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Parameter Estimation and Radar Clutter Modeling using Biparametric Compound-Gaussian Models

Presented in front of the jury composed by:

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Dedication

To those who were part of this journey, I extend my deepest gratitude and appreciation.

To my parents

Thank you for your unwavering support and sacrifices, which have been the foundation I relied on throughout these years.

To my mother and father

Your love and belief in me have been the driving force that helped me persevere despite the challenges.

To my family

You are the support I cannot do without. Your presence has had a profound impact on achieving this accomplishment.

To my friends and classmates,

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This work is a reflection of your support and standing by me. To you, I dedicate it with gratitude.

To my professors,

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Finally, to my family,

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This work is the result of everyone’s efforts, and I dedicate it to you with gratitude.

Chapter I

Radar Principal

Chapter II

Parameter Estimation of methods

Chapter III :

Results and Discussion

List of Abbreviation

- CDF : Cumulative Distribution Function
- CFAR : Constant False Alarm Rate
- CGWB : Compound Gaussian with Weibull Texture
- CCDF : Complementary Cumulative Distribution Function
- CMC : Clutter Measurement Cell
- Doppler : Doppler Effect
- EM : Electromagnetic
- FA : False Alarm
- MoFNM: Method of Fractional Negative Order Moment
- HH : Horizontal-Horizontal Polarization
- Hz : Hertz
- IPIX : Intelligent Pixel Processing
- IQ Data : In-phase and Quadrature Data
- KS : Kolmogorov–Smirnov Criteria
- MoFM : Method of Fractional Moments
- MoM : Method of Moments
- MSE : Mean Squared Error
- PDF : Probability Density Function
- PRF : Pulse Repetition Frequency
- RCS : Radar Cross Section
- SNR : Signal-to-Noise Ratio
- UAV : Unmanned Aerial Vehicle
- VV : Vertical-Vertical Polarization
- WGN : White Gaussian Noise

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General introduction

Radar systems are vital components in many military and civilian applications, including air and maritime navigation, weather monitoring, border surveillance, and autonomous vehicle systems. These systems detect targets by transmitting electromagnetic waves and receiving the reflected signals, then analyzing them to extract information about the target's presence, location, and velocity.

However, with the advancement of modern technologies and the increasing resolution of radar systems, significant challenges have emerged regarding the accurate detection of targets in the presence of what is known as random interference or environmental noise (Clutter), especially in maritime environments. The term "clutter" refers to unwanted signals resulting from electromagnetic wave reflections off natural surfaces such as the sea or land. These signals may resemble the characteristics of echoes reflected from real targets, making it difficult to distinguish between them. This leads to an increase in false alarms and degradation of system performance.

In maritime environments, particularly at low grazing angles, random signals (Sea Clutter) exhibit non-Gaussian behavior; that is, they do not follow the normal distribution. Instead, they are characterized by sharp fluctuations and high standard deviations, rendering traditional models based on Gaussian assumptions inaccurate and ineffective for modeling this phenomenon.

Therefore, it has become essential to adopt advanced statistical models capable of representing the complex nature of these random signals. Among these models, the **Compound Gaussian model with Weibull Texture (CGWB)** stands out as a flexible and effective framework for describing the statistical properties of sea clutter, especially in high-resolution radar scenarios.

However, the effectiveness of this model heavily depends on the accuracy of estimating its parameters—particularly the shape and scale parameters. Hence, researchers are developing new estimation methods that outperform traditional techniques such as the Method of Moments (MoM), the Method of Fractional Moments (MoFM), and the [z log(z)] method.

In this context arises the importance of this research work, which focuses on modeling sea clutter using the CGWB model and developing a new estimation technique called the **Method of Fractional Negative Moments (MoFNM)**, aiming to improve estimation accuracy, reduce the

Mean Squared Error (MSE), and enhance statistical matching criteria such as the Kolmogorov–Smirnov (KS) criterion.

This brings us to the core research problem addressed in this study:

How can the accuracy of sea clutter modeling be improved in high-resolution radar systems? And is it possible to develop a new estimation method that outperforms traditional approaches in estimating the parameters of the CGWB statistical model under various operating conditions?

Chapter I: Radar Principal

I.1. Introduction

In order to detect targets, the radar generates electromagnetic waves using advanced antennas, transmitting signals that vary in frequency and intensity to track targets such as aircraft in clear skies or ships Among turbulent seas. These waves interact with the environment, influenced by factors like atmospheric refraction or Water vapor uptake, shaping their journey.

Once these waves return, how does radar process the signals, It precisely measures the time taken for the waves to travel and reflect back, calculating distances with great accuracy. It also monitors frequency shifts due to the Doppler effect to determine the speed and direction of targets, even Among interference from sea waves, nearby buildings, or natural noise like fog and dust.

Finally, how might parameter estimation and clutter modeling using bi parametric compound-Gaussian models enhance this process, These models represent the complex variations in signals caused by heavy rain, rugged terrain, or multiple reflections from metallic surfaces, enabling the radar to distinguish true signals from environmental clutter in challenging conditions.

I.2. Evolution of Radar Technology

The development of radar technology has been a cornerstone in the advancement of modern sensing and detection systems, with applications spanning from military surveillance to civilian air traffic control, weather forecasting, autonomous vehicles, and maritime navigation [M. I. Skolnik 2008]. Initially conceived in the early 20th century, radar systems have undergone significant transformations, evolving from simple pulse-based detection mechanisms to highly sophisticated digital platforms capable of real-time signal processing and adaptive operation. The earliest radars, such as the British Chain Home system during World War II, relied on basic amplitude and time-domain analysis to detect airborne targets[R. A. Watson-Watt 1968, E. G. Bowen 1987]. However, as operational requirements became more complex, so too did the underlying technologies.

In the post-war era, radar systems began incorporating Doppler processing, enabling the discrimination between stationary clutter and moving targets. This led to the emergence of pulse-Doppler radar , which became essential for airborne and naval applications[M. A. Richards 2010, F. E. Nathanson 1999].

The late 20th century saw the rise of phased array , synthetic aperture radar (SAR) , and inverse synthetic aperture radar (ISAR) , all of which significantly improved spatial resolution and target imaging capabilities. With the advent of digital signal processing and computing power, radar systems transitioned from analog to fully digital architectures, allowing for more flexible and intelligent operations[M. A. Richards 2010, Curlander and. McDonough1991].

In recent decades, the increasing demand for accurate target detection in heterogeneous environments such as sea or urban landscapes has emphasized the importance of advanced statistical modeling techniques. In particular, radar clutter modeling using bi parametric compound-Gaussian models has gained prominence due to its ability to capture the heavy-tailed and non-homogeneous nature of high-resolution clutter returns[E. Conte2002, S. Watts2000]. These models are especially useful in maritime environments where traditional Gaussian assumptions fail to describe the spiky behavior of sea clutter. As radar systems continue to evolve toward cognitive and software-defined architectures, the integration of robust parameter estimation methods becomes critical for ensuring reliable performance in real-world conditions[A. Balleri 2007, S. Haykin2006].

I.3. Understanding the Role of Basic Radar Components in Clutter Modeling

Radar is a complex system composed of several components that work together to detect targets by analyzing reflected signals. Understanding the structure of the system and the role of each component within it is essential for developing accurate statistical models such as the biparametric CGWB , used in radar clutter modeling and parameter estimation.

I.4. Fundamental Components of Radar Systems

I.4.1. Antenna

The antenna is the most prominent component of the radar system. It is responsible for directing the transmitted energy toward the desired target. The direction of transmission and reception is determined using azimuth and elevation angles, and this direction can be adjusted mechanically or electronically to allow coverage over a wide angular field. In bi static radar systems, two separate antennas are used one for transmission and one for reception requiring precise coordination between them to minimize electromagnetic interference [M. I. Skolnik 2008]. Understanding antenna characteristics and signal distribution is crucial when studying the impact of heterogeneous environments on received signals, especially in maritime and urban applications.

I.4.2. Duplexer

The duplexer plays a vital role in isolating the receiver circuitry during transmission to protect it from the high power levels of the transmitted signal, which can reach up to 10 MW. It then routes the received signal to the receiver without interference from the transmitter. The design of the duplexer depends on the expected level of transmitted signal interference and the receiver's tolerance to leakage, where performance degradation occurs if leakage exceeds about 100 MW [M. A. Richards 2010]. This protection ensures a clean received signal, facilitating subsequent clutter analysis using modern statistical models.

