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Comparative study of adaptive algorithms CA CFAR and OS CFAR based on fuzzy logic in non-homogenous environment

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Thanks

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Dedication

I thank God Almighty first and foremost for

the great grace that He has bestowed upon me, then those who are not matched by anyone in the universe, to whom God has commanded us to honor them, to those who have made a great deal, and have given what cannot be returned, to you these words, my dear mother "SALIMA" and father" AZEDDINE" , I dedicate this research to you; You have been my best supporter throughout my academic career. For everyone who advised me, guided me, contributed, or directed me with me in preparing this research and connecting me to the required references and sources at any of the stages it went through, and I especially thank the distinguished professor: " " .DOUDOU FATMA ZAHRA, for helping me Supporting me and guiding me with advice, education, correction, and all that he did with me. I am also pleased to thank the esteemed college administration: "SAAD SAHLEB BLIDA 1UNIVERSITY, INSTITUTE OF AERONAUTICS AND SPACE STUDIES".

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Abstract

Constant False Alarm Rate (CFAR) and Order Statistic CFAR (OS CFAR) detectors use fuzzy logic to adjust detection thresholds in homogeneous and non-homogeneous environments. By using fuzzy logic in addition to the binary logic commonly used, these detectors dynamically adapt their thresholds according to variations in the noise, allowing more precise detection of targets in different contexts. In particular the fused fuzzy logic used in our work offers a flexible approach to model uncertainty and optimize detection performance, thereby reducing false alarms and improving the efficiency of detection systems.

Résume

Les détecteurs CFAR (Constant False Alarm Rate) et OS CFAR (Order Statistic CFAR) utilisent la logique floue pour ajuster les seuils de détection dans les environnements homogènes et non homogènes. En utilisant la logique floue par apport a la logique binaire conventuellement utilisée , ces détecteurs adaptent dynamiquement leurs seuils en fonction des variations du bruit, permettant une détection plus précise des cibles dans différents contextes. En particulier la logique floue en fusion utilisée dans notre travail offre une approche flexible pour modéliser l'incertitude et optimiser les performances de détection, réduisant ainsi les fausses alarmes et améliorant l'efficacité des systèmes de détection.

ملخص

تستخدم كاشفات معدل الإنذارات الكاذبة الثابتة (CFAR) وإحصائيات الطلب (OS CFAR) المنطق الغامض لضبط حدود الكشف في البيئات المتجانسة وغير المتجانسة. وباستخدام المنطق الغامض بالإضافة إلى المنطق الثنائي الشائع الاستخدام، تقوم هذه الكاشفات بتكييف عتباتها ديناميكيًا وفقًا للتغيرات في الضوضاء، مما يسمح باكتشاف أكثر دقة للأهداف في سياقات مختلفة. وعلى وجه الخصوص، يوفر المنطق الغامض المدمج المستخدم في عملنا نهجًا مرنًا لنموذج عدم اليقين وتحسين أداء الكشف، وبالتالي تقليل الإنذارات الكاذبة وتحسين كفاءة أنظمة الكشف.

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LIST OF ABBREVIATIONS

RADAR	The remote detection and localization of an object.
CFAR	Constant false alarm rate systems
CA-CFAR	CFAR average cell.
OS-CFAR	CFAR statistical order.
$\boldsymbol{Pdf}$	Probability density function. .
Pd	Probability of detection.
$\boldsymbol{Pfa}$	Probability of false alarm.
NPR	Critter from Neyman-Pearson
RCS	Radar Cross Section .
D	The antenna-target distance
C	The speed of light
ΔT	Time corresponding to a round trip of the wave between the radar and the target
TR	Pulse repetition period
D	Max Maximum range of the Radar
P*s*	Emitted power
Su	Power density -omnidirectional.
R1	Distance Antenna – target
Sg	Power density “directive”
P*r*	Reflected power
$\boldsymbol{\sigma}$	Radar cross section
R1	Distance Antenna target
G	Antenna gain
S*e*	Power density.

P*r*	Reflected power
R2	Target distance – antenna
PE	Overall power received by the antenna
AW	Apparent area of the antenna
A	Real (geometric) area of the antenna
Ka	Efficiency factor
λ	Wavelength

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GENERAL INTRODUCTION

Radars and CFAR (Constant False Alarm Rate) detectors are widely used technologies in the field of target detection and tracking. Radars are devices that emit electromagnetic waves and analyze the reflected signals to detect objects in their environment. CFAR detectors, on the other hand, are signal processing algorithms used to distinguish targets of interest from false alarms.

