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Research paper

Multiple targets detection in the marine environment using matlab

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Abstract

This paper implements multiple targets detection against sea clutter by mathematically modeling target as a single point target and sea-clutter as k-distribution model and observing the deterioration in the effective operation of radar using signal processing by matlab. A Variability Index (VI) algorithm is suggested for detection on the basis of constant false-alarm rate (CFAR) property even in heterogeneous conditions. Comparative analysis of VI-CFAR against various CFAR methods (CA, GO, SO, OS) for multiple targets detection in heterogeneous environment is done in this paper. Comparison and evaluation is done by means of the data which is simulated in MATLAB. The logical operation of the method is verified in heterogeneous condition.

Keywords:*Variability Index CFAR; Cell-Averaging (CA); Smallest-of (SO); Greatest-of (GO); Order –Statistic (OS); Heterogeneous; Target Detection.*

1. Introduction

In RADAR detection, the purpose is to determine presence of target or not in a clutter environment [1].The target and clutter distribution models are crucial to properly evaluate the statistical performance of the detection schemes. The widely used radar environments encountered in the literature are homogeneous, nonhomogeneous, and heterogeneous, which are distinguished by the presence or not of reverberation edges and/or interfering targets [2].
Numerous CFAR detectors operating in homogenous environments [such as the cell averaging CFAR (CA-CFAR) detector [3], the smallest of CFAR [4], and greatest of CFAR [5]], and nonhomogenous environments [such as order statistics CFAR (OS-CFAR) [6]] were developed. The drawbacks of these techniques are nothing but they will fail if the heterogeneous environment worsens by sea clutter. Here in this type of environment we are suggesting a best choice for multiple closer targets detection using variability index of second order statistic CFAR method using simulated data. The Constant False Alarm Rate (CFAR) processors dynamically generates adaptive threshold to achieve target detection such that false alarm rate is maintained constant. Adaptive threshold is computed as a product of estimated target background noise and a constant (which depends on P_{fa}). This paper discussion is as follows. Section 2 reviews the statistical echo signal modeling. Section 3 discussed concept of standard CFAR methods and VI-CFAR, Section 4 discusses performance assessment using CFAR approaches with simulation results, and Section 5 ends the paper by conclusion respectively.

2. Echo signal modeling

The echo signal modeling stage consists of modeling of target and addition of modeled sea clutter and noise which can be explained with the help of below figure:

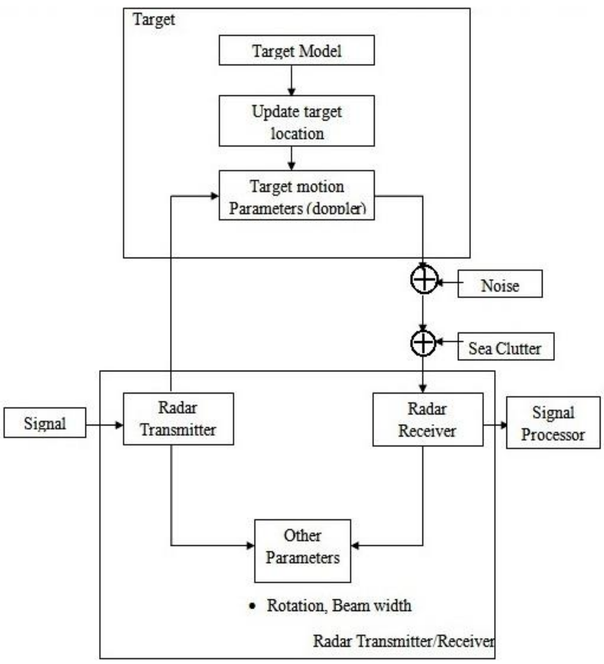

Fig. 1: Simulation Block Diagram in Matlab.

2.1. Target model

The target is modeled as swerling5/0 model that is as a single point target whose function is given by:

$$f(t) = \exp(j2\pi F_d t) \tag{1}$$

Where F_d is Doppler frequency of target model and t is the time period of target return. The targets count simulated in this simulation is 5.

