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Cyclostationarity based sonar signal processing

Reshma Rajan[a,*], Deepa B[b,**], Subhadra Bhai D[b]

[a]*Model Engineering College, Thrikkakara, Kerala*
[b]*Naval Physical and Oceanographic Laboratory, Thrikkakara, Kerala*

Abstract

This paper presents a reliable method for target vessel identification in passive sonar by exploiting the underlying periodicity of propeller noise signal, using the principles of cyclostationarity. In conventional signal processing methods, random signals are treated as statistically stationary and the parameters of the underlying physical mechanism that generates the signal would not vary in time. However, for most manmade signals, some parameters vary periodically with time and this requires that random signals be modeled as cyclostationary. In the field of sonar, the propeller noise signal generated by underwater vessels is cyclostationary. As a ship propagates in the sea, noise generated during the collapse of cavitation-induced bubbles are modulated by the rotating propeller shaft and this results in characteristic amplitude modulated random noise signal, which can be detected using passive sonar. Processing these signals, the number of blades and the shaft frequency of the propeller can be identified. In this work, cyclostationary processing technique is introduced for processing propeller noise signal and it is observed to provide better noise immunity. A detailed comparison with the conventional DEMON processing is also presented.

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Keywords: Cyclostationary signals; Spectral Correlation; Cyclic Spectral Analysis; FAM algorithm; Cavitation; DEMON processing;

1. Introduction

In stationary signal processing, the statistics of the signals under consideration consists of underlying periodicities that are not generally accounted for[1]. But the waveforms of most manmade signals, such as the signals encountered in communication, telemetry, radar and sonar systems, have statistics that vary in a periodic fashion[1]. While modeling random signals as statistically stationary, the inherent periodicities in these signals are not taken into consideration. The performance of signal processors can however be improved by recognizing and exploiting the underlying periodicities of signals. In particular, the properties inherent in communication signals are modeled more efficiently in cyclostationary statistics rather than in stationary statistics[1]. Thus, random signals have to be modeled

[*]reshmarajanmvpa@gmail.com, ph: +919400468800; [**]deepabhargavi@gmail.com, ph: +919497188849

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as cyclostationary for the efficient performance of various signal processing applications. A cyclostationary signal is the one that contain statistical parameters that vary in time with single or multiple periodicities[1]. The concept of cyclostationarity finds a lot of practical applications like propeller noise detection in passive sonar [5].

The blades of the propeller periodically beats sea water and the vibration of propeller shaft produces characteristic amplitude modulated random noise signal, which can be detected using passive sonar[5,6]. The main objective of this work is to analyze the cyclostationary properties of sensor data of passive sonar and make use of the underlying periodicity for classification of underwater vessel. The number of blades and shaft frequency of the propeller are identified from the detected signal. In this work, underwater propeller craft detection is implemented using FAM (FFT Accumulation Method) algorithm and the traditional technique of DEMON (Detection of Envelope Modulation on Noise) processing is compared with this newly implemented cyclostationary technique.

In the next section, an introduction to cyclostationarity is provided, explaining in brief the concepts of cyclic autocorrelation function (CAF), spectral correlation density (SCD) and cyclic spectral analysis. In section 3, the FAM algorithm and its implementation in AM signal are presented. Section 4 describes the passive underwater detection of propeller noise signal using the conventional DEMON processing and the proposed cyclostationary processing. Simulation results are presented in section 5 and some conclusion remarks are offered in section 6.

2. Cyclostationarity

A signal *x(t)* is said to be cyclostationary of order *n* if and only if it is possible to find some n^{th} order non-linear transformation of the signal that will generate finite amplitude additive sine wave components which produce spectral lines[1]. A process *X(t)* is said to be cyclostationary in wide sense if its mean and autocorrelation are periodic with some period *T*[1].

