Intelligent Approach to Improve Standard CFAR Detection in non-Gaussian Sea Clutter

THESIS

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Abstract

To function correctly a radar must be able to detect if the target is present. This research is examining new approaches based upon intelligent techniques to improve detection in non-Gaussian environment using standard constant false alarm rate (CFAR).

Cell-average CFAR has been shown that is the optimum in homogeneous Gaussian environment. Different CFAR processors such as Greatest of CA-CFAR, Smallest of CA-CFAR, and Order Statistics improve the performance of the detection in nonhomogeneous Gaussian environment (multiple targets, clutter edge, etc.). However, when the clutter present, the situations become more complicated.

Initial results demonstrate that different solutions are required as a function of clutter characteristics. As an example, some clutter conditions are such that the detector benefits from pre-integration whilst other clutter conditions result in better detection performance with no pre-integration. Combining time domain and frequency domain detection increase the chance to detect targets in challenging situations such that when the target has radial velocity, Doppler processing is performed. Under the circumstances where there is no radial velocity between the target and the clutter, time domain processing is performed. Combining the detections of time/frequency processing is showing improvement of target detections.
Dedication

To my parents

To my wife and daughter

For supporting my all the way!
Acknowledgments

I would like to express my sincere gratitude to my advisor Prof. Chris Baker for his guidance, motivations, and patience, during my master study. Beside my advisor, I would like to thank my thesis committee member: Prof. Fernando Teixeira, for his encouragement, and the good questions. I also would like to thank Dr. Graeme Smith for attending my master defense.

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Chapter 1: Introduction

One of the basic radar concept is to decide whether the target is present or not. This is can be done by looking at the display and wait until a bright reflection returned from the target compared with the background brightness [11]. Modern radars perform target detection automatically. There are many detection techniques were developed in the literature since long time ago [5][7][8][9][11]. The basic detection technique in the radar systems is to apply a fixed threshold on the received signal. The level of the fixed threshold is decided based on the background (thermal noise, clutter, external noise). If any sample exceed this threshold, the radar will declare the target is present. Once the target is declared, the radar process this detection to extract target information based on the radar application.

Constant false alarm rate detector (CFAR) was designed to avoid the false detection that could happen in performing the fixed threshold. The CFAR detector estimates the statistics of the background noise (or clutter) to set a threshold adaptively vary with different background conditions. Cell-averaging CFAR (CA-CFAR) is one of the earliest CFAR which was introduced by Finn and Johnson in 1986 [14]. There are many different CFAR detectors such as Greatest of CA-CFAR (GO-CFAR), Smallest of CA-CFAR (SO-CFAR), and Ordered statistics (OS-CFAR) which were designed to either maintain false alarms or improve detections based on specific situations of the background noise (or clutter).
In general, the CFAR detectors give best performance when the background is uniform distributed such as thermal noise [11]. In practice however, the radar received signal could contain an unwanted background clutter such as land, rain, and sea clutter [1]. These clutter could appear as targets in some cases which makes the detection of targets in the presence of the background clutter more difficult. Therefore, it is important to understand the characteristics of the background clutter. Statistical model is one the characteristics which is required for performance predictions, simulations, and design of detection processing [1].

The main aim of this research is to apply intelligent techniques to improve detection performance in sea clutter using standard CFAR detectors. The object here is to maintain the probability of false alarm in sea clutter and improve target detection by combining intelligent techniques together. With these objectives in mind, implementation of standard CFAR detectors were applied to a real sea clutter data. The primary focus is to understand the reason of the false detections when applying standard CFAR detectors in the sea clutter and how to avoid it using intelligent approaches.

The reminder of this thesis is organized as follow. Chapter 2 reviews the fundamentals of radar detection in background noise. Chapter 3 reviews the concept of the standard CFAR detectors and build a simulation of a point target in Gaussian noise to implement different CFAR detectors in different background conditions and compare the performance. Chapter 4 is a description of a real sea clutter datasets which were collected in South Africa in 2007. It further include a statistical analysis of the datasets. Chapter 5
investigates the intelligent approaches to improve detection of small targets in sea clutter using standard CFAR detectors. Chapter 6 conclude the thesis and highlights the results.
Chapter 2: Background

2.1. Introduction

In this chapter, the background to detection of targets in noise is introduced in order to prevent false alarms in radar systems and provide the context for the development of a more advanced approach to detection exercised in chapter 5. “Radar” is an acronym which stands for Radio Detection And Ranging. It is an electrical system that transmits an electromagnetic wave and waits until a reflection is returned back to the receiver in order to detect a target of interest [11]. The returned energy from the target is called an “Echo”. The power of the returned echo depends on a number of factors, such as transmitted power, the radar cross section (RCS) of the target, the distance between the radar and the target, and so on. There are different types of radar systems; however, the major subsystems include transmitter, antenna, receiver, and signal processing [11]. Figure 1 shows a basic block diagram of a monostatic radar system.

One of the primary tasks of any radar system is detection. The main concept of detection is to make a decision as to whether the target of interest is present or not. Most radar systems perform automatic detection rather than make an operator looking at a monitor decide if the target is present or not[11]. Automatic detection is achieved by setting a fixed threshold based on the interference power level. The rest of the chapter is referred to the reference [11].
If the return signal exceeds the threshold level, the target is declared present. If it did not exceed the threshold level, then no target is present [11]. This works with predictable performance if the interference consists of thermal noise only. The thermal noise is the noise generated by thermally-excited motion of the carriers in the electronic systems comprising the receiver. Thermal noise is approximately white, which means that the power spectrum density is almost constant throughout the spectrum.

Most modern radar systems are coherent, which means that they receive the return signal as an amplitude and phase. The synchronous detector, in the radar receiver, produces in-phase ($I$) and quadrature ($Q$) components from the received signal. The in-phase component represents the real part of the receive signal. Whereas the quadrature component represents the imaginary part.

In the absence of the target, the received noise for both $I$ and $Q$ channels is modeled as a zero-mean, independent and identically distributed Gaussian random process with
variance $\frac{\sigma_n^2}{2}$. In addition, both channels, $I$ and $Q$ are independent from each other. Therefore, the received noise signal is a complex Gaussian signal with zero-mean and $\sigma_n^2$ variance.

$$N = I + iQ$$

(2.1)

2.2. Rectifiers

After pulse compression, the signal passes through a rectifier, which convert the complex signal to an amplitude and phase. There are different types of rectifiers; however, the essential types used in modern radar systems are; the linear detector and the square-law detector. The linear detector measures only the magnitude (voltage) of the complex received signal. This magnitude follows the Rayleigh distribution. Let the magnitude of the noise be $y$:

$$y = \sqrt{I^2 + Q^2}$$

(2.2)

The probability density function (PDF) of the magnitude $y$ is given by:

$$p(y) = \begin{cases} 
\frac{2y}{\sigma_n^2} \exp \left( -\frac{y^2}{\sigma_n^2} \right), & y \geq 0 \\
0, & y < 0 
\end{cases}$$

(2.3)

The square-law detector is, in fact, only the square of the linear detector (power). The output signal from the square-law detector is distributed according to Exponential PDF.

$$y = I^2 + Q^2$$

(2.4)

The PDF of the square-law detector is:

$$p(y) = \begin{cases} 
\frac{1}{\sigma_n^2} \exp \left( -\frac{y}{\sigma_n^2} \right), & y \geq 0 \\
0, & y < 0 
\end{cases}$$

(2.5)
The phase for both linear and square-law detector is uniform distribution $\sim U[-\pi, \pi]$.

$$p(\theta) = \begin{cases} \frac{1}{2\pi}, & -\pi \leq \theta < \pi \\ 0, & \text{otherwise} \end{cases} \quad (2.6)$$

Figure 2 represents the distributions of the discussed rectifiers.