One of the approaches used in designing CFAR detectors is the use of fuzzy logic. Fuzzy logic is a branch of mathematics that allows for a more nuanced treatment of truth and falsity than traditional Boolean logic. It enables the consideration of partial degrees of truth, which can be beneficial in situations where data is imprecise or uncertain.

In the context of CFAR detectors, the use of fuzzy logic allows for the modeling and management of uncertainty associated with radar measurements and detection thresholds. By using fuzzy sets to represent signal and noise information, CFAR detectors can dynamically adapt their detection thresholds based on environmental conditions.

For example, in an environment where the noise level varies significantly, a CFAR detector using fuzzy logic can adjust its thresholds to maintain a constant false alarm rate. It can take into account factors such as noise level variations, target characteristics, and performance constraints to determine optimal thresholds.

By utilizing fuzzy logic, CFAR detectors can provide improved performance by adapting their behavior to changing environmental conditions. This enables better detection of targets of interest while reducing false alarms

CHAPTER I

GENERALITY OF RADAR

1.1 INTRODUCTION

This chapter aims to provide a comprehensive overview of the generalities of radar technology. It explores and delves into its underlying principles, highlights key applications across various domains, and discusses the crucial components that constitute a radar system. By gaining insights into these foundational aspects, readers will be equipped with a solid understanding of radar technology, paving the way for further exploration into its diverse applications and advanced concepts.

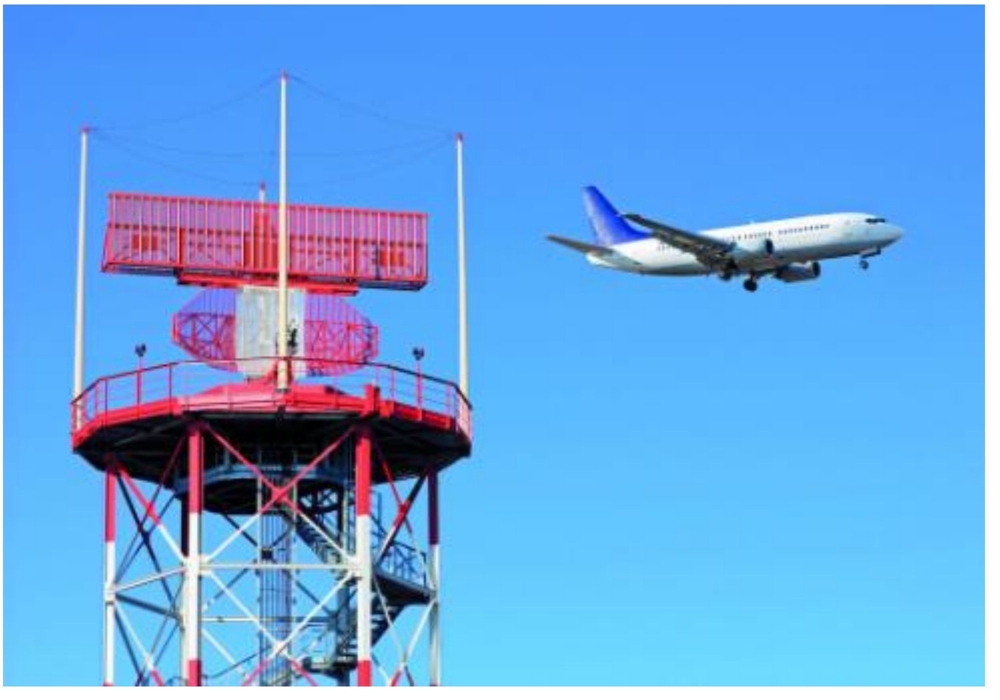


Figure 1.1 RADAR.

1.2 DEFINITION OF RADAR

Radar stands for "Radio Detection and Ranging". It is a technology that uses radio waves to detect and locate objects in the surrounding environment. The radar system sends out a radio signal, which bounces off objects in its path and returns to the radar system. By analyzing the characteristics of the returned signal, such as its frequency, amplitude, and time delay, the radar system can determine the location, speed, and other properties of the objects in its field of view. Radar technology is used in a wide range of applications, including air traffic control, weather forecasting, military surveillance, and navigate.