The cyclic autocorrelation function is the measure of the amount of time-correlation between frequency shifted versions of a cyclostationary signal[1]. It performs the time-domain analysis of cyclostationary signals and is defined as[7],

$$R_x^{\alpha}(\tau) = \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t+\tau/2)x^*(t-\tau/2)e^{-i2\pi\alpha t}dt \tag{1}$$

where *x(t)* is the signal under consideration, τ is the delay value and α is the cyclic frequency. A signal exhibits second order periodicity if and only if it's CAF is not zero for some non-zero frequency α, called the cyclic frequency[1]. Spectral correlation density is the Fourier transform of cyclic autocorrelation function[1], defined as,

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau)e^{-i2\pi f\tau}d\tau \tag{2}$$

The major advantage of cyclostationary processing is that noise does not exhibit cyclostationarity and the SCD value of noise reduces to zero for every non-zero value of α. The cyclic autocorrelation function of noise signal *w(t)* with variance σ_w is given by equation 3. Since the value of $R_w^{\alpha}(\tau)$ vanishes for all non-zero values of α, noise signal does not exhibit second-order periodicity.

$$R_w^{\alpha}(\tau) = \begin{Bmatrix} \sigma_w^2\delta(\tau) & ;\alpha = 0 \\ 0 & ;Otherwise \end{Bmatrix} \tag{3}$$

Now, when a signal *x(t)* is present along with noise *w(t)*, the effective spectral correlation density of the resultant signal *y(t)* is obtained as the sum of SCDs of *x(t)* and *w(t)*, expressed by the equation,

$$S_y^{\alpha}(f) = S_x^{\alpha}(f) + S_w^{\alpha}(f) \tag{4}$$

where $S_x^{\alpha}(f)$ is the SCD of the signal and $S_w^{\alpha}(f)$ is the SCD of noise. Thus, evaluating $S_y^{\alpha}(f)$ at an approximately chosen $\alpha \neq 0$ help to separate the signal from purely stationary additive white Gaussian noise (AWGN). This property of noise immunity forms the most important feature of cyclostationary analysis.

Cyclic spectral analysis generates the cyclostationary spectrum by plotting the SCD function in the bi-frequency plane which is the 2D plane constituting frequency *f* in one axis and cycle frequency α in the other. Cyclic spectral analysis has grown importance as a signal analysis tool[8] and is much superior to conventional spectral analysis, since it permits signal separability and provides noise immunity. Over the years, several computationally efficient cyclic spectral analysis algorithms have evolved[3,4]. Out of these, FAM is less computationally complex and hence in this work, FAM is chosen as the cyclic spectral analysis algorithm.

3. FFT accumulation method

The FFT accumulation method or FAM is the Fourier transform of the correlation product between spectral components smoothed over time[3]. The main steps involved are channelization, decimation, multiplication and Fourier transformation. The block diagram for the implementation of FAM is illustrated in Fig. 1[3].

FAM incorporates the idea of time smoothing using Fourier transform to arrive at a computationally efficient digital implementation of the SCD function using N samples from a finite observation interval of duration Δt[3,9]. The complex demodulates $X_{N'}(n, k+\alpha/2)$ and $X_{N'}(n, k-\alpha/2)$ are estimated by means of a sliding N'-point FFT, followed by a down-shift in frequency to baseband. Here, $X_{N'}(n, k+\alpha/2)$ is the $(k+\alpha/2)^{th}$ component of the N'-point FFT output of the n^{th} N'-point window[9]. The N'-point FFT is hopped over the data in blocks of L samples. The value of L is chosen to be $N'/4$ as it allows for a good compromise between computational efficiency and minimizing cyclic leakage and aliasing[3]. Next, the element-wise product between $X_{N'}(n, k+\alpha/2)$ and $X^*_{N'}(n, k-\alpha/2)$ is formed and time smoothed by a P-point second FFT[9]. The value of N' depends on the frequency resolution required, and is given by $N' = F_s/\Delta f$, where F_s denotes the sampling frequency and Δf denotes the frequency resolution. The value of P is given by, $P = F_s/L\Delta\alpha$ where $\Delta\alpha$ denotes the cycle frequency resolution. The output when plotted against the frequency-cycle frequency plane yields the cyclic spectrum of the input signal.

The FAM algorithm was implemented on single sideband AM (AMSSB) signal, double sideband suppressed carrier AM (AMDSB-SC) signal and double sideband transmitted carrier AM (AMDSB-TC) signal. The SCD plots of these signals are illustrated in Fig. 2.