![Figure 2: Output distribution of Linear and Square law detectors](image)

**2.3. Threshold Level**

Once the statistical distribution of the noise is known, false alarms can be considered. False alarms are the false detections that occur due to the random variations of the noise samples. It is the area under the noise PDF from the threshold level to positive infinity, as shown in Figure 3, and is usually a very small number (close to zero). In order to avoid too many false alarms, it is important to design an accurate threshold level based on the statistical distribution of the background noise. A fixed threshold can be calculated to given a desired $P_{FA}$ at the output of the detector as shown in equation 2.7 for linear detector.
\[ P_{FA} = \int_{T}^{\infty} \frac{2y}{\sigma_n^2} \exp\left(\frac{-y^2}{\sigma_n^2}\right) dy = \exp\left(\frac{-y^2}{\sigma_n^2}\right) \bigg|_{T}^{\infty} = \exp\left(\frac{-T^2}{\sigma_n^2}\right) \]

\[ T = \sqrt{-\sigma_n^2 \ln(P_{FA})} \]  

(2.7)

As an example, for \( P_{FA} = 10^{-3} \), the threshold level is \( T = 2.63 \) as illustrated in Figure.3.

For the square-law detector, the threshold level is different than the linear detector. It can be calculated as:

\[ P_{FA} = \int_{T}^{\infty} \frac{1}{\sigma_n^2} \exp\left(\frac{-y}{\sigma_n^2}\right) dy = \exp\left(\frac{-y}{\sigma_n^2}\right) \bigg|_{T}^{\infty} = \exp\left(\frac{-T}{\sigma_n^2}\right) \]

\[ T = -\sigma_n^2 \ln(P_{FA}) \]  

(2.8)

As an example, for \( P_{FA} = 10^{-3} \), the threshold level for the square-law detector is \( T = 6.91 \) as shown in Figure.4.
It is obvious from Figure 5, increasing the threshold level will decrease the number of false alarms in both linear and law-square detectors. Figure 5 represents the relation between the threshold level and the probability of false alarm.

Figure 5: Threshold vs Probability of false alarm
2.4. Target Models

In the presence of a target, the return signal will contain both the target signal and noise. Usually, the targets have complicated structures, which reflect scatterers with different radar cross section (RCS). A description of a good estimate of target reflection models was introduced by Peter Swerling for scanning data [13]. He described the statistical properties of the RCS of the targets by five different models.

Swerling 1: The return pulses do not change from pulse to pulse (perfectly correlated); however, they do change from scan to scan according to an Exponential distribution.

Swerling 2: The echo pulses in swerling 2 are uncorrelated from pulse to pulse as well as from scan to scan. They are different from each other during the same dwell time. The change from pulse to pulse is described as an Exponential distribution.

Swerling 3: Because some targets have a dominant scatterer, Swerling 3 uses a fourth-degree Chi-square distribution to model the return pulses. This model has the same characteristics as Swerling 1 which has constant pulses from pulse to pulse, but different scan to scan.

Swerling 4: This has same characteristics as swerling 2 but has uncorrelated echo pulses; however, these random pulses are described as 4-th degree Chi-square distribution again because the dominant echo pulses from some targets.

Swerling 5/0: It is also known as Marcum’s model. The echo pulses are constant and perfectly correlated from pulse to pulse and from scan to scan.
Table 1: Swerling Target Models

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<th>Model</th>
<th>Decorrelation</th>
<th>PDF of power</th>
<th>Illustration</th>
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</table>
| Swerling 1 | Scan to Scan      | $p(y) = \begin{cases} 
\frac{1}{y} \exp\left(-\frac{y}{\bar{y}}\right), & y \geq 0 \\
0, & y < 0
\end{cases}$ | ![Illustration](image1.png) |
| Swerling 2 | Pulse to Pulse    | $p(y) = \begin{cases} 
\frac{4y}{y^2} \exp\left(-\frac{2y}{\bar{y}}\right), & y \geq 0 \\
0, & y < 0
\end{cases}$ | ![Illustration](image2.png) |
| Swerling 3 | Scan to Scan      |                                                   |                       |
| Swerling 4 | Pulse to Pulse    |                                                   |                       |
| Swerling 5/0 | always correlate | Always constant                                  | ![Illustration](image3.png) |

2.5. Detection performance

This section describes a simulation of the return signal from the target. It is easy to control the parameters of the target in noise and optimize the theoretical approach by simulation. The parameters of the radar system used in this simulation are given as:

- **Carrier Frequency**: 1 GHz
- **Bandwidth**: 100 MHz
- **Pulse width**: 1 μsec
- **Time-Bandwidth product**: 100
- **Range Resolution**: 1.5 m
- **Blind Range**: 150 m
- **Maximum Range**: 30 Km
- **Wavelength**: 0.3 m
Target simulation is an essential step to evaluate the performance of any detection technique in a radar system. The model of the target in this simulation is a point target which has an infinitesimal spatial extent scatterer and a point target is always constant as shown in Table.1. The mathematical expression of this point target is:

\[ R_x(t) = A e^{j(\phi)} x(t - t_d), \quad t_d \leq t \leq (t_d - \tau) \]  \hspace{1cm} (2.9)

Where \( R_x \) is the received target signal, \( A \) is the amplitude of the signal, \( \tau \) is the pulse width, \( t_d \) is the time delay for the echo coming back from the target and \( \phi \) is the phase measured by the coherent detector.

\[ t_d = \frac{2 \times R}{c} \]  \hspace{1cm} (2.10)

\[ \phi = -2\pi f \left( \frac{2 \times R}{c} \right) = -\frac{4\pi R}{\lambda} \]  \hspace{1cm} (2.11)

The measured phase is a function of transmission frequency and the range of the target as shown in equation 2.11. The output of the matched filter (without adding the noise) is a sinc function with sidelobes of 13 dB as shown in Figure.6.
After adding noise, it is difficult to recognize the sidelobes due to the random nature of the noise. However, the target should stand clear, even in the presence of the noise. For a signal to noise ratio \((SNR) = 20\), the received signal with noise is as shown in Figure 7:

![Figure 6: Output of matched filter for target located at 15 km](image)

![Figure 7: Output of matched filter for target located at 15 km with noise](image)
Here the target was chosen to be 15 km away from the radar. This example is shows a relatively easy detection decision since the target is 20 dB above the noise level. As the SNR decreases, the probability of detecting the target will decrease for a given probability of false alarm. Changing the probability of false alarm will also change the detection performance. Therefore, due to the large number of the trade-off between $P_D, P_{FA}$, and $SNR$, the receiver operating characteristic (ROC) curve is used to combine all the three variable together in one curve by plotting $P_D$ vs $SNR$ and fixing the $P_{FA}$. As discussed in Figure 5, when the level of the threshold decreases, the probability of false alarm increases.

In this simulation, the threshold levels are illustrated in Figure 8 for probability of false alarms of $10^{-4}$, $10^{-6}$, and $10^{-8}$.

A monte-carlo simulation was applied in this simulation to plot the ROC curves in order to obtain the performance of the three detectors (thresholds) shown in Figure 9. The horizontal axis represents the change in the $SNR$, whereas in the vertical axis represents the probability of detection for a given $SNR$ and probability of false alarm.

![Figure 8: Optimum thresholds for different Pfa](image-url)
In Figure 9, the three graphs represent the performance of the optimum detectors for the probability of false alarm of $10^{-4}$, $10^{-6}$, and $10^{-8}$. The trade-off here is that lowering the threshold will increase the probability of detection, yet, it will also increase the probability of false alarm. Most radar system designers try to minimize the probability of false alarm and increase the probability of detection which requires higher SNR. But, ultimately, the space for this depends on the statistical properties of the target and noise (or clutter).

![Figure 9: Pd comparison of optimum detectors of different Pfa in homogeneous SNR (dB)](image)

Figure 10 illustrates an optimum environment where there is only a single target in independent and identically distributed Gaussian noise. This environment is called a homogeneous environment. However, in real measurements, the background noise may not be homogeneous. In a non-homogeneous environment (also called heterogeneous environment), a fixed threshold may yield a large number of false alarms.
Examples of a non-homogeneous environment that will be discussed later are: (i) a clutter transition region Figure.10 (a), (ii) closely spaced multiple targets Figure.10 (b).