I.4.3. Transmitter

The transmitter generates microwave pulses at the required frequency and power. It typically uses a power oscillator or an amplifier chain that boosts the signal from approximately 1 W to several MW. Common types of high-power amplification tubes include klystrons, traveling wave tubes, and crossed-field tubes, while solid-state devices such as diodes and transistors are used in the initial stages [F. E. Nathanson 1999]. The transmitted power level directly affects the strength of the returned signal and consequently the type of clutter analyzed, particularly in background-dependent models like the Compound-Gaussian .

I.4.4. modulator

The modulator stores energy between transmission intervals and releases it in short bursts during the radar pulse. Currents can reach tens of amperes, and voltages can exceed thousands of volts. The quality of the generated pulse must be tightly controlled to prevent unwanted distortions that could affect the received signal, thus influencing the performance of parameter estimation algorithms and statistical clutter models [Curlander and. McDonough1991].

I.4.5. receiver

The receiver is the most sensitive and complex part of the radar system. It amplifies and processes the received signal without distortion. Its sensitivity must be extremely high (down to 10^{-15} watts) to detect weak echoes from distant or small targets. Additionally, the receiver filters the signal to reduce external noise, with its final stage often being a simple detector or advanced processing unit. The accuracy of amplification and data updating significantly impacts the effectiveness of statistical clutter models, especially in non-homogeneous environments [E. Conte2002, A. Balleri 2007].

I.4.6.Synchronizer

The synchronizer coordinates all operations within the radar system. Using a highly stable clock, it generates precise timing signals that control transmission and reception intervals and other time-dependent functions. If the system is not accurately synchronized, information loss or corruption may occur, affecting the performance of mathematical models used in clutter analysis and parameter estimation [S. Watts2000].

I.4.7. Indicator / Display Unit

Finally, the indicator displays the relative positions of detected targets. In basic systems, a Plan Position Indicator (PPI) is used, presenting data in polar format with the radar's location at the center. Although not directly used in statistical modeling, the indicator provides an initial visual understanding of clutter and target distribution, aiding in the selection of appropriate models such as the biparametric CGWB for parameter estimation [E. Conte2002].

I.5. Core Concepts in Radar Technology

Radar is an electronic system used to detect objects by transmitting electromagnetic radio frequency (RF) waves toward a specific area and receiving the reflected signals from those objects. The main components of a radar system include the transmitter, antenna, receiver, and signal processor.

The transmitter generates the RF electromagnetic waves, and the antenna sends them into the surrounding environment. A T/R switch or circulator is placed between the transmitter and the antenna to protect the sensitive receiver circuits from the high-power transmitted signal.

When the transmitted waves reach a target, part of the energy is reflected back toward the radar. This reflected signal is captured by the receiving antenna, amplified in the receiver, and then converted from RF to an intermediate frequency (IF). After that, it is digitized using an analog-to-digital converter (ADC), and finally processed by the signal processor to detect the presence of a target.

Unwanted reflections from surfaces such as the ground, sea, rain, or other non-target objects are referred to as clutter , which can complicate the detection process and must be filtered out during signal processing.

To calculate the distance R to a detected object, the time T taken for the wave to travel to the target and back at the speed of light c is used. The formula is:

$$R = \frac{c\Delta T}{2} \qquad \text{I. 1}$$

This basic principle forms the foundation for understanding how radar systems operate in various environments and under different conditions.

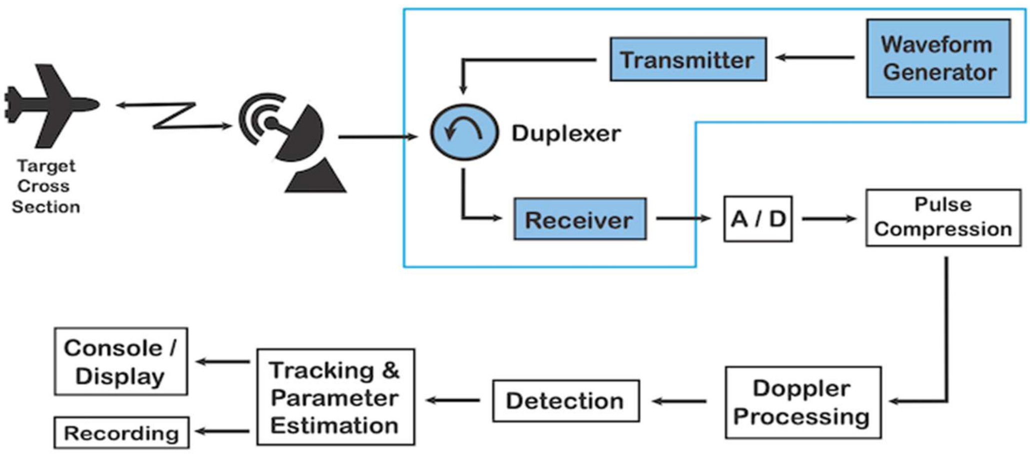


Figure I.1 : Block Diagram of a Radar System[Qorvo 2025].

where c is the speed of light in meters per second ($c \approx 3 \times 10^8$ m/s), ΔT is the time in seconds for the round-trip travel, and R is the distance in meters to the target. Received target signals exist in the presence of interference. Interference comes in four different forms, internal and external electronic noise, reflected EM waves from objects not of interest, often called clutter, unintentional external EM waves created by other human-made sources, that is, electromagnetic interference (EMI) and intentional jamming from an electronic countermeasures

(ECM) system, in the form of noise or false targets. Determining the presence of a target in the presence of noise, clutter and jamming is a primary function of the radar's signal processor. Detection in noise and clutter will be discussed further in this and subsequent chapters; it is a major concern of a significant portion of this research.

EMI is unintentional, as in the case of noise from an engine ignition or electric motor brushes. Jamming signals can take the form of noise, much like internal receiver thermal noise, or false targets, much like a true radar target[Richards2010].

I.6. Radar System Classification

I.6.1. Operation

Primary radar is a type of radar system that utilizes radio waves to detect the presence and location of objects such as aircraft, ships, weather formations, and terrain. It operates by emitting radio waves in a specific direction and then detecting the reflected signals from objects located in the path of these waves. The time delay between the transmission of the signal and the reception of the echo enables the radar system to calculate the distance to the target.

Secondary Radar Unlike primary radar, which relies on the direct reflection of transmitted signals, secondary radar involves the transmission of interrogation signals from the radar station to transponders mounted on targets such as aircraft. Upon receiving the interrogation signal, the transponder responds with an encoded reply that typically contains information about the identity, altitude, and sometimes the position of the aircraft. This allows for more accurate identification and tracking of the target[M. A. Richards 2010].

I.6.2. Illumination

Active radar is a radar system that generates its own electromagnetic signals and detects the reflections or echoes returned from objects in its vicinity. It works by transmitting continuous or pulsed radio waves toward the target and then receiving and analyzing the reflected signals. This enables active radar systems to determine the range, bearing, and sometimes the speed of the target using the Doppler effect. Active radar is widely used due to its high detection capability and independence from external sources[F. E. Nathanson 1999].

Passive radar differens from active radar in that it does not emit its own signals. Instead, it detects and tracks targets by analyzing reflections of existing electromagnetic signals, such as:

- FM radio broadcasts

- Television signals

- Mobile phone transmissions

It uses multiple receiving antennas to capture signals transmitted by other sources before and after they are reflected by moving objects. By comparing the differences between these signals, the system can determine the location and movement of targets within the airspace. Passive radar offers several advantages, including:

- Low probability of interception (LPI)

- Stealth operation (no emissions)

- Lower operational cost

This makes passive radar particularly suitable for covert surveillance and defense applications[Curlander and. McDonough1991].

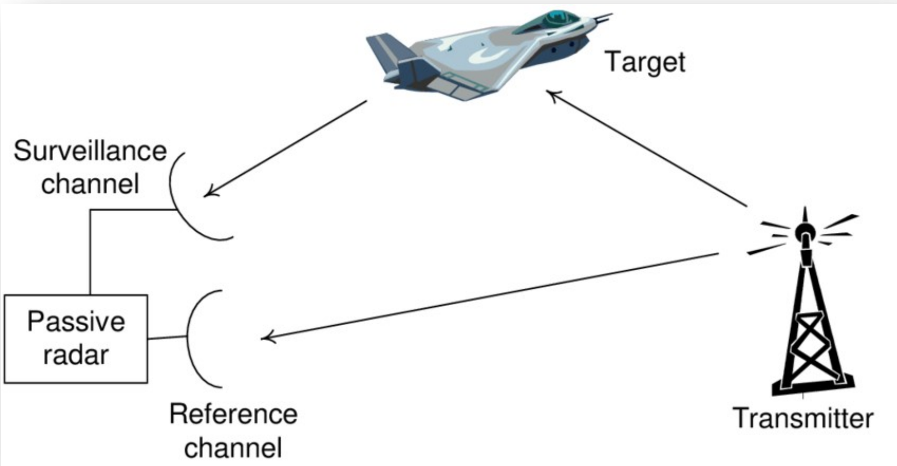


Figure I.2: Active and passive radar systems[Curlander and. McDonough1991].