2.2. Modeling of sea clutter

K-distribution is popular for amplitude modeling of sea clutter returns, which can be done by two parts: the “speckle” part and the “texture” part. The “speckle” part is a fast varying component and its amplitude can be designed as Rayleigh distribution. The “texture” part is a slowly varying component with a long temporal decorrelation period; it’s not sensitive for frequency agility. This component represents and obeying the Gamma distribution. Therefore, sea clutter can be interpreted as the product of two independent components:

$$p(z)=\frac{2c}{\Gamma(v)}\left(\frac{cz}{2}\right)^{v}\mathrm{K}_{v-1}(cz), z>0 \tag{2}$$

Where $K_{v-1}(\cdot)$ is the modified second kind Bessel function of the order $(v-1)$ and c is the scale parameter given by $c=\sqrt{\pi}b$.
In simulation, noise is considered as Gaussian noise, the assumption made in clutter modeling is the value of shape parameter v is known which is taken as 0.6434.

Table 1: Simulation Parameters

Parameter	Value
Pulse width	40us
Carrier frequency	10GHz
Bandwidth	2MHz
PRF	5000Hz
Pulse number	32
Range Resolution	75m
P_{fa}	10^{-4}

3. CFAR methods

This section will introduce VI- CFAR along with some standard CFAR detectors as follow:

3.1. Architecture of CFAR

The CFAR detector contains four main elements, (i) the cell under test (CUT), (ii) guard cells, (iii) reference cells, and (iv) the CFAR multiplier T_α, based on probability of false alarm. These four elements assist the processor to set a varying threshold which is as follows

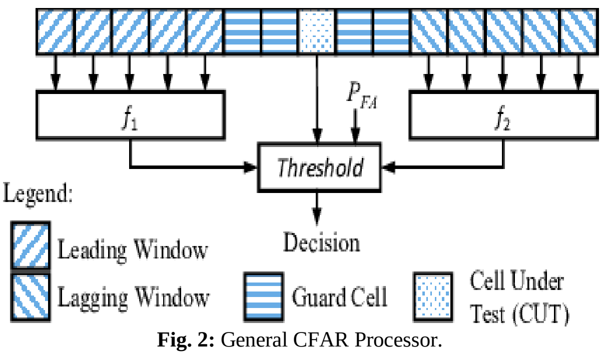

Fig. 2: General CFAR Processor.

The cell under test (CUT) is the position where the threshold is going to be applied. If the target is in the CUT, then it should exceed the threshold and declare detection. The cell under test is located at the middle of the CFAR processor.
Guard cells are present beside the test cell usually on neighboring sides that is shown in Figure.2. The samples contained in guard are not considered. The reason of having the guard cells is to eliminate any spill over from the target if the target extends to more than one sample. This produces an improved estimation of the background noise.
Reference cells are the outer cells of the CFAR processor. CFAR multiplier is also called CFAR constant.

For both 1-D CFAR detectors, the window is shifted through the data. Then the estimated average threshold and the CFAR constant are both multiplied together to produce the actual threshold value. Comparator compares the threshold value with the CUT for making decision about the presence or absence of the target [7].This section introduces four types of the standard CFAR processors along with VI-CFAR. The logical architecture of CA, GO, SO CFARs is given by:

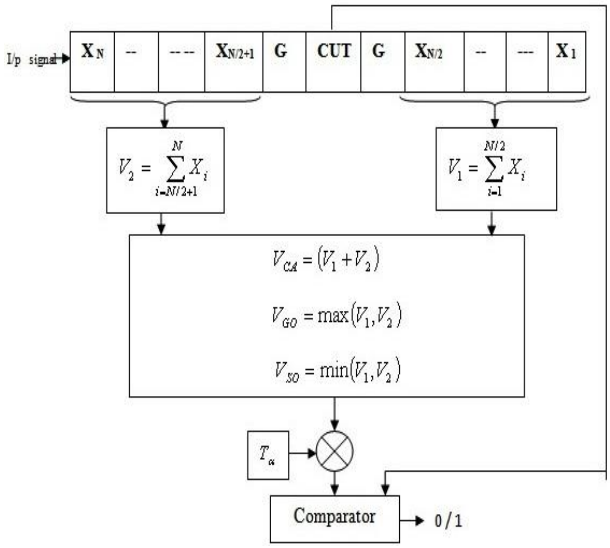

Fig. 3: Block Diagram of CA, GO, SO CFAR Methods.