Clutter transition region is defined to describe a signal transition in the background noise. One side of the background noise has low reflectivity, whereas the other side has high reflectivity. This type of clutter appears in the boundary of a precipitation. Figure.10 (a) shows a single target located in the clutter transition region (at 15 km). Multiple target interference is defined to describe the situation where multiple targets (closely spaced) are present in a Gaussian background noise. Figure.10 (b) represent a three closely spaced targets in Gaussian noise background.

Chapter 3 introduces the constant false alarm rate (CFAR) detector which can detect targets in heterogeneous environment. There are many types of CFAR detector and each type has its own application. Chapter 3 will describe four types of CFAR detectors and compare their performance in different background situations.
Chapter 3: Constant False Alarm Rate (CFAR) Concepts

3.1. Introduction

Noise and clutter power in real environments are non-stationary random process varying with time. Applying a fixed threshold in real data will cause an enormous number of false alarms. Moreover, it will not achieve the desired probability of false alarm. Constant false alarm detectors (CFAR) are designed to maintain the probability of false alarm of the background noise or clutter at a fixed level. The CFAR estimates the background power level from the surrounding samples to set a detection threshold adaptively varies with the power level of the noise or the clutter. Heterogeneous environments, such as clutter transitions, and multiple targets, are the kind of environments that the CFAR detectors can operate in and still maintain the probability of false alarm. The background noise in this chapter is assumed to be an independent Gaussian noise samples. The curious reader referred to the reference [11] for more details of this chapter. This chapter will introduce four types of CFAR detectors as follow:

(i) Cell-Averaging CFAR (CA-CFAR)
(ii) Greatest of Cell Averaging CFAR (GO-CFAR)
(iii) Smallest of Cell Averaging CFAR (SO-CFAR)
(iv) Ordered Statistics CFAR (OS-CFAR)
3.2. **CFAR Architecture**

This section examines the general architecture of the CFAR processor as shown in Figure 11. The CFAR detector contains four main elements, (i) the cell under test (CUT), (ii) guard cells, (iii) reference cells, and (iv) the CFAR multiplier $\alpha$. These four elements assist the processor to set a varying threshold which follows the structure of the background noise or clutter [11].

![General CFAR processor](image)

**Figure 11: 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 a detection. The cell under test is located at the middle of the CFAR processor.

*Guard cells* are located next to the CUT usually on both sides as shown in Figure 11. The samples contained in these cells are not used. 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 provides a better estimation of the background noise.
Reference cells are the outer cells of the CFAR processor. These cells estimate the threshold of the background noise. The more samples of the background noise in the reference cells, the better estimation of the threshold.

CFAR multiplier is also called CFAR constant. This constant is chosen based on the desired probability of false alarm to set the estimated threshold from the reference cells at the appropriate level. Usually the calculation to find the CFAR multiplier is complicated due to the complex relationship between the probability of false alarm and the CFAR multiplier.

Figure.11 represents a single dimension of the general CFAR architecture which is applied in the range direction. The data window could also be a two dimensional data set, such as in synthetic aperture radar (SAR), which consists of range and cross range [11]. An example of two dimensional CFAR architecture applied in 2-D data is illustrated in Figure.12 [11].
For both 1-D and 2-D CFAR detectors, the window is shifted through the data. Each time it is moved by a signal sample and estimates the average threshold using the samples in the reference cells. Finally, the estimated average threshold is multiplied by the CFAR constant to produce the actual value of the threshold. This value is compared with the cell under test to decide whether the target is present or not [11].

3.3. CFAR Detectors

This section introduces four types of the standard CFAR processors. Each subsection in this section uses a type of CFAR processor used in the simulation discussed in chapter 2 to compare the performance and learn how to improve detection performance in difficult situations.

3.3.1. Cell-Averaging CFAR Detector

The cell-averaging CFAR was developed in 1968 by Finn and Johnston [14]. The basic idea of the CA-CFAR is to estimate the samples contained in the reference cells by averaging across them. The average of the reference cells is multiplied by a CFAR constant to set the threshold at a level required to maintain the desired probability of false alarm. The CA-CFAR was designed to operate in a homogeneous environment where the reference cells contain independent and identically distributed samples. The target is assumed to be contained in the CUT only.

3.3.1.1. CA-CFAR Architecture

The architecture of CA-CFAR is the simplest among the other CFAR processors. It takes the average of the lagging and leading samples as shown in Figure.13.
Where \( R \) are the samples contained in the reference cells, \( G \) are the samples contained in the guard cells, \( \text{CUT} \) is the sample contained in the cell under test, and \( N \) is the number of the reference cells in both sides. The CFAR constant, \( \alpha \), for the CA-CFAR, assuming homogeneous background noise, is given by [11]:

\[
\alpha = N \left[ p_{FA}^{-1/N} - 1 \right]
\] (3.1)

### 3.3.1.2. Performance of CA-CFAR

This section examines the performance of CA-CFAR in a homogeneous environment. The implementation of the CA-CFAR, in the simulation given in chapter 2, is shown in Figure 14 for \( N = 16 \) and \( N = 32 \). It is clear from Figure 14 that the total number of the samples in reference cells, \( N \), is playing a major role in the performance of the CA-CFAR. As the number of the reference cells increases, the variance of the threshold decreases. Moreover, the threshold of the finite number of samples in the reference cells appears higher than the optimum threshold, which leads to reduction in the probability of detection.
The high values of the threshold close to the target in Figure.14 is due to the guard cells. In this simulation, the guard cell chosen to be $G = 10$ in both sides. Specifically, in this example, the number of guard cells does not affect the performance of the CA-CFAR, since the target is located in exactly a single range bin. The guard cells are used when there is a correlation from pulse to pulse in the target return.

Comparing to the optimum threshold, the CA-CFAR always has an inherent loss of detection probability in a homogeneous environment. This is because the CA-CFAR estimate of the noise power within a finite number of samples in the reference cells. Clearly, the performance of detection in CA-CFAR depends on the required false alarm rate and the number of reference cells in the CA-CFAR. Figure.15 represents the performance of the CA-CFAR detector compared to the optimum detector. A monte-carlo simulation was applied to compute this curves by averaging the probability of detection for each SNR.
For a probability of detection in the optimum detector of 90%, $SNR \approx 13.2 \, dB$, as shown in Figure.15. For the CA-CFAR of 32 reference cells, the probability of detection reaches 90% when the signal to noise ratio is approximately 14.2 $dB$. This means that the performance has decreased by 1 $dB$. For 16 reference cells, the loss is 2 $dB$ compared to the optimum detector at probability of detection at 90%. Therefore, the loss of the CA-CFAR depends on three parameters, $P_d$, $P_{FA}$, and the number of samples in the reference cells [11]. Figure.16 illustrates the CFAR loss as function of the number of samples in the reference cells for $P_{FA} = 10^{-6}$. 
The performance of the CA-CFAR degrades in environments where clutter transition occur. The main effect on the CA-CFAR performance in the clutter transition is the reduction of the probability of detection on the lower reflectivity side, especially closer to the edge. In addition, there is a larger number of false alarms near the clutter transition. Figure 17 shows an example of the CA-CFAR threshold applied in a clutter transition environment.

Figure 16: CFAR Losses vs number of reference cells

Figure 17: CA-CFAR in clutter transition environment
The target is not present in Figure 17. However, the probability to detect a false alarm is relatively higher in the clutter transition region. To overcome this problem, Hansen and Sawyers [15] proposed the Greater of Cell-averaging CFAR detector which will be introduced in the next section.

3.3.2. **Greatest of Cell-Averaging CFAR Detector**

The Greater of cell-averaging CFAR (GO-CFAR) was mainly designed to maintain the probability of the false alarm at a clutter edge region [15]. This type of environment is found when the radar is illuminating an area such as the coast where the reflectivity of the sea usually becomes lower than the reflectivity of the beach (or land).

3.3.2.1. **GO-CFAR Architecture**

The GO-CFAR architecture is shown in Figure 18. The difference between the CA-CFAR and the GO-CFAR is that the GO-CFAR computes the average noise power of both sides of the reference cell separately, and then selects the larger of them.