I.6.3. Transmission Rate

Pulsed radar is a type of radar system that transmits short bursts of electromagnetic energy and then listens for the returned echoes from targets after the transmission has ceased. This mode of operation enables accurate range measurement , as the time delay between the transmitted pulse and the received echo directly corresponds to the distance to the target [M. A. Richards 2010]. Additionally, pulsed radar allows for effective discrimination between closely spaced targets, making it suitable for applications requiring high-resolution detection.

Continuous wave radar operates by transmitting a continuous electromagnetic signal without interruption. It relies on the Doppler effect to detect moving targets by comparing the frequency of the transmitted signal with that of the reflected signal. The difference in frequency, known as the Doppler shift, provides information about the radial velocity of the target [Lewinski, J. (1983)]. Continuous wave radar systems are widely used in applications such as:

- Speed measurement (e.g., traffic radar)
- Ground surveillance
- Navigation systems

Due to its reliance on motion for detection, CW radar is generally not suitable for detecting stationary targets unless modified with frequency modulation techniques (FMCW radar).

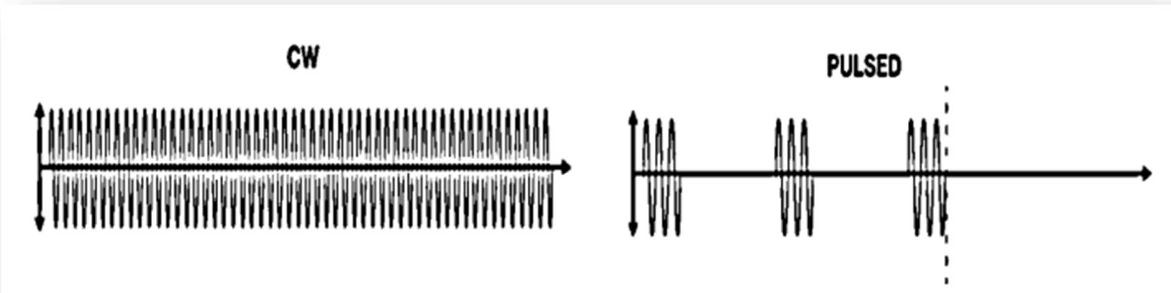


Figure I.3: pulsed and Continuous wave[Lewinski, J. (1983)].

I.6.4. Geometry

Mono static radar is a radar configuration in which the transmitter and receiver are located at the same site , often sharing a single antenna for both transmission and reception. It operates by emitting a signal toward a target and then receiving the reflected echo using the same antenna. This system benefits from a relatively simple architecture , lower cost , and the ability to function in both pulsed and continuous wave modes, making it widely used in many radar applications [M. A. Richards 2014].

In contrast, **bistatic radar** refers to a system in which the transmitter and receiver are physically separated and located at different positions. The system operates by transmitting a signal from one location and capturing the reflected signal at another location using a dedicated receiving antenna. Bi static radar offers several advantages over mono static systems, including:

- Enhanced detection performance
- Reduced susceptibility to electronic countermeasures (ECM)
- Increased spatial coverage

These characteristics make bi static radar particularly suitable for military and surveillance applications where stealth and resilience are critical [M. A. Richards 2014].

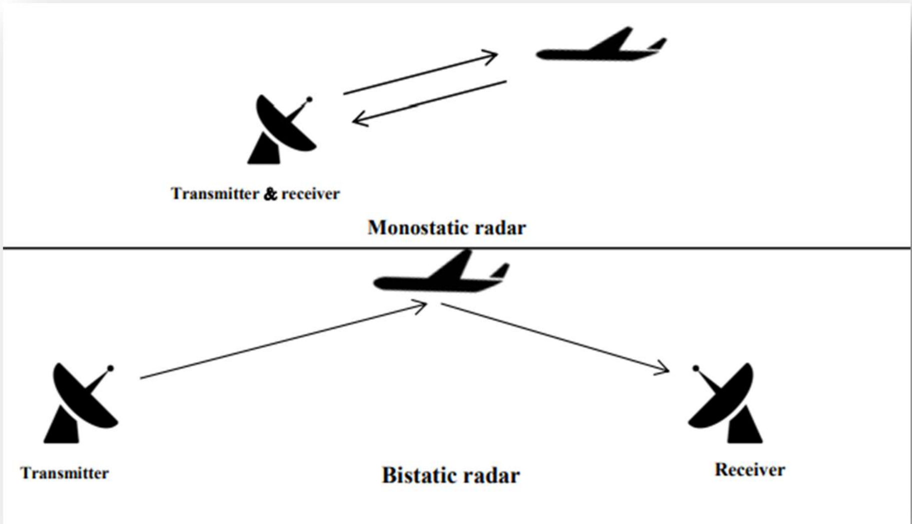


Figure I.4: bistatic and mono static radar systems[M. A. Richards 2014].

I.7. Radar equation

The radar equation enables the determination of radar's range, based on the technical specifications of the components involved in transmission, the radar apparatus the target and the transmission medium between them, assuming the radar's transmitting antenna is isotropic, meaning it radiates with equal intensity in all directions of space.

Assuming radar equipped with an omnidirectional antenna, emitting energy uniformly in all directions. Given the spherical radiation pattern characteristic of such antennas, the establishment of the peak power density (power per unit area) at any given spatial point, this equation can be derived as follows:

$$P_d = \frac{Peak\ transmitted\ power}{area\ of\ a\ sphere}\ watts/_{m^2} \qquad \text{I. 2}$$

In a lossless propagation medium, the density power in a high Range (R) written as:

$$P_d = \frac{p_t}{4\pi R^2} \qquad \text{I. 3}$$

Where pt is the peak transmitted power and $4\pi R2$ is the surface area of a sphere of radius R Characterizing directional antennas will enhance power density in a specific direction as follow:

$$G = \frac{A_e}{\lambda^2} \qquad \text{I. 4}$$

Where G is the gain and Ae is the antenna effective aperture and λ is the wavelength The gain of the arbitrary antenna is the ratio of its maximum power density. The surface power density Pt in the direction of maximum radiation of an antenna expressed according to the following equation:

$$Pd = \frac{P_t\, G}{4\pi R_2} \qquad \text{I. 5}$$

In detection process the radar concentrate energy on the target, the resulting surface currents on the target emit electromagnetic energy in various directions. The emitted energy is directly related to the target's characteristics, including its size, orientation, shape, and material composition, all previous are call them Radar Cross Section (RCS) denoted by σ, and its expression written as:

$$\sigma = \frac{P_r}{P_d} m^2 \qquad (I.6)$$

Where P_r is the power reflected from the target.

The total power supplied to the radar signal processor by the antenna

$$P_{dr} = \frac{P_t G \sigma}{(4\pi R^2)^{\,2}} A_e \qquad (I.8)$$

Substituting the value of A_e Equation (I.3) into Equation (I.6) giving:

$$\mathrm{P_{dr}} = \frac{\mathrm{P_t G^2 \lambda^2 \sigma}}{(4\pi)3\ \mathrm{R}4} \qquad (I.9)$$

Let S_{min} the minimum detectable power from the reception, and R_{max} the radar range [M. A. Richards 2010].

$$\mathrm{R_{max}} = \left(\frac{\mathrm{P\,t\,G^2\,\lambda^{\,2}\sigma}}{(\,4\pi)^3 \mathrm{S_{min}}} \right)^{\frac{1}{4}} \qquad (I.10)$$

I.8. Target Detection in Radar Systems

I.8.1. Definition

In the context of radar, detection is defined as the fundamental process used to determine the presence or absence of a target after receiving the echo signal. This received signal typically contains both:

- The desired return from the target
- Undesired components such as background clutter and noise

The detection process involves computing a detection threshold based on the statistical variations in clutter power. Once this threshold is determined, the received signal amplitude is compared to it. If the signal exceeds the threshold , it indicates the likely presence of a target. Conversely, if the signal does not exceed the threshold , it suggests that no target is present.