1.3 CLASSIFICATION OF RADAR SYSTEM

Depending on the information they must provide, radar equipment uses different qualities and technologies. This results in a first classification of radar systems:

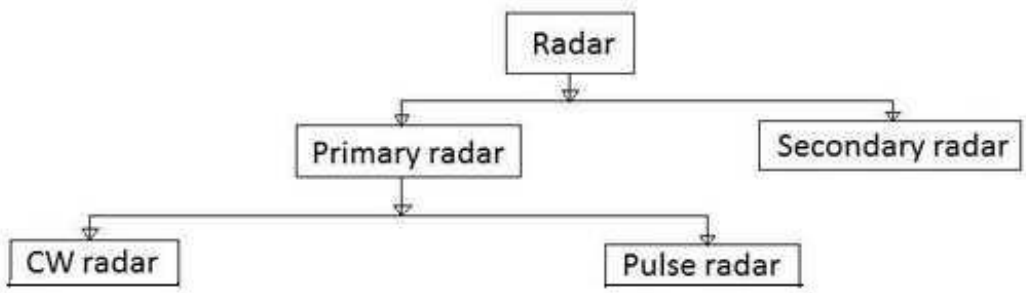


Figure 1.2 RADAR classification.

1.3.1 Secondary RADAR

Secondary radar is a radar system that operates by sending out an interrogation signal to a target, which responds with a coded reply containing identification and other information. It is commonly used in air traffic control (ATC) systems and military applications for enhanced target identification and tracking. The use of secondary radar improves the accuracy and reliability of target identification in crowded airspace. [1]

1.3.2 Primary RADAR

Primary radar is a radar system that operates by transmitting radio frequency signals and detecting the echoes reflected back from targets in its coverage area. It provides information on the range, bearing, and relative motion of the detected objects. Primary radar is commonly used in applications such as air traffic control (ATC), weather monitoring, and military surveillance. It is particularly useful in situations where the targets do not have transponders or are not actively cooperating with radar systems.[2]

1.3.3 Pulse RADAR

Pulse radar is a radar system that uses short-duration pulses of radio frequency energy to detect and locate targets. By transmitting these pulses and measuring the time it takes for the echo to return, pulse radar can determine the range to the target. It is widely employed in various applications such as air traffic control, weather monitoring, and military surveillance. [3]

1.3.4 Continuous wave (CW) RADAR

Continuous wave (CW) radar is a type of radar system that transmits a continuous, uninterrupted signal and measures the phase shift of the reflected signal to determine the range and velocity of the target. According to Skolnik (2008), CW radar is commonly used for applications that require high accuracy velocity measurements, such as speed guns and Doppler radar systems. One of the advantages of CW radar is its simplicity and reliability, but it is also susceptible to interference from other sources of radio frequency energy. This can limit the effectiveness of CW radar in certain environments, such as urban areas with high levels of electromagnetic interference. Despite its limitations, CW radar remains an important technology in many fields, including military and civilian applications. [4]

1.3.5 Types of radar

Radar technology has evolved over the years, and there are now many types of radar systems used for a variety of applications. According to Stimson (2015), some of the most common types of radar include pulse radar, continuous wave (CW) radar, frequency modulated (FM) radar, and Doppler radar. Pulse radar is used for applications that require high range resolution, such as weather radar and air traffic control radar systems. CW radar is used for applications that require high accuracy velocity measurements, such as speed guns and Doppler radar systems. FM radar is used for applications that require high target discrimination, such as radar altimeters and ground-penetrating radar systems. Doppler radar is used for applications that require the detection of moving targets, such as weather radar and air traffic control radar systems. The choice of which type of radar to use depends on the specific application and the desired performance characteristics. [5]

1.4 RADAR COMPONENTS

Radar systems consist of several key components, including a transmitter, a receiver, an antenna, and a signal processor, In addition to these basic components, modern radar systems may also include complex digital signal processing algorithms, data storage systems, and other advanced features. Another way to categorize radar systems is by the number of radar channels they use, Single-channel radar systems use a single transmitter and receiver, while multi-channel radar systems use multiple transmitters and receivers to improve performance. Multi-channel radar systems can provide improved sensitivity, range, and resolution, but they are also more complex and expensive to build and operate. The choice of which type of radar system to use depends on the specific application and the desired performance characteristics. [6]