![Figure 18: Greatest of CA-CFAR processor](image)

\[ T = \hat{g} \alpha \]

\[ \hat{g} = \max(\hat{f}_{lag}, \hat{f}_{lead}) \]

\[ 
\begin{cases} 
\text{CUT} \geq T: H_1 \\
\text{CUT} < T: H_0 
\end{cases} 
\]
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 [11]. It is clear in the equation that the number of the reference cells involved in the calculation is only one side of the reference cells $\frac{N}{2}$:

$$P_{FA} = 2 \left\{ \left[ 1 + \alpha \right] \frac{N}{2} - \left[ 2 + \alpha \right] \frac{N}{2} \sum_{k=0}^{N-1} \left( \frac{N}{2} - 1 + k \right) \left[ 2 + \alpha \right]^{-k} \right\}$$  \hspace{1cm} (3.2)

### 3.3.2.2. Performance of GO-CFAR

In a homogeneous environment, it is obvious that the CA-CFAR is performing better than the GO-CFAR, since the CA-CFAR has more number of samples in the reference cells. This means that it has a better estimation of the background noise. Hansen and Sawyers [15] showed that the GO-CFAR has an additional CFAR loss compared to CA-CFAR loss in a homogeneous environment. The additional loss was found in the range between 0.1 to 0.3 dB. Figure.19 represents the ROC curves of the performance of the CA-CFAR and the GO-CFAR compared with the optimum detector. The total number of reference cells is 16 and the total number of the guard cells is 2. The probability of false alarm is $10^{-6}$. 

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The ROC curve of the GO-CFAR appears to the right of the CA-CFAR curve. Due to the fewer number of the samples in the reference cells. At $P_d = 90\%$, the CFAR loss of the GO-CFAR is 0.2 dB compared to the CA-CFAR loss and 2.2 dB compared to the optimum detector.

In a heterogeneous environment, such as a clutter transition, the GO-CFAR perform better than the CA-CFAR in the clutter edge region. It was designed to push the threshold higher than CA-FAR or the clutter boundary to maintain the probability of false alarm. Figure.20 shows the implementation of the CA-CFAR and GO-CFAR in the clutter transition environment.

Figure 19: Pd vs SNR of Optimum threshold vs CA-CFAR and GO-CFAR
Another example of a heterogeneous environment is the presence of the multiple targets in the reference cells of the CFAR processor. This is also called “target masking” and can be divided in two categories: “self-masking” and “mutual target masking”. Self-masking occurs in the case of an extended target. Increasing the number of guard cells will solve the problem of the self-masking to prevent the extended sample of the target to be involved in the calculation of the threshold. On the other hand, the mutual masking target is the case where more than a target is distributed across the reference cells as well as the CUT. 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.

Figure 21 shows the implementation of the CA-CFAR and the GO-CFAR in a mutual masking environment. Both the CA-CFAR and the GO-CFAR detected the first target, 1m RCS located at 15 km. However, both detectors miss the second target which
has RCS of 0.5m located at 15.012 km away from the radar. Missing the second target is not because the RCS of the target is too small. It is because that the value of the return from the target is included in the estimation of the background noise.

Figure 21: Optimum threshold, CA-CFAR and GO-CFAR in mutual target interference

If is now assumed that both targets have the same RCS, since they are close to each other, both detectors will miss both targets as shown in Figure.22.

Figure 22: Optimum threshold, CA-CFAR and GO-CFAR in mutual target interference
Mutual target masking can be detected using other CFAR techniques. Such techniques include the Smallest of cell-averaging CFAR, and the Order Statistics CFAR. Both detector will be introduced in the next two sections.

3.3.3. **Smallest of Cell-Averaging CFAR Detector**

The Smallest of cell-averaging CFAR was mainly designed to solve the mutual target masking issue. It was proposed by Trunk [16] in 1978. Closely spaced targets create the type of environment where the SO-CFAR can perform better than CA-CFAR and GO-CFAR.

3.3.3.1. **SO-CFAR Architecture**

When the target is contained in the CUT and another target appears in the reference cells at the same time, the SO-CFAR suppresses the presence of the target in the reference cells by estimating both the lagging and the leading windows and selects the smaller of the two average estimation. The architecture of the SO-CFAR is almost the same as the GO-CFAR except selecting the smaller side in the SO-CFAR. Figure.23 represents the architecture of the SO-CFAR.

\[
\hat{\beta} = \min(f_{\text{lag}}, f_{\text{lead}})
\]

Figure 23: Smallest of CA-CFAR processor
Numerically, the CFAR constant of the SO-CFAR can be calculated from the average probability of false alarm as [11]:

\[ P_{FA} = 2[2 + \alpha]^{N} \sum_{k=0}^{\frac{N}{2} - 1} \binom{\frac{N}{2} - 1 + k}{k} [2 + \alpha]^{-k} \]  

(3.3)

### 3.3.3.2. Performance of SO-CFAR

Generally, the SO-CFAR detector performs worse than CA-CFAR and GO-CFAR in a homogeneous environment. The losses associated with the SO-CFAR are relatively large compared to the CFAR detector described in the previous sections. At a probability of detection of 90%, the SO-CFAR loss is 1.8 dB compared to the CA-CFAR and 1.6 dB compared to GO-CFAR, which is about 3.8 dB compared to the optimum detector as illustrated in Figure 24. The total number of reference cells is 16 and the total number of the guard cells is 2. The probability of false alarm is $10^{-6}$.

![Figure 24: Pd vs SNR of Optimum threshold vs CA-CFAR, GO-CFAR, and SO-CFAR](image-url)
Therefore, in practical applications the SO-CFAR is not a preferred detector due to the large number of false alarm that can occur and the reduction of the probability of detection.

In a heterogeneous environment, the SO-CFAR can detect targets close to the clutter edge on the low reflectivity side; however, it also detects a large number of false alarm at the beginning of the clutter transition. Figure.25 shows an implementation of the CA-CFAR, GO-CFAR, and SO-CFAR in the clutter transition environment.

![Figure 25: Optimum threshold, CA-CFAR, GO-CFAR, and SO-CFAR in clutter transition environment](image)

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 Figure.27. The performance of SO-CFAR will degraded when there are targets present on both sides of the reference cells. Figure.26 represents the case where the targets appears on both sides of the reference cells and the SO-CFAR cannot detect the target which is contained in the CUT at 15 km.
The target, located at 15 km was detected only by SO-CFAR detector in Figure.26. Whereas in the case of mutual target masking on both sides of the reference cells, none of the three detectors detect the target as shown in Figure.27. The next section will introduce a technique where the CFAR can overcome this problem using a detector called “Order Statistics” CFAR.

Figure 26: Optimum threshold, CA-CFAR, GO-CFAR, and SO-CFAR in mutual target interference

Figure 27: Optimum threshold, CA-CFAR, GO-CFAR, and SO-CFAR in mutual target interference
3.3.4. **Order Statistics CFAR Detector**

Rohling proposed the Order statistic CFAR detector (OS-CFAR) [7], which was designed to overcome the issues reviewed in the previous sections, such as clutter transition, self-masking target, and mutual masking targets. This CFAR detector processes in a way that is quite different than the CFAR detectors. It estimates the average background noise by a signal sample from the reference cells using order statistics processing.

**3.3.4.1. OS-CFAR Architecture**

The order statistics was developed to address the heterogeneous environment. The OS-CFAR detector ranks the samples in the reference cells according to increasing power. 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 in Figure 28.

![Figure 28: Ordered Statistics CFAR processor](image)
The CFAR constant is calculated from the average probability of false alarm as:

\[ P_{FA} = k \binom{N}{k} \frac{(k - 1)! (\alpha + N - k)!}{(\alpha + N)!} \]  

(3.4)

Clearly, the CFAR constant of the OS-CFAR not only depends on the number of reference cells and probability of false alarm, but also depends on the selection of the \( k^{th} \) sample.

### 3.3.4.2. Performance of OS-CFAR

The OS-CFAR detector has a CFAR loss that is higher than a CA-CFAR in a homogeneous environment. However, it is more robust in a heterogeneous environment. Increasing the number of the reference cells will improve the estimation of the \( k^{th} \) sample and reduce the CFAR loss. For example, the CFAR loss for \( N = 24 \) in an OS-CFAR is equivalent to a CFAR loss in a CA-CFAR for \( N = 16 \) as shown in Figure.29 [7].