3.2. Cell-averaging CFAR method

The cell-averaging CFAR was developed in 1968 by Finn and Johnston [3]. The ideology of the CA-CFAR is to estimate the samples possessed in the reference cells by averaging across them. The architecture of CA-CFAR is the simplest among the other CFAR processors. Where X_1, X2… XN are the samples which are there in reference cells N, G is the guard cells, CUT is the cell under test, The CFAR constant, T_α, for the CA-CFAR, assuming homogeneous background noise, is giving by [7]:

$$T_\alpha = N(P_{fa}^{-1/N} - 1) \tag{3}$$

The disadvantage of the CA-CFAR is degradation in environments where clutter edge occurs. To solve this problem, Hansen and Sawyers [5] proposed the GO-CFAR detector.

3.3. Greatest of cell-averaging CFAR method

The Greatest of cell-averaging CFAR (GO-CFAR) was mainly designed to maintain the probability of the false alarm at a clutter edge region [5]. The GO-CFAR architecture is shown in Figure.3.The difference between the CA-CFAR and the GO-CFAR is that the GO-CFAR calculates the average noise power of both lead and lags separately, and then selects the larger of them. Solving the GO-CFAR constant for a given probability of false alarm is much complex than in the CA-CFAR. To calculate the CFAR constant in the GO-CFAR, numerical techniques is used to solve the given equation [7].

$$P_{fa} = 2\left\{[1+\alpha]^{\frac{-N}{2}} - [2+\alpha]^{\frac{-N}{2}} \sum_{K=0}^{\frac{N}{2}-1} \binom{\frac{N}{2}-1+K}{K} [2+\alpha]^{-K}\right\} \tag{4}$$

Both the CA-CFAR and the GO-CFAR degrade in a mutual masking target environment. Since the calculation of the average will include the target, this will increase the threshold level and will also increase the losses in the CFAR performance.

Mutual target masking can be detected using other CFAR techniques. Such techniques include the Smallest of cell-averaging CFAR, and the Order Statistics CFAR which are as follows.

3.4. Smallest of cell-averaging CFAR method

The Smallest of cell-averaging CFAR was mainly designed to solve the mutual target masking issue. It was found by Trunk[4] in1978.When the target is contained in the CUT and another target appears in the reference cells at that particular time, the SO-CFAR suppresses the existence of the target in the window cells by estimating both the lagging and the leading windows and estimation is done by considering smaller of the two averages.
Figure.3 represents the architecture of the SO-CFAR. Numerically, the CFAR constant of the SO-CFAR can be calculated from the average probability of false alarm as [7]:

$$P_{fa} = 2[2+\alpha]^{-\frac{N}{2}} \sum_{K=0}^{\frac{N}{2}-1} \binom{\frac{N}{2}-1+K}{K} [2+\alpha]^{-K} \tag{5}$$

With mutual target masking, the SO-CFAR can detect the target, which is contained in CUT in a multiple target masking environment, if and only if the targets appear in either side of the reference cells as shown in Figure3. The following section will introduce a technique where the CFAR can overcome this problem using a detector called “Order Statistics” CFAR.

3.5. Order statistics CFAR method

Rohling proposed the OS-CFAR detector (OS-CFAR) [6], which was designed to solve the issues reviewed in the previous sections, such as self-masking target, and mutual masking targets. It estimates the average background noise by a signal sample from the reference cells using order statistics processing.
The order statistics was proposed to address the heterogeneous environment. The OS-CFAR detector ranks by increasing power of samples in reference cells. It then selects the k[th] sample based on the CFAR statistics to estimate the average threshold of the environment. The architecture of the OS-CFAR is shown below:

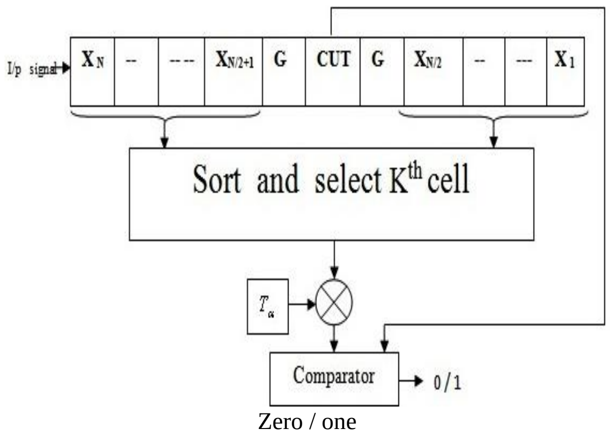

Fig. 4: Ordered Statistics CFAR Processor.