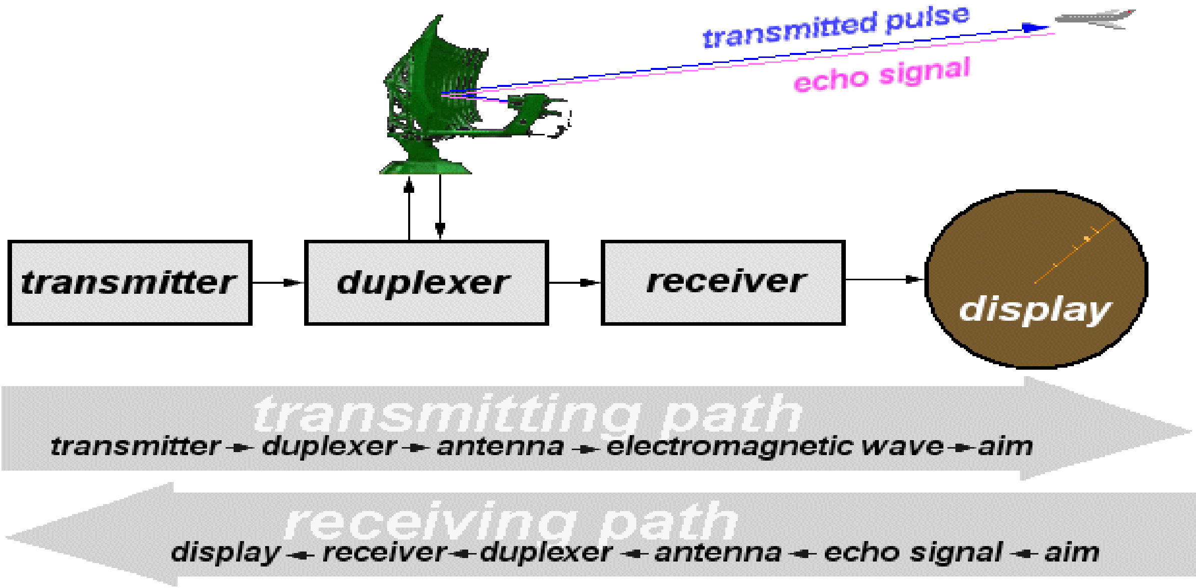


Figure 1.3 The RADAR components.

1.5 THE PRINCIPLE OF RADAR OPERATION

Radar operates by transmitting a radio frequency (RF) signal from an antenna and then listening for the echoes that bounce back from objects in the environment. The time delay between the transmission and reception of the echoes is used to calculate the distance to the object, while the Doppler shift of the echoes is used to calculate its velocity, the basic principle of radar operation is based on the reflection and scattering of electromagnetic waves by objects in their path. By measuring the time delay and frequency shift of the reflected waves, radar systems can provide information about the location, distance, speed, and other characteristics of objects in the environment. This principle has been applied in a wide range of applications, from air traffic control and weather monitoring to military surveillance and scientific research. [7]

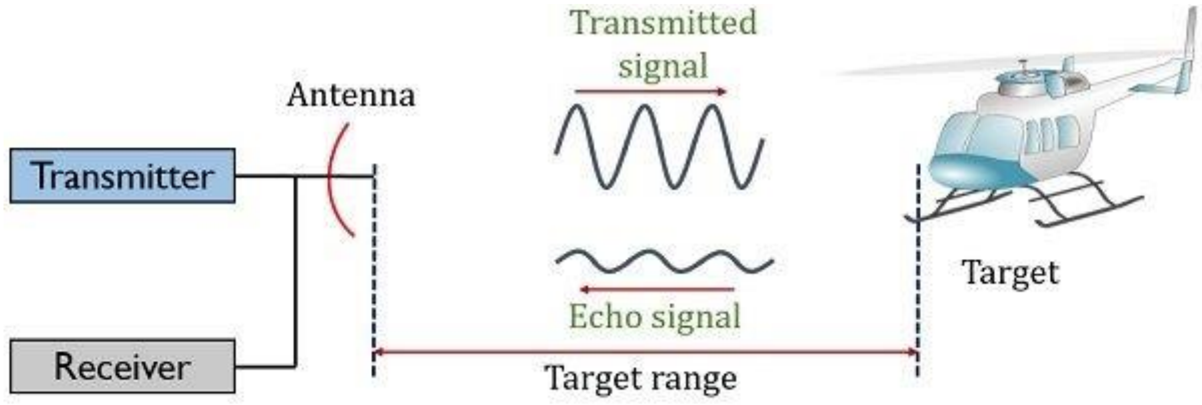


Figure 1.4 The principle of RADAR operation.