This binary decision-making mechanism forms the basis for modern radar detection strategies and plays a crucial role in distinguishing actual targets from unwanted interference.

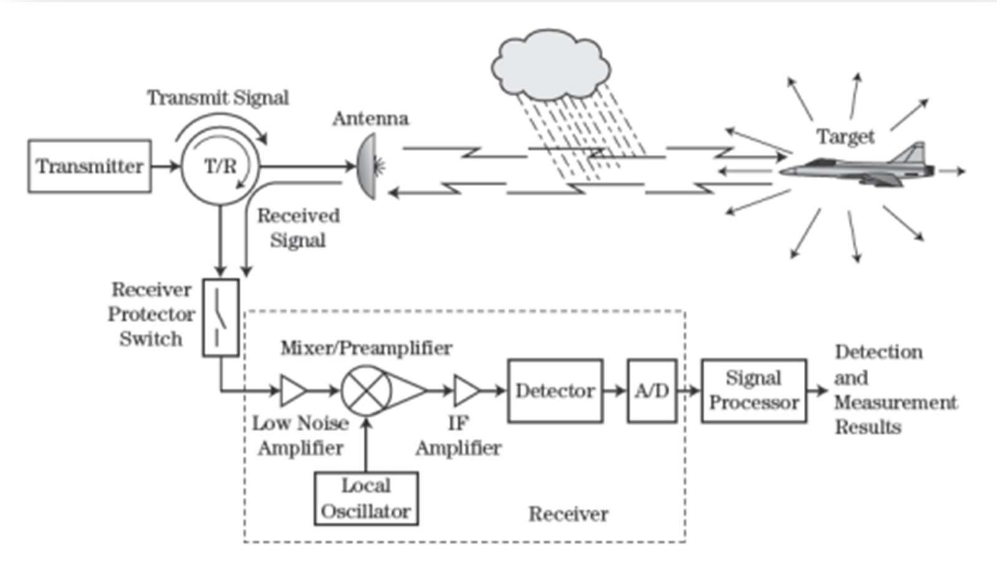


Figure I.5: Major elements of radar transmission reception process[Echard1991].

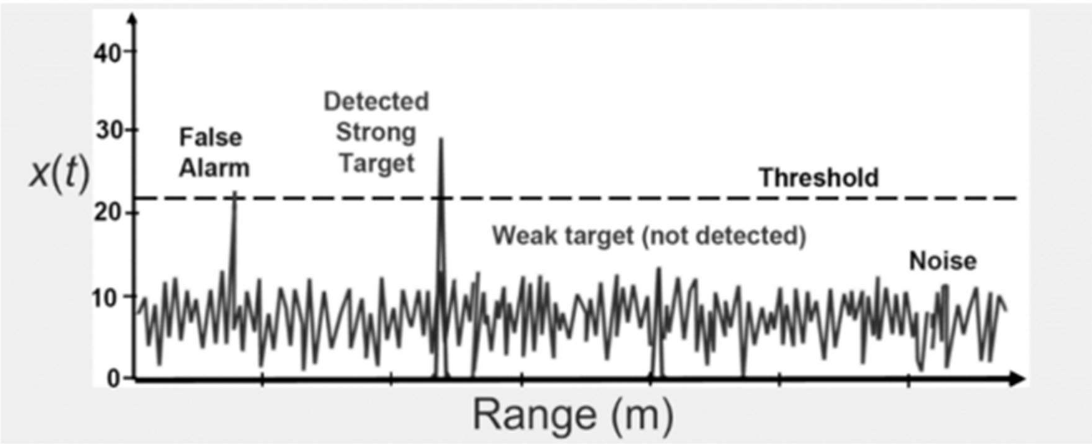


Figure I.6: Example of decision process[Echard1991].

In the decision-making process of radar systems, there are four possible outcomes due to detection challenges, the random nature of clutter, and target fluctuations. These cases are as follows:

1. Target present when the target is actually present: This outcome occurs when the radar correctly identifies the presence of the target in the environment. The received signal exceeds the detection threshold, called the detection probability PD .
2. Target missing when the target is present: This scenario occurs when the radar fails to detect the presence of the target that is actually present in the environment. It is called the non-detection probability or the probability of Miss $1-PD$.
3. Target present when the target is missing: This situation arises when the radar incorrectly detects the presence of the target even though no target is actually present. This could occur due to false alarms triggered by noise or clutter in the environment PFA .
4. Target missing when the target is missing: In this case, the radar correctly concludes that no target is present in the environment. The received signal does not exceed the detection threshold, indicating the absence of the target, and this assessment corresponds to the actual absence of the target $1-PFA$ [Echard1991].

I.8.2. Bayes Criterion for Hypothesis Testing

In the context of decision-making between two competing hypotheses , the system faces the task of selecting the most probable hypothesis based on the received data. In this framework, the problem is formulated as Binary Hypothesis Testing , where a choice must be made between two mutually exclusive hypotheses

I.8.2.1. Prior Probabilities

The approach begins with the assumption that we have prior knowledge regarding the likelihood of each hypothesis being true before any data is observed. These probabilities are referred to as Prior Probabilities , and are expressed as follows:

- $P(H_0) = P_0$:The prior probability of hypothesis H_0, which represents the Null Hypothesis .
- $P(H_1) = P_1$:The prior probability of hypothesis H_1, which represents the Alternative Hypothesis .

These prior probabilities serve as the foundation for computing posterior probabilities and are widely used in statistical decision rules such as the Bayes Test .

I.8.2.2. Costs associated with decisions

Introduce the concept of costs associated with each possible decision it could make. These costs represent the consequences of each decision depending on the truth of the hypothesis. Formally, if i is a decision, j is the true hypothesis, C_{ij} is the cost associated with decision i given that hypothesis j is true. [Barkat 2005]

The Bayes criterion aims to minimize the Bayes risk C by defining decision regions Z0 and Z1.

$$E[C] = C_{00}p(D_0, H_0) + C_{10}p(D_1, H_0) + C_{01}p(D_0, H_1) + C_{11}p(D_1, H_1) \qquad (I.11)$$

Every conjoint probability in this expression written in this way:

$$P(Di, Hj) = p(H_j)p(D_j/H_j) = p(H_j)p(q \in Z_j/H_j) = p(H_j)\int_{Z_j} p_{Qi/H_j} Z_j (q / H_j)dq \qquad (I.12)$$

Observe that the two decision regions are complementary. Hence, it can state:

$$\int_{Z_j} p_{Qi/Hj}\left({q}/{H_j}\right)dq = 1 - \int p_{Qi/Hj}\left({q}/{H_j}\right)dq \quad, i \neq j, \ \ i,j = 0,1 \qquad (I.13)$$

From the last equation the expression of the average Bayes cost differently as:

$$E[c] = C_{11}P_1 + C_0\int_{Z_0}\left[P_1(C_{01} - C_{11})p_{Q/H_1}\left({q}/{H_1}\right) - P_0(C_{10} - C_{00})p_{Q/H_0}\left({q}/{H_1}\right)\right]dq \qquad (I.14)$$

Upon observation, it becomes evident that the first two terms in previous equation are not influenced by the decision regions , so minimizing the integral will lead to minimize the average cost $E[C]$, all points in the observation space leading to a negative integral should be allocated to Z_0 while $\Lambda(Q)$ represents the likelihood ratio

$$\Lambda(Q) = \frac{p_Q / H_1\,({q}/{H_1})}{p_Q / H_0\,({q}/{H_0})} \underset{H_0}{\overset{H_1}{\gtrless}} \frac{p0\,(C_{10} - C_{00})}{p1\,(C_{01} - C_{11})} = T \qquad (I.15)$$

I.8.3 Neyman-Pearson Test

The Neyman-Pearson test is a statistical method used to make decisions between two hypotheses by comparing two possible explanations for an observed event and determining which one is more probable based on the available data.

- Two Hypotheses : the null hypothesis (denoted $H0$) and the alternative hypothesis (denoted $H1$). The null hypothesis typically represents the current state or default assumption, while the alternative hypothesis represents a new or different claim.
- Likelihood Ratio : the Neyman-Pearson test focuses on the likelihood ratio, which is the ratio of the probability of observing the data under the null hypothesis to the probability of observing the data under the alternative hypothesis. It indicates how much more likely the data are under one hypothesis compared to the other.
- Controlled Error Rates : the test aims to control the probability of making a Type I error (false positive), which occurs when the null hypothesis is rejected despite being true. This probability is denoted by α and is set in advance by the experimenter as the significance level.
- Optimized Decision Rule : the Neyman-Pearson test selects a decision rule that maximizes the probability of correct detection PD while keeping the probability of a Type I error below the specified significance level. This rule often involves comparing the likelihood ratio to a critical value or threshold.
- Applications : the Neyman-Pearson test is widely used in various fields such as signal detection theory, medical diagnostics, and quality control, where it is essential to make decisions while effectively controlling error rates.