![Figure 29 Pd vs SNR of CA-CFAR and OS-CFAR](image-url)
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 practical application [7]. Figure 30 shows the ROC curve of the OS-CFAR for $N = 16$, $k = 12$ and $P_{FA} = 10^{-6}$ with different detectors which discussed in the previous sections.

![ROC Curve](image)

Figure 30: Pd vs SNR of Optimum threshold vs CA-CFAR, GO-CFAR, SO-CFAR, and OS-CFAR

As shown in Figure 30, At 90% of probability of detection, the OS-CFAR loss is 1 dB more than the CA-CFAR, 0.8 dB more than GO-CFAR, and almost 0.9 dB less than SO-CFAR detector. Which is about 3.1 dB loss compared to the optimum detector for $N = 16$ and $P_{FA} = 10^{-6}$.

In a clutter transition environment, the OS-CFAR has the capability to reduce the false alarm detection at the clutter edge when the selection of $k$ sample is larger than $N/2$ [7]. Figure 31 shows the implementation of the OS-CFAR in a clutter transition environment for $N = 16$, $k = 12$, and $P_{FA} = 10^{-3}$.

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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. The OS-CFAR can reject \((N - k)\) interfering targets and give the same performance as for a single target in a homogeneous environment. After sorting the samples in the reference cells, all the interfering targets (or cells that have high power) are automatically excluded from estimating the background noise. Figure 32 represents a multiple target interfering scenario, where the targets appear on both sides of the reference cells. The CUT contains a target located at 15 km. This figure also shows the implementation of the OS-CFAR and SO-CFAR with \(N = 16, G = 2, k = 12,\) and \(P_{FA} = 10^{-6}\) compared with optimum detector. The SO-CFAR does not detect the target in the middle (at 15 km), whereas the OS-CFAR all the targets.

Figure 31: Optimum threshold, CA-CFAR and OS-CFAR in clutter transition environment
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 [7].

3.4. Summary

CFAR detection is one of the techniques for radar systems to detect targets in different background conditions. The main goal of the CFAR processors is to maintain the false alarm rate constant in both homogeneous and heterogeneous environment. Choosing the type of CFAR and its parameter is extremely dependent on the environment conditions. The CA-CFAR is the best CFAR performing in homogeneous environment. However, this CFAR regrades in the presence of clutter transition regions and mutual target interference. The GO-CFAR improves detection at the edge of the clutter in the clutter transition region.
But, it fails and might miss targets when there are multiple target interfering. The SO-CFAR has the highest CFAR loss among the CFAR detectors that were discussed in this chapter. However, it perform better than CA-CFAR and GO-CFAR in the multiple target interfering situation. The OS-CFAR combines the advantages of the basic CFAR together (CA-CFAR, GO-CFAR, SO-CFAR). This CFAR has fairly good performance in homogeneous environments. In addition, it automatically adapts itself to detect multiple target even in heterogeneous environments.

There are many different CFAR processors exist and each of which has its own application. Some of the CFAR techniques combine couple of CFAR processors in one processor and make the CFAR adaptively vary the techniques based on the background environment. There is no one CFAR processor is always better than all the other CFAR. Each radar system designs it CFAR processor based on the application. The CFAR techniques used in this chapter are called standard CFAR processors. All the parameters and the results were calculated by assuming Gaussian noise background.

In practical, radar received signal does not contain only thermal noise and target, but also clutter. The basic definition of the clutter is the unwanted radar reflection. Generally, the clutter is categorized into reflection from rain, land, and sea. High reflections from the clutter sometimes looks as a target which makes the detection processing very complicated. Next chapter will introduce sea clutter analysis based on a real data sets from South Africa. The analysis of the sea clutter will include the statistical analysis, correlation, and Doppler representation. The reflection from clutter with thermal noise will deviate the statistical distribution of the background noise from Gaussian noise to another distributions. The
question is, does the standard CFAR detectors still can be implemented on a real sea data to achieve reasonable probability of false alarm? Chapter 5 introduces the implementation of standard CFAR detectors on the sea clutter data.
Chapter 4: Sea clutter analysis

4.1. Introduction

This chapter introduces the background (or environment) to detect a small targets in sea clutter. In a maritime environment, it is very difficult for the radar operator to distinguish between reflection from a target and reflections from the sea surface. Sea clutter is the backscatter returns from sea surface illuminated by radar pulses. The detection of a small target (such as an inflatable boat) on the sea surface in the presence of sea clutter is a significant problem in radar signal processing [12]. Sea clutter echoes are usually non-Gaussian (or Spiky), especially in presence of waves, wind, and different sea conditions at low grazing angles. The ill-behaved nature of the sea reflections make sea clutter difficult to model and the detection of targets can be very complicated. A great deal of work has been done to understand the nature of sea clutter and subsequently, how to improve radar detection performance in presence of sea clutter, e.g. [1].
4.2. **Real Data Overview**

The Council for Scientific and Industrial Research (CSIR) in South Africa provides the measurement data that used in this thesis. The radar (MeCort) was deployed on Signal Hill, Cape Town, South Africa in 2007. The distance from the radar to the sea is 1250 m and the ground height was 294 m above mean sea level [17]. Figure.33 shows a picture of MeCort operating in a trial.

![Figure 33: MeCort Radar in Signal Hill Trial, 2007](image)

4.2.1. **Radar Specifications**

This section describes the radar which captured the data in the Signal Hill trial [17]. These specifications are an important part of understanding the performance for both the analyses of the real data and detection processing. The frequency of the radar is X-Band (8 to 12 GHz), and the PRF of the measured data used in this research is 2000 Hz. The grazing angle is between $10^\circ$ (coastline) to $0.1^\circ$. The pulse bandwidth is 10 MHz, which means that the range resolution is:

\[
\text{Range resolution} = \frac{c}{2B} = \frac{3 \times 10^8}{2(10 \times 10^6)} = 15 \text{ m}
\]  

(4.1)
Where $c$ is the velocity of light and $B$ is the pulse bandwidth. The datasets were acquired in good weather conditions. Since the radar is operating in X-band, any atmospheric effects, such as rain, may cause an attenuation and scattering [18].

Figure 3.4 illustrates a basic geometry of the trial showing some of the radar parameters.

![Figure 34: Geometry of the trial in Signal Hill, South Africa](image)

4.2.2. Dataset Overview

The data used in this thesis is with the radar staring. Specifically, the radar was looking at a fixed angle for between a minute and a minute and half to capture a single data set. Figure 3.5 (a) and (b) shows two different data sets in both the time and frequency domains. The left-hand plots are range verses time and show an entire duration of about 30 seconds. The structure of the wave in the time-domain images are very clear and become stronger as the waves are closer to the radar.

![Diagram of radar parameters](image)
The right hand plots are range Doppler maps where sequence pulses, for each range bin, have been Fourier transformed into the Doppler domain. The number of time samples used in this example was 64. In the frequency domain, the range-Doppler map shows that the background clutter is not stationary (not located in zero frequency component) due to the movement of the waves. At these factors make the detections of small targets very complicated, and impossible in some cases. Therefore, it is important to understand these characteristics in order to build suitable detection processors and therefore to improve and evaluate radar performance under different sea and target conditions.

Figure 35: Example of two different datasets
4.2.3. Targets in the Measurements

Four small boats were involved in the measurements. MTU Nadine Gordimer has a length of 10 m, which is the longest of them. Rotary Endeavour is 5.5 m length. SAN Parks RIB is 4.8 m. Finally, pencil duck has 4.2 m length. Figure 36 shows pictures of the targets [17].