1.6 The Doppler Shift

The Doppler shift, also known as the Doppler Effect, is a phenomenon observed in waves, including radio waves used in radar. It occurs when there is relative motion between the wave source and the observer, causing a change in the frequency or wavelength of the wave observed by the observer. In radar applications, the Doppler shift is used to measure the relative velocity between the radar system and a target, another way to describe the Doppler shift in radar is as a frequency change that results from the motion of a target relative to the radar antenna. If the target is moving towards the radar, the frequency of the reflected signal will be higher than the frequency of the transmitted signal, while if the target is moving away from the radar, the frequency of the reflected signal will be lower. By measuring the Doppler shift, radar systems can determine the velocity and direction of moving targets, which is useful for applications such as air traffic control, weather monitoring, and military surveillance. [8]

The general form of the Doppler shift equation is as follows:

$$f_d = \frac{v_r}{\lambda} \qquad (1.1)$$

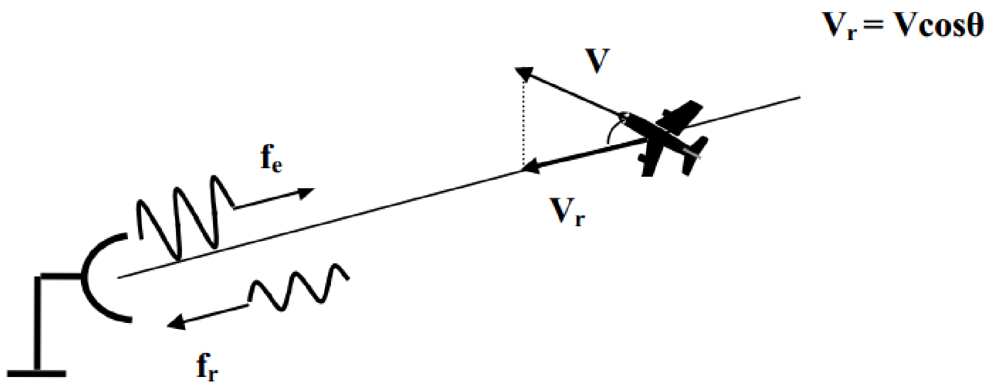


Figure 1.5 Radial speed $\mathbf{V_r}$

1.7 RADAR EQUATIONS

1.7.1 Radar range equation

This equation is used to calculate the maximum range of a radar system, based on the transmitted power, the antenna gain, the radar cross section of the target, and the noise figure of the receiver. The radar maximum range equation is:

$$R_{max} = \sqrt[4]{\frac{P_C\, G^2 \lambda^2 \sigma}{(4\pi)^3 S_{min}}} \qquad (1.2)$$

Where:

- R_{max} = maximum range.
- λ = wavelength of the transmitted signal.
- σ = radar cross section of the target.
- G=antenna gain.
- S_{min} = minimum power.

1.7.2 Doppler Radar equation

This equation is used to calculate the Doppler shift of a radar signal, based on the velocity of the target and the frequency of the transmitted signal. The basic form of the Doppler radar equation is:

$$\Delta f = \left(\frac{2v}{c}\right) \times f_0 \qquad (1.3)$$

Where:

Δf = Doppler shift

v = velocity of the target

c = speed of light

f_0 = frequency of the transmitted signal [16]

1.8 THE ELECTROMAGNETIC WAVES

Electromagnetic waves are a fundamental aspect of electromagnetism, which is a branch of physics that deals with the interactions between electric and magnetic fields.

These waves are composed of oscillating electric and magnetic fields that propagate through space, carrying energy and momentum. They arise from the acceleration or change in velocity of electric charges, which disturbs the surrounding electric and magnetic fields, leading to wave formation

Electromagnetic waves can travel through a vacuum as well as through various materials. They are not dependent on a medium for propagation, unlike mechanical waves like sound waves.

Electromagnetic waves find applications in various fields, such as medicine (e.g., X-rays and MRI imaging), astronomy (e.g., studying celestial objects using different wavelengths), remote sensing, spectroscopy, and scientific research.