The decision rule is given as: [Barkat2005]

$$\Lambda(Q) = \frac{p_{Q}/_{H_1}(q/H_1)}{p_{Q}/_{H_0}(q/H_0)} \underset{<}{>} \lambda \tag{I.16}$$

λ is the Lagrange multiplier.

I.8.4. Minimax test

Minimax test deals with the difficulty of prior probability knowledge previously experienced. To derive this test, first examine how the choice of threshold affects the Bayes risk. Assuming a fixed decision threshold η, the test's performance relies on comparing the likelihood ratio against this threshold. Consequently, the resulting decision rule from the minimax decision is given as:[Barkat 2005]

$$\Lambda(\mathrm{Q}) = \frac{(1 - \mathrm{p}_1)(\mathrm{C}_{10} - \mathrm{C}_{00})}{\mathrm{p}_1 (\mathrm{C}_{01} - \mathrm{C}_{11})} = \eta \qquad (\mathrm{I}.17)$$

Selecting an appropriate threshold for the PFA and PM values to ensure equality, the test's result will be certain

$$\mathrm{C}_{11} - \mathrm{C}_{00} + (\mathrm{C}_{01} - \mathrm{C}_{11})\mathrm{P}_{\mathrm{M}} - (\mathrm{C}_{10} - \mathrm{C}_{00})\mathrm{P}_{\mathrm{FA}} = 0 \qquad (\mathrm{I}.18)$$

The Minimax Test is a statistical decision-making approach used when prior probabilities are unknown or uncertain . It serves as a practical solution to the challenge of making reliable decisions in the absence of accurate prior information, which is a major limitation in applying the Bayes criterion.

Concept of the Test:

To understand how the Minimax Test works, we begin by analyzing how the choice of threshold affects the Bayes risk .

Assuming a fixed decision threshold η , the performance of the test depends entirely on comparing the likelihood ratio to this threshold.

The resulting decision rule from the Minimax Test is given by [24]:

$$\Lambda(Q) = p_1(\mathrm{C}_{01} - \mathrm{C}_{11})(1 - p_1)(\mathrm{C}_{10} - \mathrm{C}_{00}) = \eta \qquad (I.19)$$

Where:

- $\Lambda(Q)$: Likelihood ratio.

- p_1 : Prior probability of hypothesis H_1 (target present).
- C_{ij} : Cost associated with decision i when the true hypothesis is j .

Optimal Threshold Selection:

In the Minimax Test, the threshold is selected such that the Bayes risk is equal under all possible prior probabilities .

This is achieved by choosing η so that:

$$C_{11} - C_{00} + (C_{01} - C_{11})P_M - (C_{10} - C_{00})P_{FA} = 0 \qquad (I.20)$$

Where:

- P_M : Probability of miss (failure to detect a target).
- P_{FA}: Probability of false alarm.

This condition ensures that the maximum expected risk remains constant , regardless of variations in the prior probabilities. Thus, the system is designed to be least sensitive to uncertainties in these probabilities .

I.9. Conclusion

In this chapter, we dived into understanding the fundamentals of radar systems and their principles of operation, starting from their basic components such as the antenna, transmitter, receiver, and synchronizer, all the way to the core concepts of how targets are detected and located. We also discussed the historical evolution of radar technology, which has led to the emergence of modern systems capable of operating in complex and unstable environments, such as the Naval environment.

the focus was on how environmental factors, noise, and interference affect the quality of the received signal, especially regarding the phenomenon known as clutter, which results from unwanted reflections from the sea surface or ground. We understood the importance of using advanced statistical models such as the Compound-Gaussian model to characterize and process this type of noise, thereby improving detection accuracy and reducing false alarms.

We were also introduced to decision tests such as Bayes Test, Neyman-Pearson Test, and Minimax Test, which are used to make accurate decisions regarding target presence under high interference conditions. These concepts have direct applications in the field of telecommunications, particularly in designing intelligent sensing systems and enhancing signal detection in noisy channels.

In summary, this chapter helped us connect the theoretical concepts of radar with telecommunications, understand the challenges facing modern sensing systems, and appreciate the importance of using mathematical and statistical models to improve performance in difficult interference environments.

Chapter II: Parameter Estimation of CGWB

II.1. Introduction

In modern communication systems, electromagnetic signals are not only used for transmitting information, but also play a key role in technologies like radar, which rely on the same fundamental principles of signal propagation and detection.

Radar systems are essential in transportation, defense, and environmental monitoring — especially in maritime environments where they face harsh and complex conditions. One of the biggest challenges in radar operation is clutter, which refers to unwanted echoes reflected from natural surfaces such as the sea surface. This clutter can easily mask real targets and degrade system performance.

In marine environments, clutter behavior is often unpredictable and non-Gaussian, especially at low grazing angles. Traditional models, such as the Gaussian distribution, are no longer sufficient to accurately describe this kind of interference.

This has led to the development of more advanced statistical models, such as the Compound-Gaussian model with Weibull texture (CGWB). This model is flexible and powerful enough to represent the heavy-tailed and random nature of sea clutter, making it highly suitable for high-resolution radar systems.

However, the usefulness of the model goes beyond description it plays a crucial role in improving detection performance. This is where parameter estimation becomes important. Estimating the shape and scale parameters of the CGWB model allows the radar system to adapt to changing environmental conditions. The accuracy of this estimation directly affects two key performance indicators, the probability of detection and the probability of false alarm.

Therefore, this chapter focuses on studying and developing methods for estimating the parameters of the CGWB model, including the Method of Moments, Fractional Order Moment Method, and logarithmic regression techniques. It also introduces a new method called the Fractional Order Moment Negative Method (MoFNM), aimed at improving estimation accuracy and enhancing detection performance in complex cluttered environments.

In summary, this work contributes to building a strong statistical framework for modeling sea clutter using the CGWB model. This helps improve the reliability and efficiency of radar systems in challenging maritime environments, supporting better sensing and surveillance capabilities in real-world communication applications.

II.2. CGWB Model

CGWB distribution belongs to the family of bi parametric compound-Gaussian distributions. CGWB distribution is proposed in [P. Zou2024.], where a good modeling performance for low-resolution sea clutter data at small grazing angles is achieved. In literature, several CG distributions are used to model the sea clutter. CG distributions differ from each other by the texture distribution.

The bi Parametric CG distributions are a mixture of two components; speckle and texture. CGWB distribution is based on the use of Weibull texture and the speckle component obeys the distribution of Rayleigh. The overall PDF of the CGWB is given as:

b and η are the scale and shape parameters of the Weibull distribution, respectively, and Γ (·) denotes the gamma function the amplitude z of the complex clutter:

$$f(z;\ b,\eta)=\frac{2\eta\left[\Gamma\left(1+\frac{1}{\eta}\right)\right]^{\eta} z}{b^{\eta}}\int_{0}^{+\infty}\tau^{\eta-2}\exp\left\{-\frac{z^2}{\tau}-\left[\frac{\tau\Gamma\left(1+\frac{1}{\eta}\right)}{b}\right]^{\eta}\right\}d\tau \qquad (\mathrm{II.1})$$

Where η and b are the shape and the scale parameters respectively.