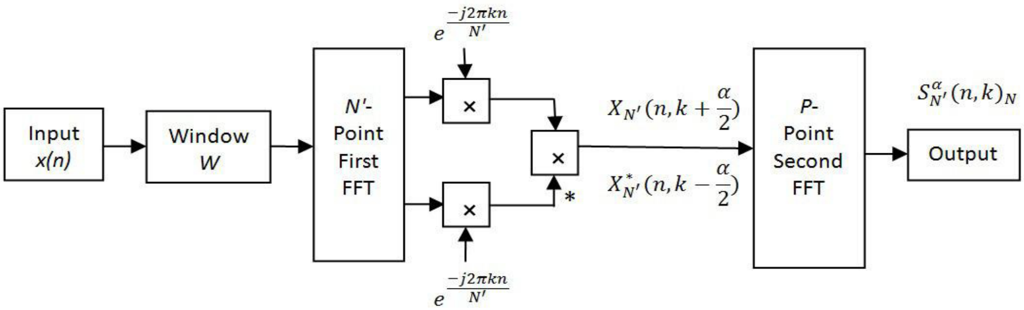

Fig. 1. Block diagram for implementation of FAM

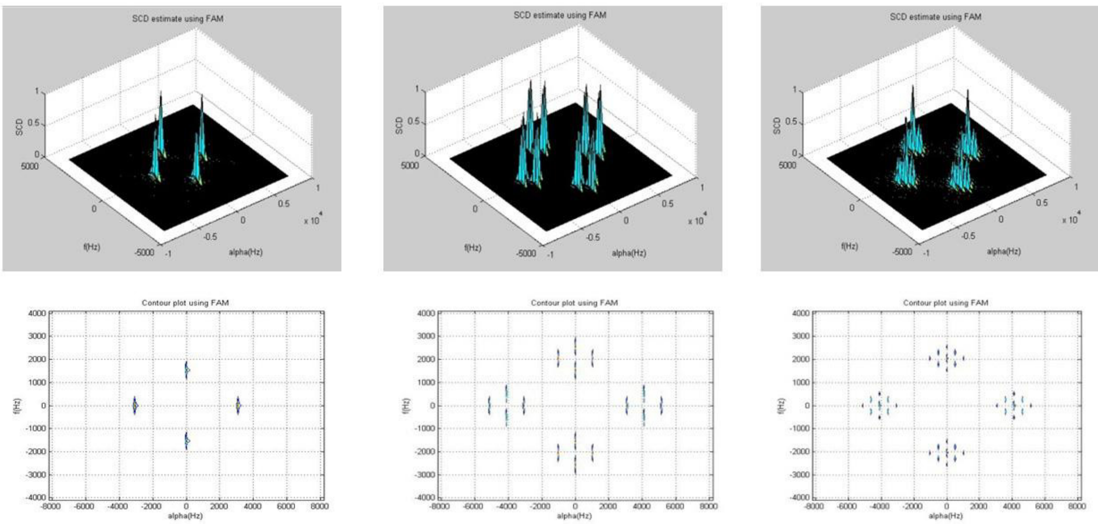

Fig. 2. SCD estimate and contour plot of (a)AMSSB (b)AMDSB-SC (c)AMDSB-TC using FAM

Consider the AMSSB signal defined as, $x[n] = 1/4\cos[2\pi(f_c + f_m)n]$, where f_c represents carrier frequency and f_m represents modulating frequency. The SCD function of $x[n]$ is calculated as the Fourier transform of its cyclic autocorrelation function and is given as,

$$S_x^{\alpha}(l) = \begin{cases} \frac{1}{4}\{\delta[f-(f_c-f_m)]+\delta[f+(f_c-f_m)]\} & ;\alpha = 0 \\ \frac{1}{8}\delta[f] & ;\alpha = \pm 2(f_c - f_m) \end{cases} \quad (5)$$

The plot of equation 5 is illustrated in figure 2(a). The SCD equations for AMDSB-SC and AMDSB-TC can be derived in similar manner and their corresponding SCD plots are illustrated in Fig. 2(b) and Fig. 2(c) respectively. From these plots, it can be clearly observed that different modulation schemes leave different signatures in the cyclostationary spectrum. This will aid in effective signal classification.

4. Underwater detection of propeller craft

Cyclostationary principles can be applied so as to aid efficient classification of underwater vessels. The sound waves (pressure waves) emanating from an acoustically active underwater target (also known as radiated noise) carries very valuable information about important parameters of the target. Passive sonar detects the target by processing this radiated noise and extracting all important parameters using an array of hydrophones. After detecting the target, the signature is further analysed for characteristic amplitude modulated random noise signal produced as the blades of the propeller pass through water. The radiated noise of the underwater target will get modulated by the frequencies corresponding to shaft and blade RPM. These signals can be processed to identify various characteristics of the vessel, such as blade and shaft frequencies.