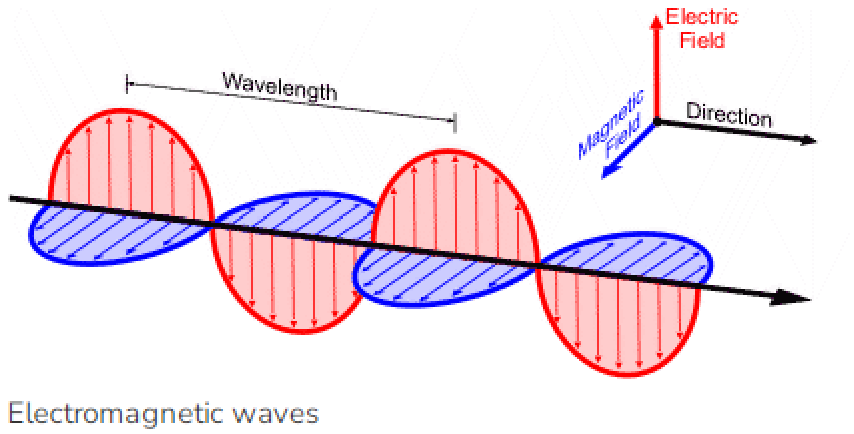


Figure 1.6 The electromagnetic waves.

$\overrightarrow{\boldsymbol{E}}$:Electric field.

$\overrightarrow{\boldsymbol{B}}$: Magnetic field.

1.9 CLUTTER AND NOISE

Clutter and noise are two major sources of interference in radar signals that can affect the accuracy and reliability of radar measurements. Clutter refers to the unwanted signals that are reflected from stationary or slow-moving objects in the environment, such as buildings, mountains, and clutter on the ground. Noise, on the other hand, refers to any unwanted signals that are not related to the target being detected, such as thermal noise generated by the receiver electronics and atmospheric noise. To mitigate the effects of clutter and noise, radar engineers use a variety of techniques, including advanced signal processing algorithms, multiple-input multiple-output (MIMO) radar systems, and digital signal processing techniques such as averaging and filtering. These techniques are constantly evolving as radar technology continues to advance, and they are essential tools for researchers, engineers, and technicians working in the field of radar technology.

1.9.1 Clutter definition

Clutter in radar technology refers to the unwanted echoes or reflections of radar signals that originate from stationary or slow-moving objects in the environment, and are received by the radar system along with the echoes from the desired targets. These echoes can cause interference and produce a large amount of noise in the radar signal, which can make it difficult to detect and measure the signals from moving targets such as aircraft or ships. The presence of clutter in the radar signal can reduce the accuracy and reliability of the radar measurements, and is a significant challenge in radar technology. [9]

1.9.1.1 Non-homogeneous Clutter

When the reference cells scans the environment in a given direction, different non homogeneous situations can affect the configuration of the cells of reference. These situations are caused by the presence of interfering targets (targets secondary) and/or clutter edge at the reference channel. A clutter edge is characterized by the presence, at the level of the cell of reference, of an abrupt transition in the power of the background noise. In detection radar, this transition describes the limit between two environments of different nature: transition land-sea, clear-cloud zone. . .

We will be representing different situations of non-homogeneous environments in the next illustrations :