The CFAR constant is calculated using:

$$P_{fa} = K\binom{N}{K}\frac{(K-1)!(\alpha+N-K)!}{(\alpha+N)!} \tag{6}$$

To reach near to the minimum of the CFAR loss of the OS-CFAR, as a rule of thumb, the k^{th} sample should be chose at $3N/4$ order which is well fit for real time application [6].
For the mutual target interference, the OS-CFAR performs better than SO-CFAR even if the targets appear in both sides of the reference cells. In OS-CFAR, the guard cells are not necessary since ranking the samples push the high values to the end of the reference cells. This means that the self-masking target is not an issue in OS-CFAR detector. Therefore, it is possible to apply the OS-CFAR without guard cells [6].

3.6. Variability index CFAR method

The VI CFAR, one of efficient CFAR algorithms, is the mostly accepted composite CFAR method is shown in figure 5. Dynamic selection of one of CFAR methods of mean level, on the basis of variability index and a mean ratio test is done by VI-CFAR for performing in robust manner especially for multiple targets environment [9].

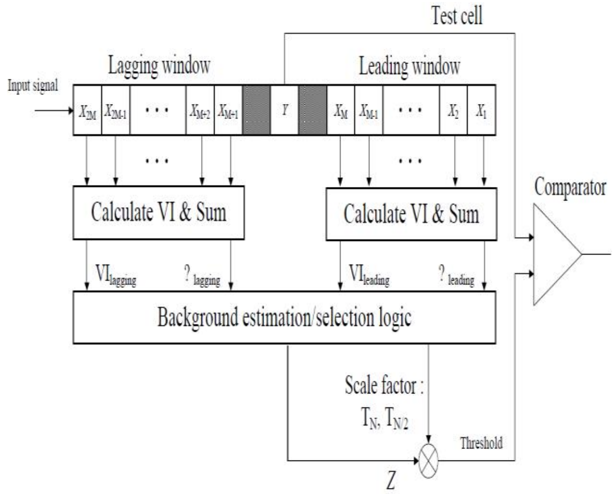

Fig. 5: Block Diagram of VI-CFAR [6].

Variability index (VI) is computed for leading as well as lagging windows using:

$$VI = 1+\frac{\sigma^2}{\mu^2} = 1+\frac{1}{n}\cdot\sum_{i=1}^{n}\left(X_i-\bar{X}\right)^2/\left(\bar{X}\right)^2 \tag{7}$$

Where, μ is mean and σ^2 is variance of window, $\bar{X}$ is the mean of n cells in a leading or lagging half of reference window [9].
Where X_i is the power of reference cell i.Variability of window is estimated by applying hypothesis test given by Eq. (8) and Eq. (9).

$VI \le K_{VI} \Longrightarrow$ Non-Variable window(8)

$VI > K_{VI} \Longrightarrow$ Variable window(9)

Table2: Adaptive Threshold Generation [6]

Leading Window Variable	Lagging Window Variable	Different Means among Windows	Adaptive Threshold	Equivalent CFAR
No	No	No	$T_N.\Sigma AB$	CA- CFAR
No	No	Yes	$T_{N/2}$.max (ΣA, ΣB)	GO -CFAR
Yes	No	-	$T_{N/2}$. ΣB	CA- CFAR
No	Yes	-	$T_{N/2}$. ΣA	CA- CFAR
Yes	Yes	-	$T_{N/2}$.min (ΣA, ΣB)	SO- CFAR

The Mean Ratio (MR) is computed as ratio of the mean of leading to mean of lagging window as in eq. (10)

$$MR = \frac{\bar{X}_A}{\bar{X}_B} = \frac{\sum_{i\in A} X_i}{\sum_{i\in B} X_i} \tag{10}$$

Where

$$K_{MR}^{-1} \le MR \le K_{MR} \Rightarrow Same\ \ means \quad MR < K_{MR}^{-1} \quad Or \quad MR \ge K_{MR} \Rightarrow Different\ \ means$$