The propeller is a part of the propulsion machinery of a vessel and it gives rise to noise by generating pressure waves in water. The cavitation induced by rotating propellers forms the major source of underwater sound. When propellers rotate, regions of low pressure are formed at the tips and on the surface of the propeller blades. When the pressure value drops below some critical value, water ruptures and cavities in the form of minute bubbles begin to appear on and around the blades. The process is known as cavitation. The cavitation-produced bubbles initially grow in size and collapse a short time later. This emits a sharp pulse of noise. The broadband radiated acoustic noise signal that reaches the passive sonar is a result of many such random bursts caused by bubble collapse. The production and collapse of cavities formed by the action of the propeller is called propeller cavitation. The propeller amplitude modulates the radiated noise level and this modulation is at a rate of shaft frequency times the number of blades which is defined as the propeller blade rate. This property of the propeller helps in identification, classification and speed estimation of the target vessel. An example of propeller noise signal is illustrated in Fig. 3.

4.1. DEMON processing

Detection of Envelope Modulation on Noise or DEMON processing is a popular technique for the passive detection of underwater targets. It is a technique to detect the presence of propeller craft and it is commonly employed by most submarines. It is based on the observation that the modulation in time of the pressure signal can be detected from the FFT of the envelope of band pass filtered sonar signal. The schematic of DEMON processing is shown in Fig. 4.

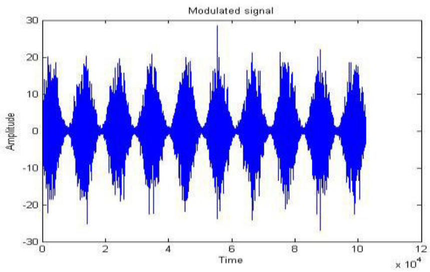

Fig. 3. Propeller Noise signal

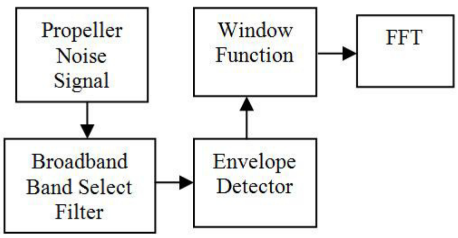

Fig. 4. Schematic of DEMON processing

The frequencies of modulation in case of propeller cavitation – shaft and blade pass frequencies – are detected through DEMON processing. The propeller noise signal is first given to a broadband band select filter, where the frequency band in which the modulation is most distinct to the operator is isolated. Then the envelope of filtered noise band is extracted and is Fourier transformed to obtain the desired output. The output is finally modified to obtain a waterfall spectrogram. The spectrogram or DEMONgram is a time-frequency spectrum and it shows the harmonics associated with the rotating components of the propeller. This allows the vessel to be identified.

The major drawback of this technique is the selection of noise band, which requires good operating skill. The design of bandpass filter is an integral part of DEMON processing and it is controlled by trained sonar operators or fuzzy logic based optimal tuned filters. Another drawback is its low noise immunity. When the SNR value of the propeller signal decreases, the plot becomes blurred, thereby reducing the reliability of the technique. Hence it is advisable to move on to other detection techniques in noisy sonar environment.

4.2. Cyclostationary processing

The cyclostationary processing technique can be developed for propeller craft identification by recognising the fact that the characteristic amplitude modulated propeller signal is cyclostationary. This technique helps to overcome the weakness of DEMON processing by eliminating the need for pre-filtering. It also provides sufficient improvement in the case of noise immunity. The spectral correlation property of cyclostationary signals can be exploited to identify the propeller components in a noisy sonar environment. In place of time-frequency spectrum (DEMONgram), cyclostationary technique concentrates on frequency v/s cyclic frequency spectrum known as cyclic modulation spectrum (CMS).

This work introduces an efficient cyclostationarity based processing technique for CMS calculation by implementing the FAM algorithm. Since the propeller signal is similar to an amplitude modulated double sideband signal with transmitted carrier, the cyclic spectrum reveals spectral lines at the carrier frequency and modulation frequency. The output of the FAM algorithm is however the SCD value that lies in the frequency v/s cyclic frequency domain.