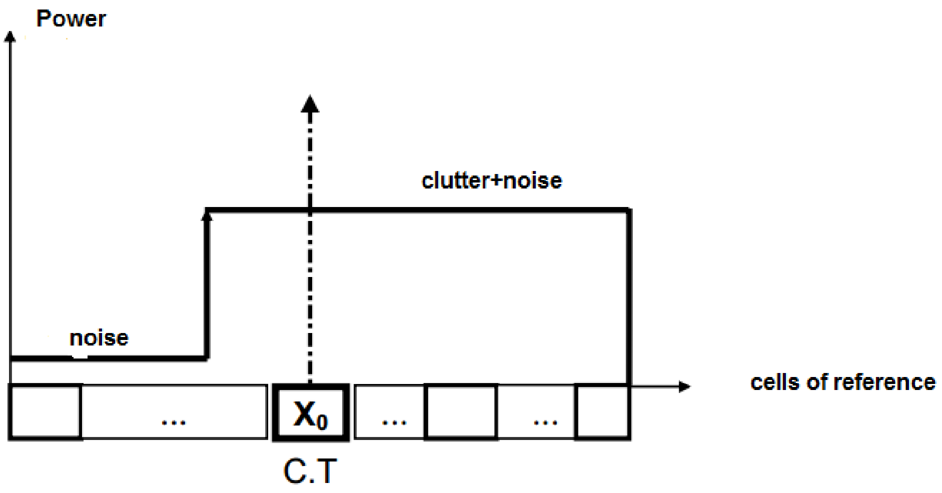


Figure 1.7 cell under test embedded in the clutter region

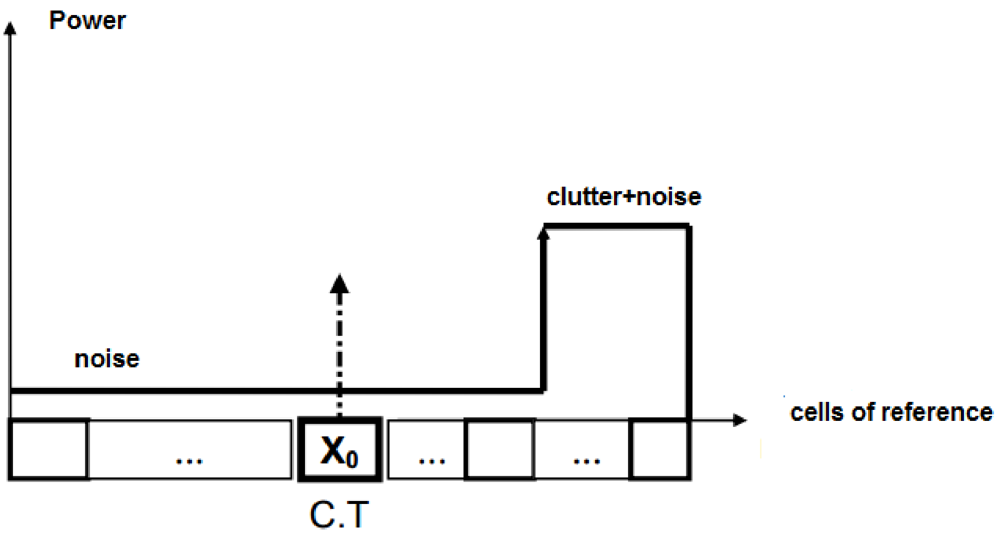


Figure1.8 cell under test drowned in thermal noise.

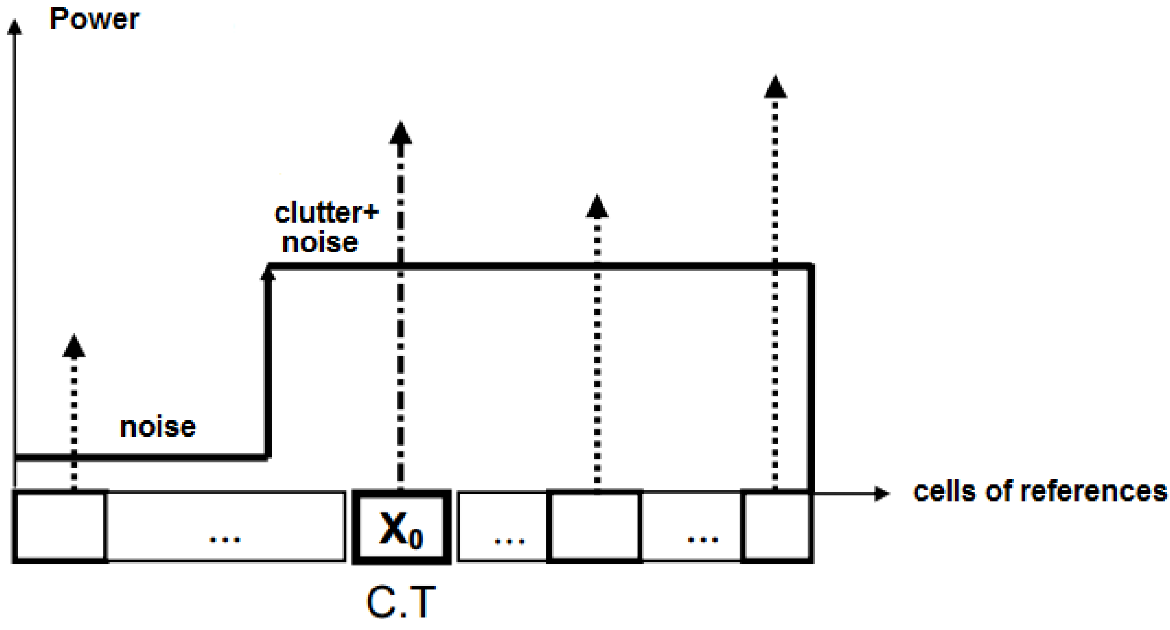


Figure1.9 Presence of clutter edge and interfering targets.