Using the PDF in (1), the CCDF of the CGWB distributed amplitude z is expressed as:

$$F(z;b,\eta)=1-\frac{\eta\left[\Gamma\left(1+\frac{1}{\eta}\right)\right]^{\eta}}{b^{\eta}}\int_{0}^{+\infty}\tau^{\eta-1}\exp\left\{-\frac{z^2}{\tau}-\left[\frac{\tau\Gamma\left(1+\frac{1}{\eta}\right)}{b}\right]^{\eta}\right\}d\tau \ (\mathrm{II.2})$$

The moment expression of the CGWB is given as [P. Zou2024]:

$$m_x\,(z\,;\,b,\eta)=\,b^{x/2}\,\Gamma\left(1+\frac{x}{2\eta}\right)\Gamma\left(1+\frac{x}{2}\right)\left[\Gamma\left(1+\frac{1}{\eta}\right)\right]^{-x/2} \qquad (\mathrm{II.3})$$

Give x > 0, the x the moment of the Weibull texture distribution satisfies the following:

$$m_x(\tau;b,\eta)=\frac{b^x\Gamma\left(1+\frac{x}{\eta}\right)}{\left[\Gamma\left(1+\frac{1}{\eta}\right)\right]^{x}}\ ,\qquad x>0 \qquad (\mathrm{II.4})$$

In consideration of the independence of the texture and speckle components, the moment of the amplitude of the CGWB distribution can be easily derived, where the envelope of the complex Gaussian speckle is a Rayleigh distributed random variable with σ = 1, the original moments of the CGWB-distributed random variable satisfy [Shui, P.-L.2016]:

$$m_x\,(z;\ b,\eta)=m_{\frac{x}{2}}(\tau;b,\eta)m_x(|u|)=\ b^{x/2}\,\Gamma\left(1\ +\frac{x}{2\eta}\right)\Gamma\left(1\ +\frac{x}{2}\right)\left[\Gamma\left(1\ +\frac{1}{\eta}\right)\right]^{-x/2}\quad(\text{II}.5)$$

II.3. Parameter Estimation Of CGWB

II.3.1 MoM method

As a new family of bi parametric distributions in the amplitude modeling of sea clutter, the parameter estimation of the CGWB distributions is important for the applications of the CGWB distributions in practice. I the joint of the original moments can derive different moment-based estimators. By using the second- and fourth-order moments, a moment-based estimator (MoM) is given as follows:

$$\Phi_{24}(\eta)=\ \eta\ \frac{\Gamma(2/\eta)}{\Gamma^2(1/\eta)}\ =\frac{\widehat{m}^4(z)}{4\widehat{m}_2^2(z)}\quad(\text{II}.6)$$

$$m_x(z)=\frac{1}{N}\sum_{i=0}^{N}z_i^x\,,x>0\quad(\text{II}.7)$$

• $\hat{mx}\ (z)\ =\ \frac{1}{N}\ \sum_{i=1}^{N}\ z_i^X$ is the x-th sample moment of the amplitude data$\{z_1\,,z_2\,,\dots\,.,z_3\,\}$

• b is estimated as

• $\hat{b}\ =\ \hat{m}_2(z)$

II.3.2. [zlog(z)] method

The [Zlog(Z)] method is one of the moment-based statistical techniques used to estimate the parameters of non-Gaussian distributions such as the Compound-Gaussian model with Weibull texture (CGWB) . This method relies on logarithmic moments of the data and provides accurate estimates for both the shape parameter and the scale parameter of the distribution.

The core idea of this method is based on computing the logarithmic moments of the received radar signalsZ_i , and then equating these values with the theoretical expressions derived from the assumed statistical distribution (in this case: CGWB). By solving the resulting equations, estimates for the desired parameters are obtained.

The [Zlog(z)] based estimator uses log-based moments to estimate parameters:

$$\Phi_{\mathrm{zlog(z)}}(\eta) = 2 - \ln(2) + \frac{1}{2\eta}\left[\Psi\left(\frac{1}{2\eta}\right) - \Psi(1)\right] \tag{II.8}$$

$$= \frac{\widehat{m_{\mathrm{zln(z)}}}(z)}{\widehat{m_1}(z)} - \widehat{m}_{\ln(z)}(z) \tag{II.9}$$

where

- $\widehat{m_{\mathrm{zln(z)}}}(z) = \frac{1}{N}\sum_{i=1}^{N} zi\ln(zi)$
- $\widehat{m}_{\ln(z)}(z) = \frac{1}{N}\sum_{i=1}^{N} \ln(zi)$
- $\Psi(.)$is the digamma function
- η : Shape parameter of the Weibull distribution.
- $\hat{b} = \hat{m}_2(z)$: Scale parameter.

II.3.3. MoFM method

the method of fractional-order moments (MoFM) estimators through the first and the 1/2-order sample moments are given by the following:

$$\Phi_{1-1/2}(\eta) = \frac{\eta\,\Gamma\left(1/2\eta\right)}{\Gamma^2\left(1/4\eta\right)} = \frac{\Gamma^2\left(1/4\right)\hat{m}_1(z)}{64\sqrt{\pi\hat{m}_{\frac{1}{2}}(z)}}, \qquad \hat{b} = \hat{m}_2(z) \tag{II.10}$$

Similarly, it can be verified that the functions $\Phi_{123}(\cdot)$ and $\Phi_{1\text{-}1/2}(\cdot)$ for the MoLM and MoFM estimators are also implicit monotonically decreasing functions, and the lookup table method can be used to calculate their inverse functions and then for estimation of the shape parameter η.

The MoFM estimator uses the first and 1⁄2 order fractional moments,

$$\Phi 1-1/2\ (\eta)=\eta\ \frac{\Gamma(1/2\eta)}{\Gamma\, 2(1/4\eta)}\ =\frac{\Gamma^{2}(1/2)\widehat{m}_{1}(z)}{64\sqrt{\pi\widehat{m}^{1}_{1/2}}(z)} \qquad (\text{II}.11)$$

Where,

$\hat{m}$ 1⁄2 (z) is the fractional moment of order (1/2).

The [z log(z)]-based estimator uses log-based moments to estimate parameters :

$$\Phi z\log(z)(\eta)=\ 2\ -\ \ln(2)+\frac{1}{2\eta}\left[\Psi\left(\frac{1}{2\eta}\right)-\Psi(1)\right] \qquad (\text{II}.12)$$

$$=\frac{\widehat{m}_{z\ln(z)}\,(z)}{\widehat{m}1\,(z)}-\ \widehat{m}_{z\ln(z)}\,(z) \qquad (\text{II}.13)$$

Where

- $\hat{m}zln(z)\ =\frac{1}{N}\ \sum_{i=1}^{N}\ z_i\ ln\ (zi)$
- $\Psi(.)$ is the digamma function
- $\hat{b}\ =\ \hat{m}_2(z)$

II.3.4. Proposed MoFNM method

In this section, MoFNM estimator is developed based on the theorical expression of moment and using negative order. MoFNM estimator is developed previously to estimate the parameters of the K distribution and the CGWB II,14 and II.15 The negative order moment is considered:

$$m_{-x}\,(z;\,b,\eta)=\ b^{\,-x/2}\Gamma\left(1\ -\frac{x}{2\eta}\right)\Gamma\left(1\ -\ \frac{x}{2}\right)\left[\Gamma\left(1\ +\ \frac{1}{\eta}\right)\right]^{x/2} \qquad \text{II}.14$$

Based on(II. 8) and $(II.14)$ after multiplication and simplifications, the MoFNM is obtained as,

$$\langle m_x\rangle\langle m_{-x}\rangle=\ \Gamma\left(1\ +\frac{x}{2\eta}\right)\Gamma\left(1\ -\ \frac{x}{2\eta}\right)\Gamma\left(1\ -\ \frac{x}{2}\right)\Gamma\left(1\ +\ \frac{x}{2}\right) \qquad \text{II}.15$$

To assess the estimation accuracy of the proposed MoFNM method in the next section, the obtained results will be compared with the existing MoM, MoFNM and [zlog(z)] estimators.

II.4. Conclusion

Radar systems are fundamental in the field of telecommunications and remote sensing technology, as they rely on transmitting electromagnetic waves and receiving their reflections to detect targets with high accuracy. These systems face significant challenges related to environmental noise (Clutter), which arises from unwanted echoes reflected from natural surfaces such as the sea or ground. These reflections can closely resemble the characteristics of signals returned from real targets, thus complicating the detection process and affecting system performance. Therefore, advanced statistical models have been adopted to accurately model this noise, especially in high-resolution maritime environments where the behavior of clutter is non-Gaussian. One such model is the Compound-Gaussian model with (CGWB). This model is based on two parameters: the shape parameter and the scale parameter, and its application requires precise techniques for estimating these parameters, such as the Method of Moments (MoM), the logarithmic moment method [z log(z)], and the Fractional Order Moment Method (MoFM). In addition, this work introduces a proposed method called the (MoFNM), which has demonstrated noticeable improvement in estimation accuracy, positively impacting target detection enhancement and reducing false alarms. These methods were tested using real data from the IPIX radar and simulated data, proving their effectiveness in handling complex sea clutter, making them highly valuable for modern radar applications under challenging interference conditions.

Chapter III: Results and Discussion

III.1 Introduction

This section presents a comprehensive performance analysis of the proposed MoFNM introduced in this study. The evaluation is conducted through comparative experiments with established estimators in the literature, namely the MoM, MoFM, and the [zlog(z)] estimator. The accuracy and robustness of the MoFNM estimator are assessed using two primary evaluation criteria: the Mean Squared Error (MSE) and the Kolmogorov-Smirnov (KS) statistic.