![Image of MTU Nadine Gordimer](image1)

(a) MTU Nadine Gordimer

![Image of Rotary Endeavour](image2)

(b) Rotary Endeavour

![Image of SAN Parks RIB](image3)

(c) SAN Parks RIB

![Image of Pencil Duck](image4)

(d) Pencil Duck

Figure 36: Picture of targets used in the trial [17]

These small targets are difficult to detect in the sea clutter. Therefore, it is important to understand the statistics of the reflections from the sea surface in order to distinguish between the reflections from the small targets and the reflections from the sea surface. Statistical models of the Sea clutter are introduced in the next section and example of datasets are represented to illustrate the fitting distribution compared with the theoretical PDFs.
4.3. Statistical Model

One of the features that is used to characterize the clutter returns is the distribution of amplitude or power of the clutter. The instantaneous amplitude received from each single radar cell will vary. This variation is characterized by the probability density function (PDF) of the returns. Initially, the Rayleigh probability distribution function was used to model the envelope of sea clutter. This model proved accurate for radars with low range resolution; however, with the rapid improvement of radar technology, high range-resolution radars became feasible [12]. High range resolution reduces the area of sea that is illuminated and hence reduces the echo that competes with the target echo. However, these improvements also result in a deviation from the amplitude of the sea clutter being Rayleigh distributed and results in non-Gaussian distributions. The non-Gaussian characteristic of sea clutter distribution led different to researches employing different distributions to model sea clutter. These distributions include the Weibull, log-normal, $K$ and compound-Gaussian distributions [1].

In order to fit the distribution of the real data to a theoretical PDF, it is necessary to estimate the scale and shape parameters of the measured data. There are several techniques for estimating the parameters of the different distributions, such as the Method of Moments (MoM), and the Maximum Likelihood (ML) methods. In this thesis, the MoM was used to estimate the parameters of the measured data distributions [1]. MoM is a method of estimating the characteristic parameters of a theoretical PDFs, which compares the moments of real data with the corresponding theoretical moments.
In general, MoM can be defined as [1]:

$$M_n = \frac{E[x^n]}{E[x]^n} \quad (4.2)$$

4.3.1. Lognormal Distribution

The Lognormal distribution is the logarithm of the normal distribution. The PDF of lognormal distribution is given by:

$$P(x) = \frac{1}{x\sqrt{2\pi}\sigma^2} \exp\left(-\frac{\left(\log(x) - m\right)^2}{2\sigma^2}\right); \quad x \geq 0 \quad (4.3)$$

Where $m$ is the scale parameter and $\sigma$ is the shape parameter of this distribution. The moments of lognormal distributions is given by:

$$E[x^n] = \exp\left(nm + \frac{n^2\sigma^2}{2}\right) \quad (4.4)$$

Which is the mean value of $x$ to the power of $n$.

Figure.37 presents curves of pdf of lognormal distribution. As the shape parameter increases the tail of the Lognormal distribution increases, which means the probability of observing large values of the clutter amplitude increases.
4.3.2. Weibull Distribution

The PDF of Weibull distribution is given by;

\[ P(x) = \beta x^{\beta - 1} \exp \left( -\frac{x}{\alpha} \right) ; \quad x \geq 0 \]  

(4.5)

Where \( \alpha \) and \( \beta \) are the scale and shape parameter, respectively. Rayleigh distribution is a special case of Weibull distribution for \( \beta = 2 \) [4]. The moments of Weibull distribution is given by;

\[ E[x^n] = \alpha^n \Gamma \left( \frac{n}{\beta} + 1 \right) \]  

(4.6)

Where \( \Gamma(.) \) is a gamma function.

Figure 38 presents curves of pdf of Weibull distribution. This distribution has longer tail as the shape parameter decreases. For \( \beta = 5 \) in Figure 38, the tail of the Weibull distribution became shorter than Rayleigh. Therefore, Weibull distribution is modeled as radar clutter distribution for the shape parameter \( \leq 2 \) only.
4.3.3. **Compound K Distribution**

Clutter speckle, which is a fast time and space varying component in the sea surface, is modeled in the K–distribution as a Gaussian process, while the slowly varying mean power level of the clutter is modeled as gamma process. The fast varying component of the K-distributed is a complex-valued Gaussian random variable with zero mean and random variance $X$ [1]. The real components and the imaginary components of each complex-valued random variable are independent from each other. The envelope (or magnitude) of each clutter sample is a random variable with the conditional Rayleigh distribution,

$$f(y|X) = \frac{2y}{X} \exp\left(-\frac{y^2}{X}\right), \quad \text{where } y > 0$$  \hspace{1cm} (4.7)

The variance $X$ of the complex-valued Gaussian random variable is a gamma random variable, and is equal to its mean power [1]. Its probability density function is given by

$$f(X) = \frac{b^\nu}{\Gamma(\nu)} X^{\nu-1} \exp(-bX),$$  \hspace{1cm} (4.8)

where $\nu$ is the shape parameter and $b$ as the scale parameter, and where $X > 0$.

The overall amplitude distribution $f(y)$ of the sea clutter is given by

$$f(y) = \int_0^\infty f(y|X)f(X)dy$$  \hspace{1cm} (4.9)

$$= \frac{4y^2b^{(\nu+1)/2}}{\Gamma(\nu)} K_{\nu-1}(2y\sqrt{b})$$

where $K_{\nu-1}(\cdot)$ is the modified Bessel function of the second kind and order $(\nu - 1)$. From eq. (3.8), the probability distribution of the squared envelope is derived as
\[ f(Z) = \frac{2b^{(\nu+1)/2}Z^{(\nu-1)/2}}{\Gamma(\nu)} K_{\nu-1}(2\sqrt{bZ}), \quad (4.10) \]

where \( Z = y^2 \).

Figure 39 presents curves of pdf of K-distribution. The scale parameter was chosen to normalize the mean square of the distribution to unity (i.e. so that \( \nu \) equals \( b \)). As the shape parameter of K – distribution increases, the pdf become closer and closer to a Rayleigh distribution, which is a particular case of the K – distribution for \( \nu \to \infty \). On the other hand, as \( \nu \to 0 \) [1], the data become more spiky [1].

The nth order moment of the distribution is given by [1]

\[ E[y^n] = b^{-n/2} \frac{\Gamma(1+n/2)\Gamma(\nu+n/2)}{\Gamma(\nu)} \quad (4.11) \]
4.4. Amplitude PDF analysis of Real Data

This section represents an analysis of the amplitude of the real data to examine the fit of its distribution with the theoretical pdfs. The amplitude of sea clutter has a long tail due to the spiky reflections. Lognormal, Weibull, and K-distributions were proposed to model spiky clutter in literature [1, 2, and 4]. An example of plotting the amplitude histogram of data with the theoretical PDFs, to examine the fit distribution, is illustrated in the real data which contains a stationary target in Figure.40. The radar illuminated the area from 3 km to 4.6 km for about 90 seconds. The time domain plot, as shown in Figure.40, can be divided in three parts. The first part is the area closer to the radar, which has high or reflection from the sea waves (Rough sea state). The second part is the area where the reflections are less than the reflections from the area in part one and the structure of the waves reduced. The third part is the target which is standing at the range 4 km during the ninety seconds.

Figure 40: Sample of real dataset with different sea conditions and target
Figure.40 (b) shows the time domain plot of the two different area from Figure.40 (a). Figure.41 represents the extraction of the target by searching for the maximum values around the range 4 km during the 90 seconds.

The three parts of this dataset, in Figure.40, can be plotted as an amplitude histogram, using Matlab© software, by taking the magnitude of the complex samples and plot the histogram of these magnitude. Figure.42 represents the amplitude histogram of the slight clutter area, the rough clutter area, and the target reflections. Since the data has high values, it is difficult to separate the tails of the amplitude distribution using the linear scale. Therefore, the log scale plot is represented in the right side of Figure.42 to make the tails more obvious. The separation of the samples at the end of the log scale plot of the histogram are explained the few numbers of high values comparing to the other samples in the dataset. The amplitude histogram of the slight clutter area has the shortest tail of the three parts and most of the amplitude values lies around 0.3. The rough clutter area shows a longer tail than the slight clutter area. The amplitude of the three parts overlap in top of each, which makes the detection of the target a complicated task.

Figure 41: Extract target using maximum value near target
Therefore, estimating the amplitude distribution of the data is one of the steps to characterize the sea clutter and to improve the detection processing. Using MoM, Figures [43 - 45] illustrate the fit of the distribution of the pdfs of the only clutter for different datasets are compared with lognormal, Weibull, and K-distributions.