The threshold multiplier formulae are given by:

$$T_N = P_{fa}^{\left(\frac{-1}{N}\right)} - 1 \tag{11}$$

$$T_{N/2} = P_{fa}^{\left(\frac{-1}{N/2}\right)} - 1 \tag{12}$$

3.6.1. VI-CFAR decision logic

Case I: Same means, both windows Non-Variable
When the leading window and lagging window both are non-variable, they don’t have targets; and when both windows have similar means, then the reference window probably doesn’t have a reverberation edge. The CUT, then, is mostly expected to be in a homogeneous environment. VI-CFAR, then, utilizes CA-CFAR.
Case II: Variable Leading Window, Non-Variable Lagging Window
As leading window is variable it gives representation of high spikes of power along with a sensible signal to noise ratio, these spikes are mostly expected as targets which represents third row of table 2. The average power, then, of the leading window wouldn’t be representative of the noise/clutter possessed. In this scenario, VI-CFAR chooses to use CA-CFAR with the lagging window only. As the lagging window is non-variable, it is expected to possess noise/clutter only.
Case III: Variable Lagging Window, Non-Variable leading window
This is an alternate case of Case II which represents fourth row of table 2. The lagging window is variable and leading is non-variable, the lagging window is expected to possess targets and the leading noise/clutter only.
Case IV: Both Variable windows
When the leading window and lagging window both are variable, then both windows are expected to possess targets.
Case V: Non-Variable but Different Mean
When the leading window and lagging window both are non-variable but having different mean, then the CUT is expected to be nearer to a clutter wall.

4. Performance assessment

The step wise simulation results as discussed in simulation flow diagram is given below:

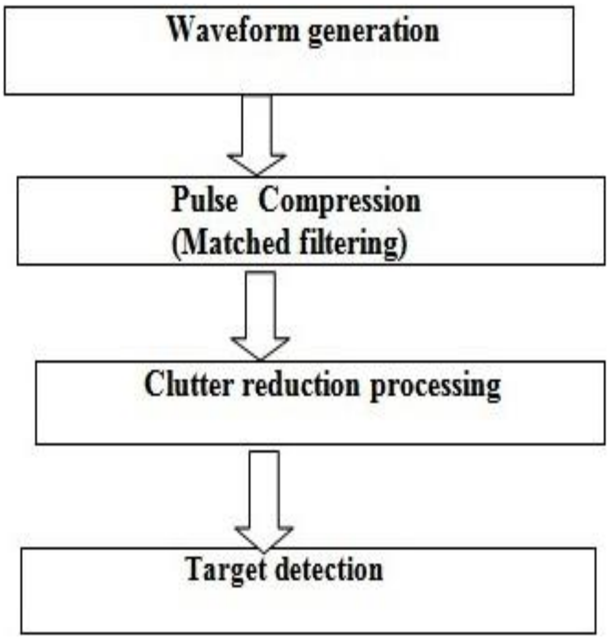

Fig. 6: Flow Diagram of Signal Processing Steps.

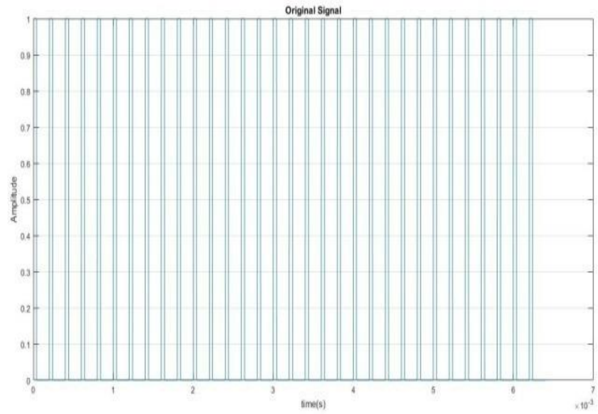

Fig. 7: Transmitted Signal.

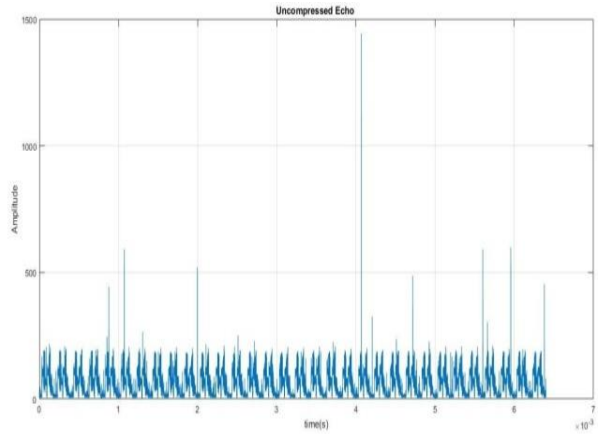

Fig. 8: Uncompressed Echo Signal.