To ensure a thorough validation, the comparison is carried out using both synthetically generated data based on the Compound Gaussian with Weibull texture distribution and real-world radar clutter data obtained from the IPIX (Intelligent Pixel Processing) high-resolution sea clutter database [39]. The simulated CGWB data allows for controlled experiments under various parameter settings, while the IPIX dataset provides practical insights into the estimator's performance in realistic maritime radar environments.

The inclusion of both simulated and empirical data ensures that the results are not only theoretically sound but also practically relevant, especially in applications such as maritime surveillance, target detection, and radar signal processing where accurate modeling of sea clutter is crucial.

III.2. IPIX Data:

IPIX stands for Intelligent PIXel Processing, a radar system developed at McMaster University in Canada during the 1990s to collect high-resolution sea clutter data [IPIX McMaster University]. This system was specifically designed to capture radar returns from the ocean surface under various environmental conditions, making it a valuable resource for maritime radar research.

Key Features of the IPIX Radar System

Frequency and Resolution:

The IPIX radar operates in the X-band, around 9.3 GHz, with a variable spatial resolution ranging from 1 meter to 30 meters, depending on the system settings [K. D. Ward1990]. It uses a pulse repetition frequency (PRF) of approximately1 kHz, allowing for detailed time-domain analysis of radar echoes.

Polarization

The radar supports dual-polarized operation, including both HH (Horizontal-Horizontal) and VV (Vertical-Vertical) polarization modes [M. Greco2012]. This dual-polarization capability allows researchers to study how different polarizations affect clutter statistics and target detection performance.

Doppler Processing

The system includes Doppler signal processing capabilities, enabling the separation of moving targets from stationary or slow-moving sea clutter [E. Conte2002]. This feature is especially useful for detecting small or slow-moving vessels in complex maritime environments.

Data Format

Data is stored in IQ format (In-phase and Quadrature), which contains full information about the received signals, allowing for advanced signal processing techniques such as spectral analysis and waveform reconstruction [R. K. Ranjan2003]. Additionally, magnitude, phase, and Doppler data are available for further analysis.

Environmental Conditions:

Along with radar measurements, environmental parameters such as wind speed, wave height, air temperature, and grazing angle were recorded [J. B. Billingsley2002]. These data help researchers understand how weather and sea state influence radar clutter behavior.

The IPIX radar data was collected from several coastal locations in Canada, including:

- Dartmouth, Nova Scotia

- St. John’s, Newfoundland

These sites offer diverse sea and weather conditions, providing a rich dataset for studying sea clutter under varying operational scenarios [M. Rangaswamy2000].

III.3. Results and discussion

III.3.1. Results using simulated data

At the initial stage, the performance of the proposed MoFNM estimator is evaluated using simulated data generated according to the CGWB distribution. The estimation accuracy is assessed through the (MSE) criterion, calculated over L = 10 000 independent Monte Carlo trials. In these experiments, each trial involves processing a dataset consisting of M = 1000 independent and identically distributed (i.i.d) samples. For the MoFNM method, a fractional order moment of n = 0.1 is employed, which was selected based on preliminary sensitivity analysis to ensure stable and accurate estimation.

Figure III.1 presents the variation of MSE with respect to the shape parameter of the CGWB. As observed from the plot, the MoFNM estimator outperforms existing methods namely MoM, MoFM, and [zlog(z)] over a wide range of shape parameter values (from 0 to 1), demonstrating its demonstrating its robustness and high precision in challenging scenarios where the clutter statistics deviate from Gaussian behavior.

However, when the shape parameter increases from 1 to 2, the Method of Moments (MoM) becomes more effective, achieving the lowest MSE among all estimators in this range. This suggests that classical methods may still be preferable under certain parametric conditions where the data exhibits less heavy-tailed characteristics.

In addition, it is observed that the Method of Fractional Moments (MoFM) provides performance closely matching that of the [z log(z)] estimator across most of the tested parameter range, indicating a similar sensitivity to variations in the shape parameter and comparable robustness in moderate non-Gaussian environments.

These results highlight the adaptability of the MoFNM estimator and confirm its effectiveness in accurately estimating CGWB parameters, particularly in highly heterogeneous sea clutter conditions.

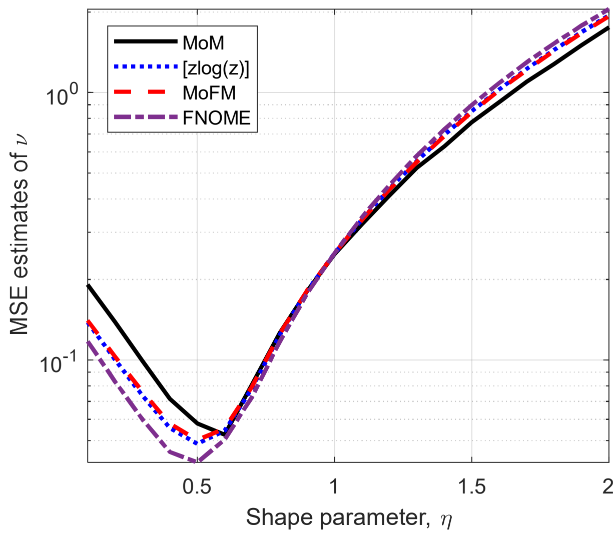


Figure III.1. MSEs curves of the shape parameter η by MoM, [z log(z)], MoFM and MoFNM methods.

III.3.2. Results using Real data

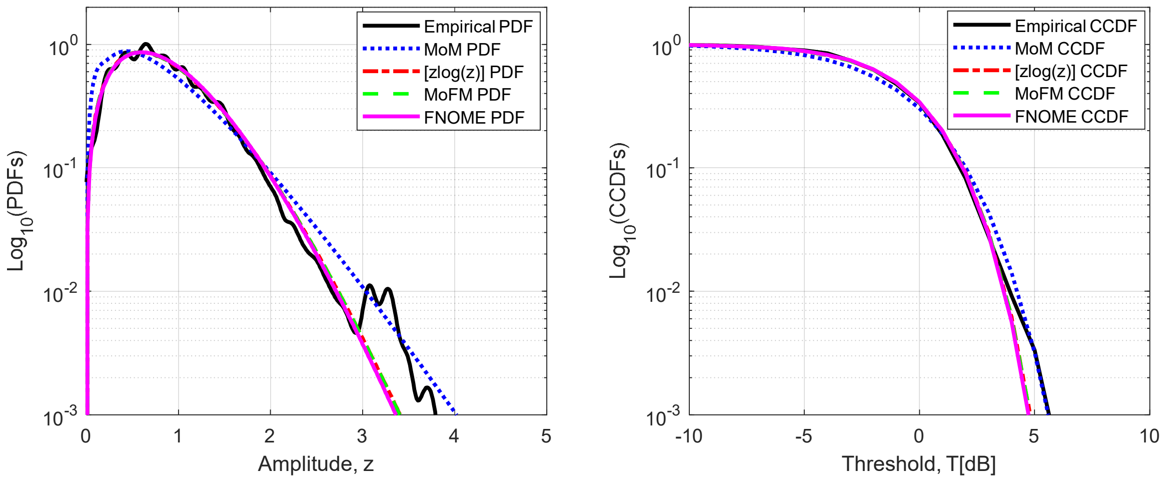
The IPIX sea clutter database is also used to validate the simulation results. The empirical Complementary Cumulative Distribution Function (CCDF) and (PDF) of the real data will be compared with the theoretical CCDFs and PDFs of the Compound Gaussian with (CGWB) distribution, obtained using the estimated parameters from the (MoM), [z log(z)], Method of Fractional Moments (MoFM), and (MoFNM). The Kolmogorov-Smirnov (KS) statistic and the Mean Squared Error (MSE) are also calculated to evaluate the accuracy of the estimation. Table III.1 presents the obtained values of KS and MSE.

The PDF and CCDF curves plotted in Figure III. 2 are based on Vertical-Vertical (VV) polarization, the 7th range cell, and a resolution of 3 meters. The results demonstrate the ability of the proposed estimators to fit real data, which is evident from Table III.1, where the MoFNM estimator provides the lowest MSE for both PDF and CCDF, followed by MoFM and [z log(z)] estimators. Regarding the KS statistic, MoFNM yields the best result for CCDFs.

