirical, underscore the advantages of the proposed technique. Specifically, the results highlight notable improvements in SLR, when applied to DeepShip data set indicating that the introduced method has the potential to enhance the discriminatory power and clarity of stable line spectra within the LOFAR processor. This advancement holds significant implications in passive sonar, where precise detection and characterization of signals are paramount.

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