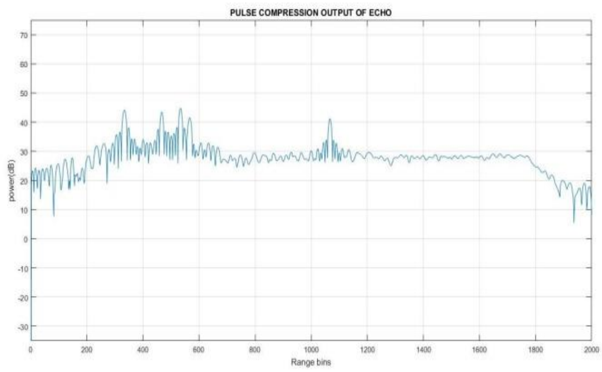

Fig. 9: Compressed Echo Signal Output Using Matched Filtering.

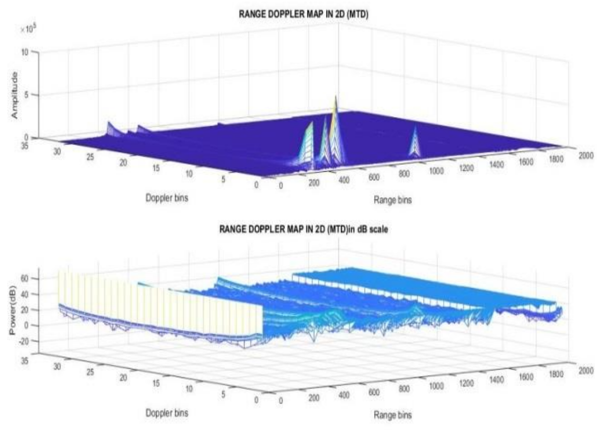

Fig. 10: Range Doppler Map (2D) of Moving Target Detection (MTD).

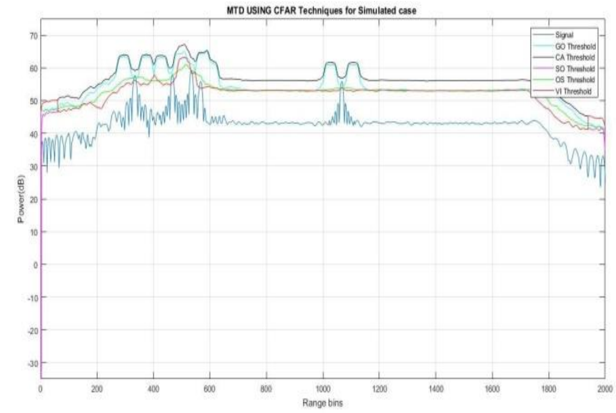

Fig. 11: Comparison of Different CFAR Thresholds on the MTD Signal for Simulated Case.

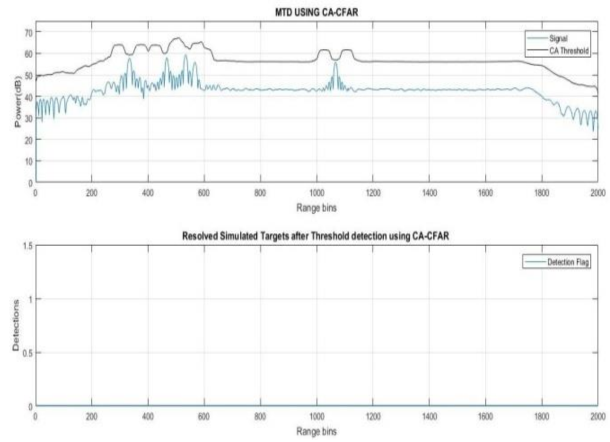

Fig. 12: Resolved Simulated Targets after Threshold Detection Using CA-CFAR.