For Horizontal-Horizontal (HH) polarization, the 1 st range cell, and a resolution of 30 meters, the CCDF and PDF curves are plotted in Figure III.3. In this case, the MoM method offers a better fit to the empirical PDF, as indicated by the minimum MSE obtained. Meanwhile, the MoFM and [z log(z)] methods provide better MSE and KS values for the CCDF curves, as shown in Figure III.3 and Table III. 1.

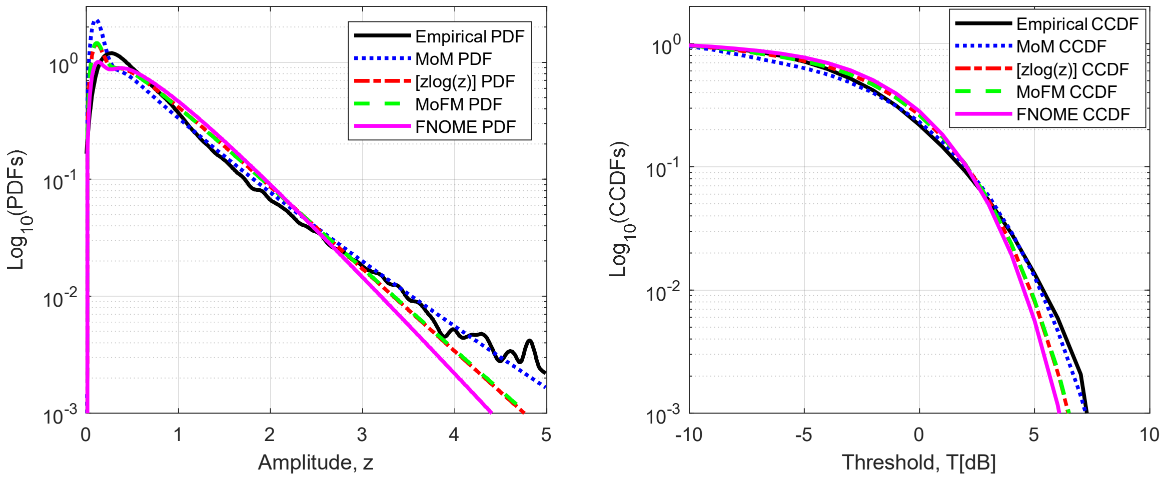
Table III.1. MSE and KS criteria.

IPIX data	MSE		MoM	[z log(z)]	MoFM	MoFNM
7^{th} cell range resolution 3m polarization VV	**PDFs**	**MSE**	0.0073	8.7928×10^{-4}	8.7696×10^{-4}	8.7150×10^{-5}
		KS	0.0725	0.1550	0.1575	0.1675
	CCDFs	**MSE**	1.0421×10^{-4}	1.5874×10^{-6}	1.5668×10^{-6}	1.4519×10^{-6}
		KS	0.9667	0.9677	0.9677	0.9677
1st cell range resolution 15m polarization VV	**PDFs**	**MSE**	0.0078	0.0065	0.0021	0.0023
		KS	0.3050	0.3100	0.3450	0.4025
	CCDFs	**MSE**	9.8594e-04	7.9562×10^{-04}	1.2374×10^{-04}	2.3249×10^{-05}
		KS	0.9687	0.9687	0.9677	0.9569



(a) (b)

Figure III.2. PDFs (a) and CCDFs (b) of CGWB obtained by MoM, [zlog(z)], MoFM and MoFNM methods using IPIX data of the 7th cell range, resolution 3m and polarization VV.



(a) (b)

Figure III.3. PDFs (a) and CCDFs (b) of CGWB obtained by MoM, [z log(z)], MoFM and MoFNM methods using IPIX data of the 1st cell range, resolution 15m and polarization HH.

III.4. Conclusion

The parameter estimation of the CGWB distribution is assessed. The proposed estimator MoFNM is compared with the existing methods; MoM, MoFM, and the [zlog(z)] estimator. The CGWB distribution is a biparametric Compound-Gaussian with Weibull texture characterized by two parameters; shape and scale. Through several tests using both simulated and the real IPIX sea clutter data, the obtained results shows that the proposed MoFNM estimator provide the better estimation performance in terms of MSE and KS statistics, particularly in the case of very spiky clutter. These results highlight also the robustness and the capability of the CGWB to model high resolution sea clutter under different clutter conditions. The practical implications of this work are significant for maritime radar applications, such as target detection and surveillance, where accurate clutter modeling and parameter estimation are critical to build robust detection schemes.

General conclusion

This master's thesis is focused on the parameter estimation and radar clutter modeling using biparametric compound-Gaussian with Weibull distributed texture. This research tackled the critical challenge of modeling and parameter estimation of sea clutter in high-resolution radar systems, where non-Gaussian behavior often degrades target detection performance. In literature, the CGWB parameter estimation techniques that exist are the Method of Moments, Method of Fractional Moments, and [zlog(z)] estimator, in order to enhance the estimation accuracy, the novel Method of Fractional Negative Moments is proposed and developed in this work.

In this work, the parameter estimation of the CGWB distribution is assessed. The proposed estimator MoFNM is compared with the existing methods; MoM, MoFM, and the [zlog(z)] estimator. The CGWB distribution is a biparametric Compound-Gaussian with Weibull texture characterized by two parameters; shape and scale. Through several tests using both simulated and the real IPIX sea clutter data, the obtained results shows that the proposed MoFNM estimator provide the better estimation performance in terms of MSE and KS statistics, particularly in the case of very spiky clutter. These results highlight also the robustness and the capability of the CGWB to model high resolution sea clutter under different clutter conditions. The practical implications of this work are significant for maritime radar applications, such as target detection and surveillance, where accurate clutter modeling and parameter estimation are critical to build robust detection schemes.

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Abstract

This master's dissertation focuses on parameter estimation and modeling of sea clutter using the CGWB (Compound Gaussian with Weibull Texture) model, which is non-Gaussian distribution introduced to model high-resolution radar clutter. The research focuses on developing and improving methods for estimating the parameters of this model, the existing method are MoM (Method of Moments), [zlog(z)], and MoFM (Method of Fractional Moments). A new method called MoFNM (Method of Fractional Negative Moments) has also been proposed to improve the estimation accuracy. The performance of these methods was tested using real data from the IPIX radar as well as simulated data. Probability density functions (PDFs) and complementary cumulative distribution functions (CCDFs) of the model were compared with real. The results showed that the MoFNM estimator can accurately estimate the parameter of the CGWB model.

الملخص

تركز هذه المذكرة على تقدير المعاملات ونمذجة فوضى البحر باستخدام نموذج CGWB (الغاوسي المركب مع نسيج ويبل)، وهو توزيع غير غاوسي تم تقديمه لنموذج فوضى الرادار عالية الدقة. يركز البحث على تطوير وتحسين طرق تقدير معاملات هذا النموذج، والطرق الحالية هي MoM (طريقة اللحظات)، و[zlog(z)]، وMoFM (طريقة اللحظات الكسرية). كما تم اقتراح طريقة جديدة تسمى MoFNM (طريقة اللحظات السالبة الكسرية) لتحسين دقة التقدير. تم اختبار أداء هذه الطرق باستخدام بيانات حقيقية من رادار IPIX بالإضافة إلى بيانات المحاكاة. تمت مقارنة وظائف كثافة الاحتمالات (PDFs) ووظائف التوزيع التراكمي التكميلي (CCDFs) للنموذج بالبيانات الحقيقية. أظهرت النتائج أن مقدر MoFNM يمكنه تقدير معلمة نموذج CGWB بدقة.

Résumé

Ce mémoire porte sur l'estimation des paramètres et la modélisation du fouillis marin à l'aide du modèle CGWB (Gaussien composé avec texture de Weibull), une distribution non gaussienne introduite pour modéliser le fouillis radar haute résolution. La recherche se concentre sur le développement et l'amélioration des méthodes d'estimation des paramètres de ce modèle. Les méthodes existantes sont MoM (Méthode des moments), [zlog(z)] et MoFM (Méthode des moments fractionnaires). Une nouvelle méthode appelée MoFNM (Méthode des moments fractionnaires négatifs) a également été proposée pour améliorer la précision de l'estimation. Les performances de ces méthodes ont été testées à l'aide de données réelles du radar IPIX ainsi que de données simulées. Les fonctions de densité de probabilité (PDF) et les fonctions de distribution cumulative complémentaires (CCDF) du modèle ont été comparées aux données réelles. Les résultats ont montré que l'estimateur MoFNM peut estimer avec précision les paramètres du