However the entire cyclostationary spectrum has too many dimensions making it difficult to directly use for signal classification. Fortunately, all points of the cyclic spectrum are not necessary, a lower dimensional vector consisting of some typical features extracted from it, called a cyclic feature vector, is sufficient for our purpose. In order to reduce the dimensionality of the data, α domain profile is introduced as, $profile(\alpha) = \max_f [S_x^\alpha(f)]$ where $S_x^\alpha(f)$ is the cyclic spectra estimated using FAM. Spectral lines in the α domain profile are obtained at the shaft frequency value and at the shaft rate value, which is shaft frequency times the number of blades. Taking the ratio of these yields the number of blades of the propeller.

The most important property of a cyclostationary signal is its noise immunity and this forms the major advantage of the proposed cyclostationary processing technique. Even for very low values of SNR, the CMS remains unchanged. Another advantage is the elimination of the pre-filtering stage. The pre-filtering stage requires trained sonar operators or fuzzy logic based optimal tuned filters for operation. Absence of these in cyclostationary processing technique makes the processing much easier. Another important property of cyclostationary signals is signal separability - cyclostationary signals can be easily separated from other interfering signals.

5. Results

The proposed cyclostationary processing was compared with DEMON processing through simulation results. A propeller signal with a blade pass frequency of 3Hz modulated by a broadband carrier component of 3KHz is considered for processing and the outputs of DEMON and cyclostationary processing for different noise cases are depicted in Fig. 5 and Fig. 6 respectively. The variation in the spectrum with respect to the modulation index is observed and it is depicted in Fig. 7. Then, the identification of the number of blades of the propeller is carried out. The propeller is considered having four blades. The results of DEMON processing and cyclostationary processing in the identification of the number of blades are depicted in Fig. 8.

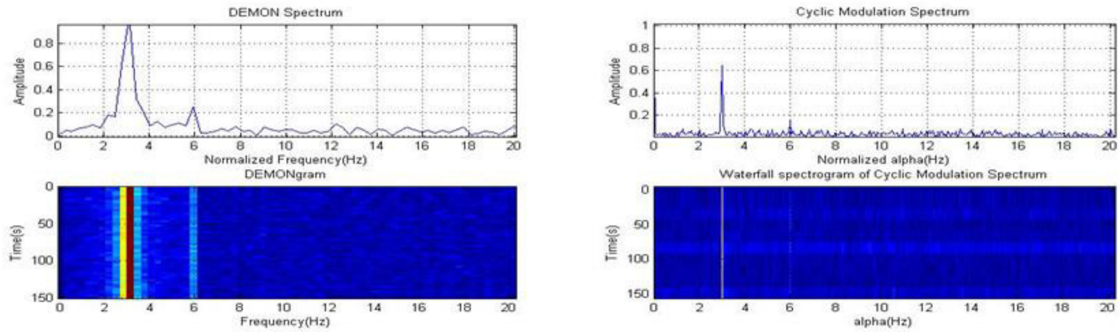

Fig. 5. Spectrum obtained in DEMON Processing and Cyclostationary processing for SNR=-5dB

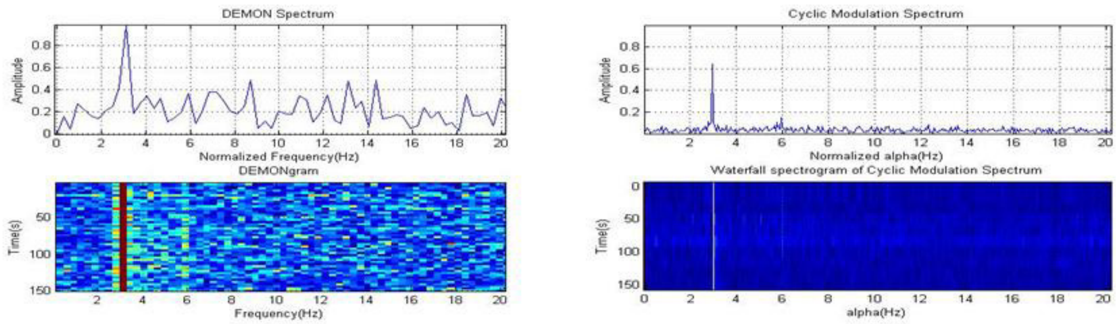

Fig. 6. Spectrum obtained in DEMON Processing and Cyclostationary processing for SNR=-15dB