Figure 42: Amplitude distribution of Slight clutter, Rough clutter, and target

Figure 43: Amplitude distribution of dataset1 with theoretical PDFs and Normalized moments
Figure 43 represents fitting the distribution of the real data with the theoretical distributions. Figure 43 (a) shows 31 seconds of staring data (i.e. at the same location). Strong returns (high intensity) to the radar are expected, since the radar is only about 4 km from the illuminated area. Figure 43 (b) provides a plot of the amplitude histogram of the real data with theoretical pdfs. From (b) and (c), it seems by observation that the data best fit is the K– distribution.

The K-distribution pdf followed both the data amplitude distribution and the first six moment order. The other distribution deviate from the real data distribution. The estimated shape parameter of the K-distribution is \( \nu = 3.21 \).

Figure 44: Amplitude distribution of dataset2 with theoretical PDFs and Normalized moments
Although the distance between the radar and the illuminated area is now 40 km in Figure 44, there are still strong reflections. The performance of the estimator shows that the distribution of the data is also follows the K-distributions. The shape parameter is now $\nu = 1.49$. The value of the shape parameter indicates the likelihood of getting large echo values is increased.

Figure 45: Amplitude distribution of dataset3 with theoretical PDFs and Normalized moments

Figure 45 represents a different case where the distance between the radar and the illuminated area was 60 km. The dataset in Figure 45 (a) looks much more like noisy data without any structure of waves. Fitting distributions shows that the data best fit Rayleigh distributions and the shape parameter for both Weibull and K-distribution are $c = 1.9986$ and $\nu \approx 720$, respectively. The higher shape parameter means the fit is close to a Rayleigh distribution and this is observed in the PDF plot. Here the likelihood of getting high values reduced.
4.5. Correlation

Computing and understanding the correlation of the sea clutter in range and time can assist the processors to distinguish between the targets and sea clutter spikes [6]. The correlation function of samples $x(t)$, where $t = 1, 2, ..., T$ is:

$$R(\tau) = \frac{1}{T} \sum_{t=1}^{T} x(t)x(t-\tau)$$  \hfill (4.12)

The correlation coefficient function is the covariance over the power of the signal, assuming zero mean.

$$\rho(\tau) = \frac{C(\tau)}{C(0)} = \frac{R(\tau) - \mu}{R(0) - \mu}$$  \hfill (4.13)

Visually, the correlation in the datasets shown in Figure.43 and Figure.44 are very clear from the structure of the waves. For the grazing angle of $\sim 6^\circ$, as the data in Figure.43, the reflection from the waves is very strong and the autocorrelation function can be plotted as shown in Figure.46 (a). For the grazing angle of $\sim 3^\circ$, as the dataset in Figure.44, the waves also can be noticed and the autocorrelation function is shown in Figure.46 (b).

![Figure 46: Autocorrelation function of two different datasets](image_url)
Figure 4.6 (a) and (b) looks very much the same and both of them show the presence of a wave structure which are going up and down [6]. There are number of techniques can be done to reduce the effect of the correlation to improve detection in sea clutter which will be discussed in Chapter 5.
Chapter 5: Intelligent Techniques for Detection Performance in Sea Clutter

5.1. Introduction

It is expected that many false alarms will be observed when applying the standard CFAR detectors in a non-Gaussian environment such as sea clutter. This is because standard CFAR detectors were designed assuming a homogeneous environment as discussed in more detail in chapter 3. This chapter introduces an intelligent based approach aimed to both reducing the probability of false alarm whilst improving the probability of detection. Since there are huge variation of the sea surface, these intelligent type techniques are not guaranteed to improve the detection performance in all cases. However, it will help to decide when and which technique to use to either reduce the false alarms or improve detection processing. An alternate is cognitive sensing which makes the radar adapt its parameters based on a self-assessment of what is required to improve detection performance.

Three intelligence based techniques will be presented in this chapter:

1. Pre-integration processing
2. Scan to scan logic processing
3. Time domain and frequency domain detection processing

Each technique has its advantage and disadvantage as discussed in the following sections.
5.2 Intelligent Detection Techniques

The performance of the standard CFAR detectors (CA-CFAR, GO-CFAR, SO-CFAR, and OS-CFAR) is, in general, the same in a given sea clutter environment. Therefore, CA-CFAR is used in conjunction with the intelligent techniques as if representative of the rest of the standard CFAR detectors.

5.2.1 Pre-integration processing

This technique is used to improve the signal to interference ratio by averaging a number of range profiles together [11]. If the background is noise only, the signal to noise ratio for a coherent integration is improved by factor $N$ dB. Where $N$ is the number of the integrated pulses (assuming the target return is coherent). However, the background of the real sea clutter data does not contain noise only as there are strong reflections from the sea surface. Coherent integration of the sea clutter return will increase the clutter to noise ratio but not the target to interference ratio. However, this is not always the case, for some situations the reflections from the sea surface do have characteristics close to the noise like Gaussian.

Here, two example cases are considered for two different datasets that has been discussed in chapter 4. The first is where the clutter is noise like (but not the same as noise) and the data consists of near independent samples as shown in Figure.47. The second case uses clutter that exhibits very non-noise like behavior and has strong correlation in both space and time as shown in Figure.48. Both datasets were produced by taking the magnitude of the complex raw data and the intensity of each sample is represented in dB scale.
By applying a CA-CFAR, many false alarms occur due to spikes from the sea surface as mentioned in chapter 4. Figure.49 represents the same dataset as in Figure.47 but with detections shown as black dots using a standard CA-CFAR detector (which discussed in chapter 3) with 16 reference cells on both sides and 2 guard cells in either side of the detector. The desired probability of false alarm of the CFAR is $P_{FA} = 10^{-4}$.
There are no targets in this dataset, it contains only clutter and so the black dots represents false alarms and it can be seen many of them and the probability of false alarm is $P_{FA} = 16 \times 10^{-4}$ which is much higher than the desired $P_{FA}$. Figure.50 shows a coherent integration of 32 pulses for the same dataset in Figure.47. The same CA-CFAR detector is now applied to this dataset after coherent integration of 32 pulses. The coherent integration processing improves the detector by reducing the number of false alarms to $P_{FA} = 0.61 \times 10^{-4}$, which is lightly lower than the desired $P_{FA}$. This is shown in Figure.51.

Figure 49: CA-CFAR detection in noise like dataset

Figure 50: CA-CFAR detection in noise like dataset after integration of 32 pulses
Visually, false alarms in both datasets in Figure.49 and Figure.50 (without integration and with integration), are dropped significantly because the number of the samples of the dataset without integration is so huge compared to the dataset with integration.

Figure.51 shows the probability of false alarm in the vertical axis with the number of integrated pulses of the dataset in the horizontal axis. It is clear that pre-integration processing of the data reduces the number of false alarms in this particular dataset as the number of integrated pulses increases. This happens when the dataset is relatively noise like clutter with nearly independent samples. As shown in Figure.51, the probability of false alarm becomes closer to the desired probability of false alarm after 20 pulses integration and more. It is also notices that the probability of false alarm increases in the first 4 pulses and then decrease gradually. This increase happens because of correlation in the sea clutter data. The more correlated the data, the less effective integration will be in reducing false alarms as will be discussed in the second case.

![Figure 51: Pfa vs number of integrated pulses of noise like dataset](image-url)
The second case, as shown in Figure.48, is another dataset which was captured in different day, illuminated different area, and contained different sea state condition. This dataset has clear structure in the sea clutter showing correlation in both space and time. Now, the processes of the first case will be repeated in this dataset to show how different conditions of sea clutter affect the integration processing.

Results of running the CA-CFAR with 16 reference cells in both sides and 4 guard cells in both sides on the dataset is illustrated in Figure.52. The desired probability of false alarm is also \( P_{FA} = 10^{-4} \). The actual probability of false alarm of this dataset without integration is \( P_{FA} = 23 \times 10^{-4} \).