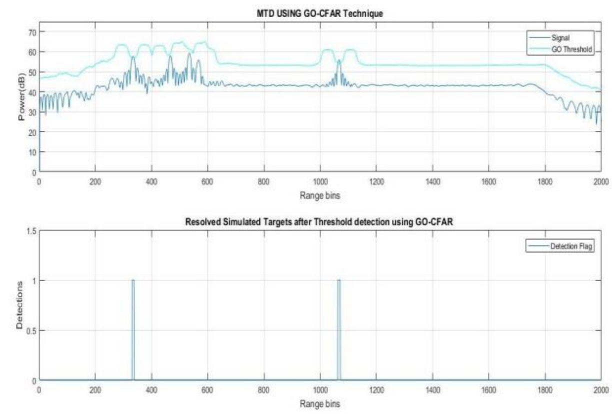

Fig. 13: Resolved Simulated Targets after Threshold Detection Using GO-CFAR.

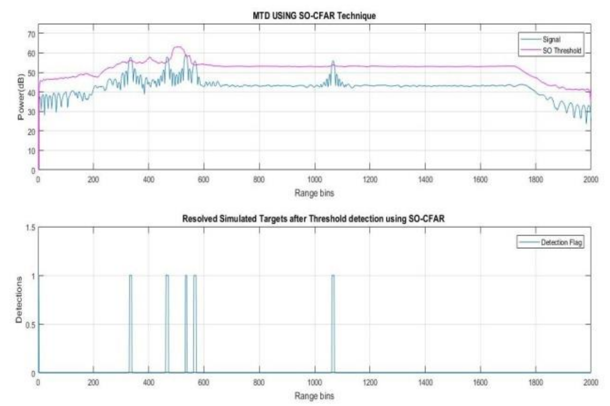

Fig. 14: Resolved Simulated Targets after Threshold Detection Using SO-CFAR.

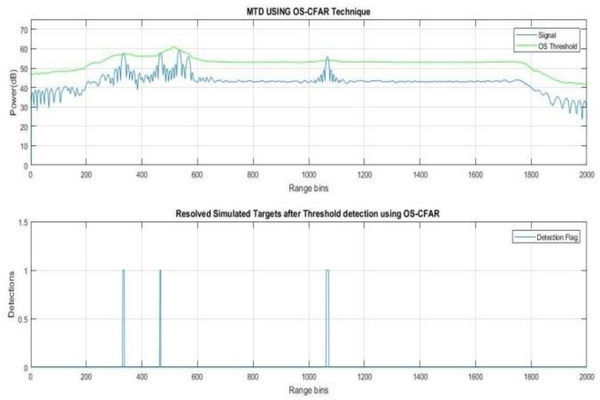

Fig. 15: Resolved Simulated Targets after Threshold Detection Using OS-CFAR.

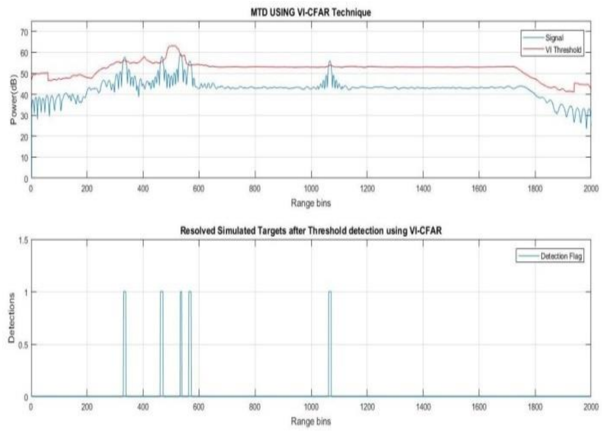

Fig. 16: Resolved Simulated Targets after Threshold Detection Using VI-CFAR.

5. Conclusion

The Variability Index CFAR on the basis of a constant false-alarm rate (CFAR) property is applied for multiple targets detection against unwanted sea clutter. It combines the best from the CA-CFAR, GO-CFAR and SO-CFAR. Using dynamic background estimation algorithm VI-CFAR adapts to changing environment and applies best of CA, GO and SO CFAR. The performance of this technique is checked and comparative analysis of VI-CFAR against CA-CFAR, GO-CFAR, SO-CFAR and OS-CFAR for multiple targets detection in heterogeneous environment by using simulated data which is modeled by Matlab, is done. It is concluded that VI-CFAR offers better probability of detection (P_d) in heterogeneous environment by keeping the low threshold compared to GO-CFAR, OS-CFAR and better False Alarm probability (P_{fa}) compared to SO-CFAR.

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