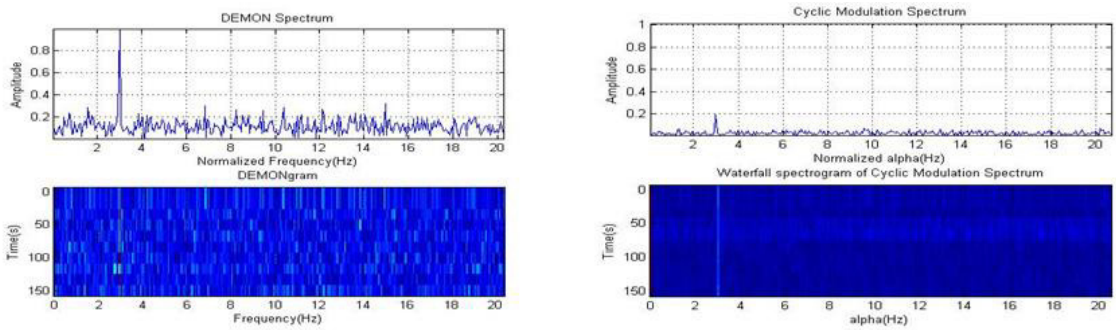

Fig. 7. Spectrum obtained in DEMON Processing and Cyclostationary processing (Modulation index=0.25)

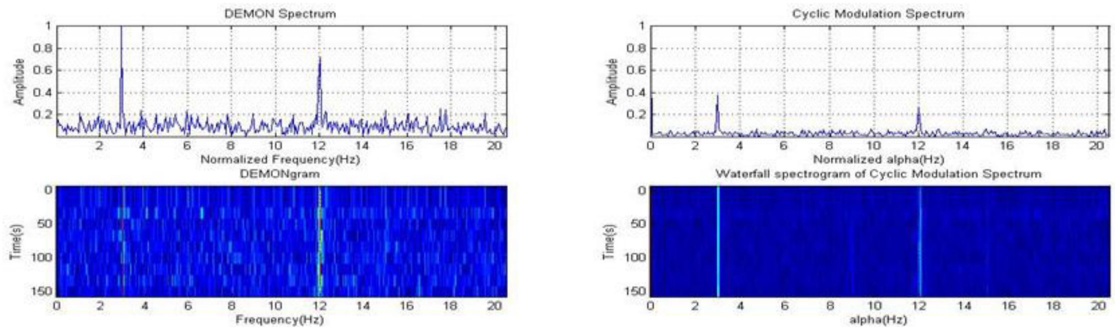

Fig. 8. Number of blades identification in DEMON Processing and Cyclostationary processing (SNR=-15dB)

Both the DEMONgram and the CMS spectrogram identifies modulation frequency and its harmonics effectively. However at low values of SNR, the DEMONgram becomes blurred and the frequencies cannot be identified, as illustrated in Fig. 6. But, the CMS spectrogram exhibits no variation even when the SNR value is decreased. Hence, at low values of SNR, the DEMON processing technique becomes unreliable and the cyclostationary processing technique remains unaffected. Further observing the variation with respect to modulation index, CMS spectrogram gives superior results compared to the DEMONgram, as depicted in Fig. 7.

In the identification of the number of blades, CMS spectrogram provides better results, owing to higher noise immunity. Though the DEMONgram produces spectral lines at the shaft frequency and shaft rate, as in Fig. 8, these cannot be identified distinctly. However, the CMS remains unaffected. The ratio of shaft rate to shaft frequency gives the number of blades. Hence, the proposed cyclostationary processing technique is superior to the existing DEMON processing technique.

6. Conclusion

The noise signal generated at the propeller is cyclostationary and hence cyclostationary principles can be applied so as to aid efficient identification and classification of underwater vessels. Passive sonar detects the characteristic amplitude modulated random noise signal produced as the blades of the propeller pass through water. These signals can be processed to identify the various characteristics of the vessel, such as the number of blades and the shaft frequency. Popular techniques including DEMON processing aids in the detection of these properties. This paper presents a reliable cyclostationarity based technique that overcomes the drawbacks of DEMON processing and aids in efficient identification of the number of blades and shaft frequency of the signal detected from passive sonar. The technique uses FAM algorithm for the analysis of propeller noise signal and provides better noise immunity. The application of cyclostationarity in the field is thus found to provide superior results.

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