![Figure 52: CA-CFAR detection in heavy clutter dataset](image)

Applying 32 pulses integration to this dataset does not improve the detection processing as shown in Figure.53. The actual probability of false alarm with integration is \( P_{FA} = 71 \times 10^{-4} \). The probability of false alarm increases as the number of integration increases. This is because the high correlation of this dataset in both space and time; in addition to the high clutter to noise ratio.
Visually, it seems that after integration the number the false alarms is less than the number of false alarm without integration. But still the probability of the false alarm with integration is larger compared to the total number of samples. Figure 54 shows the probability of false alarm verses the number of integrated pulses. After integrating a few pulses the probability of false alarm start to increase gradually. The high correlation of the strong reflections increases the power of the clutter which exceed the threshold level and declare detection. The increase of the probability of false alarm in Figure 54 reflect the increase in the clutter to noise ratio of this dataset.

Figure 54: Pfa vs number of integrated pulses of heavy clutter dataset
The pre-integration processing technique depend so much on the dataset. This reinforce the need to have a more intelligent approach because the clutter properties varies such that is sometimes is good to integrate and sometimes is not. If there is an approach where it determines the structure of different datasets and the correlation properties in the clutter then it can make the decision whether to integrate or not.

5.2.2 **Scan to Scan logic processing**

The radar is staring at fixed area for the period between a minute to minute and half. However, it is possible to process the data as if it was collected using a scanning radar. This is done by processing only 32 pulses and then waiting one second (2000 Hz), which is the period rotation and then processing a further 32 pulses. 32 pulses is therefore considered as a single scan. Figure 55 illustrates the transfer from staring data to scanning data.

![Figure 55: Transfer the data from staring data to scanning data for the datasets](image)

Figure 55: Transfer the data from staring data to scanning data for the datasets
This section and the next section will discuss the intelligent techniques on the three datasets shown in Figure.56. These datasets were chosen carefully to illustrate the benefits of the intelligent techniques in different clutter types and conditions. Each dataset contains a small target. There are three cases in these datasets. Figure.56 (a) represents a stationary target at 8.2 km away from the radar in calm sea conditions. Figure.56 (b) represents a moving target coming towards the radar with a speed of 26 km/h in more correlated clutter and strong reflections of the waves. Finally, Figure.56(c) represents another moving target coming towards the radar with a speed of 57 km/h with correlated clutter.
Figure 57 shows the datasets after transferring from staring to scanning data. The figures look almost the same but have a fewer number of pulses. By applying a CA-CFAR, with 16 reference cells in both sides and 2 guard cells in each side, to the scanning data, it will give the same performance as with the staring data. It is expected to have many false alarms as confirmed in Figure 58.

![Figure 57: Scanning datasets](image)

Not only are there many false alarms, but also there are some of the false detections that look like targets as shown in Figure 58 (b) and (c). If lines were drawn to connect the dots in these two figure, they will consider as multiple targets. This is due to the highly correlated nature of the sea clutter. The intelligent technique used in this section is a scan to scan logic based concept. This technique takes advantage of the decorrelation from scan to scan by applying:
scan to scan logic = (scan 2 ∩ scan 1) ∪ (scan 2 ∩ scan 3)  \hspace{1cm} (5.1)

The scan to scan logic technique improves the detection performance in both datasets as shown in Figure.59 (a) and (b). However, in Figure.59 (c), this technique reduces the false alarms as well as the target detection, because the target is moving so fast. Figure.59 (c) represents one of the most difficult situations of detection of a small target in sea clutter, where the reflections from the target and the waves of the sea are almost the same. It can be noticed by eye that the target is crossing the waves in Figure.59 (c); however, the radar has to declare a target detection after receiving a small number of pulses. Doppler processing can be used when the target is moving so fast as will be discussed in the next section.
5.2.3. **Combination of Detection in Time and Doppler processing**

Estimating the radial velocity of a moving target is one of the advantages of Doppler processing since a moving target is separated from the clutter region (zero Doppler) [11]. Which means it has a different radial velocity. In the case of the fast moving target in Figure.57 (c), it can be easily detected using a 2D CA-CFAR with 16 reference cells around the cell under test and 9 guard cells as illustrated in chapter 3 Figure.12.

Figure 59: Scan to scan logic after applying CA-CFAR in scanning datasets
Figure 60: Range/Doppler map of fast moving target in dataset

Figure.60 represents the range/Doppler map of the dataset in Figure.57 (c) as discussed in chapter 4. As it can be seen, the clutter is not concentrated at exactly zero Doppler. This is because the background of the sea is not stationary. The blue area in the range/Doppler map has been found to be Rayleigh distributed and the target is clearly well separated from the clutter. After applying the 2D CA-CFAR, the detection of the target can be plotted in top of the range/time map and the overall result shows a good detection of the target even in difficult low target to interference situations as shown in Figure.61. There are number of assumptions used in this technique such as the number of detections in each scan should be more than 12 out of 32 in each range bin to declare a target.

Figure 61: Doppler 2D CA-CFAR detections in top of time domain image
This technique is not valid when the target is stationary as the dataset in Figure.57 (a). Here, plot of the range/Doppler map shows the target barred in the clutter region as shown in Figure.62. Therefore, under the circumstances where there is no radial velocity between the target and the clutter, this technique does not have improvement in the Doppler processing as seen in Figure.63.

Figure 62: Range/Doppler map of stationary target in dataset

Figure 63: Doppler 2D CA-CFAR detections in top of time domain image
However, applying the regular CA-CFAR to the range/time data in this particular dataset can detect the target easily as shown in Figure.64. This is the same process as what has been discussed in the previous section. Except here the assumption of the number of detections in each range bin of scan is considered. This assumption shows fewer false alarms in Figure.64 compared to the number of false alarms in Figure.58 (a).

Combining the frequency domain and time domain detection using “or logic” allow the detection of the target for both domains complete each other. However, the false alarms are also involved. Therefore, scan to scan logic is also combined here to reduce the false alarms. Figure.65 shows the results of combining the time and frequency domain.

Figure 64: CA-CFAR detections in time domain technique
Therefore, combining both the range/Doppler and range time to detect the target in different conditions can improve detection in sea clutter as seen in Figure 65. This is can be done by including a feedback in the processor to decide whether the time domain detection apply or frequency domain detection. It can improve further more if the scan to scan logic technique is involved in the intelligent process, especially for the reduction of the number false alarms.
Chapter 6: Conclusion

The CFAR detectors show a good performance when the background noise is complex Gaussian (or Rayleigh distributed amplitude). The CA-CFAR is the best CFAR performing in homogeneous environment. However, this CFAR regrades in the presence of clutter transition regions and mutual target interference. The GO-CFAR improves detection at the edge of the clutter in the clutter transition region. But, it fails and could miss targets when there are multiple target interfering. The SO-CFAR has the highest CFAR loss among the CFAR detectors that were discussed in chapter 3. However, it perform better than CA-CFAR and GO-CFAR in the multiple target interfering situation. The OS-CFAR combines the advantages of the basic CFAR together (CA-CFAR, GO-CFAR, SO-CFAR). This CFAR has fairly good performance in homogeneous environments. In addition, it automatically adapts itself to detect multiple target even in heterogeneous environments.

In real data, it is very complicated to model the exact clutter behavior, because unpredictable things could happen very big variation in real life and change all the expectation. However, models of clutter are extremely useful to help assigning the radar systems. Most of the datasets of the real sea clutter used in this thesis follow the moments of the K-distribution; although, a few of them fit well to a Rayleigh distribution. Further, there is a large range of K-distribution shape parameter that are a good fit to the data. This indicates the large range of behaviors exhibited by the real data.
The results of applying the standard CFAR detectors in the real datasets shows many false alarms as expected due to the spikes of the sea clutter. The use of the intelligent techniques shows the improvements of the detection performance. Pre-integration techniques shows the need of intelligent approach to decide whether the integration can be done or not based on the background clutter and the correlation properties of the clutter. Scan to scan logic improves the probability of false alarm in most cases of the real datasets by taking the advantage of the decorrelation samples from scan to scan. Finally, the combination of the time/frequency detection processing shows the huge improvement, even with difficult situation, of detecting the small targets. Furthermore, it can be combine also with scan to scan logic to reduce the false alarms.
Bibliography