The use of the CA-CFAR detector in situations similar to those of the 3 figures leads to a large loss of detection or an increase in the rate of false alarm. In the case where the cell under test is immersed in clutter (fig 1.7), the cells drowned in thermal noise contribute to underestimating the detection threshold, which results in an excessive false alarm probability (Pfa). In (1.8) the cell under test being in the thermal noise, the cells belonging to the clutter tend to increase the detection threshold and, consequently, to degrade the probability of detection. This particular situation is known as the "effect of mask” (masking effect). The capture effect, on the other hand, is obtained in the presence interference in a homogeneous (uniform) clutter, when these contribute to increasing the detection threshold.

1.9.1.2 Clutter Stats Properties

Maintaining a constant Pfa at a CFAR detector requires the prior knowledge of the statistical distribution of the clutter echoes, at the exit of the quadratic detector or the envelope detector. This probability density (Pdf) depends on the nature of the clutter (land, sea, precipitation, clouds) as well as the resolution and angular aperture of the radar used. In low-resolution radars, the fluctuations of clutter echoes are described by independent random reflections, having the same order of magnitude. This classical modeling leads to consider that the signal received at the input of the detector quadratic is a Gaussian process with zero mean and constant variance μ constant (for a uniform region). In linear detection, the envelope signal x, measured at level of cell i, follows a Rayleigh distribution

$$f_{xi}(x) = \left(2.\frac{x}{\mu}\right).exp\left(-\frac{x^2}{\mu}\right), x \geq 0 \qquad (1.4)$$

In quadratic detection, the signal x at the level of cell i obeys an exponential law as :

$$f_{xi}(x) = \left(\frac{1}{\mu}\right).\exp\left(-\frac{x}{\mu}\right), x \geq 0 \qquad (1.5)$$

If, at the output of the quadratic detector, the video signal undergoes a non-integration coherent of M pulses, the amplitudes of the reference cells will be described by a Gamma distribution. Indeed, the Pdf of the sum of M processes independent and exponential, follows a Gamma law with parameters (μ,M):

$$f_{xi}(x) = \frac{x^{M-1}\exp\left(-\frac{x}{\mu}\right)}{\Gamma(M)\mu^M}, x \geq 0 \qquad (1.6)$$

Where Γ(M) represents the usual Gamma function: Γ(M)=(M-1)! . It is easy to see that for a single-pulse treatment (M=1) the distribution (1.5) coincides with the exponential law.

1.9.1.3 Target Models

The echo received is linked to the reflective power of the target. In low resolution, both classic moving target models are defined by

a. The target is considered as a set of elementary reflectors of same sizes. The envelope x of the reflected signal follows a Rayleigh law.

$$f(x) = \frac{x}{x_0^2} exp\left(-\frac{x^2}{2x_0^2}\right) \qquad (1.7)$$

x_0 being the mean value of the signal related to the radar cross section (RCS).

b. The target is seen as a large reflector surrounded by several small reflectors. The envelope of the received signal fluctuates according to the law:

$$f(x) = \frac{9x^3}{2x_0^4} exp\left(-\frac{3x^2}{2x_0}\right) \qquad (1.8)$$

To study the target signal in the case of several pulses (noncoherent), it is necessary to take into account the movements of the target during the exposure time T_{ot}

Two types of fluctuation are considered:

a. Slowly fluctuating target: the target echo does not change during the emission of M pulses (T_{ot}). Therefore, the samples received are the same for all impulses; it is a single realization of the same random variable (complete correlation from one pulse to another).
b. Rapidly fluctuating target: The echo changes in value from one pulse to the next. The received samples are different realizations of the same random variable (de-full pulse-to-pulse correlation). [15]

1.9.2Noise definition

Noise in radar technology is defined as any unwanted signal that is not related to the target being detected, and can include electronic noise, atmospheric noise, and interference from other sources. In radar systems, noise can reduce the signal-to-noise ratio (SNR), which is a measure of the strength of the desired signal relative to the level of the unwanted noise. A low SNR can make it difficult to detect weak signals from distant or low-reflectivity targets, and can therefore reduce the accuracy and reliability of the radar measurements. To minimize the effects of noise, radar engineers use a variety of techniques, including the use of low-noise amplifiers and high-performance analog-to-digital converters, as well as digital signal processing techniques such as averaging and filtering. [10]

1.10 DEFINITION OF DISTANCE AMBIGUITY

Range ambiguity in radar technology refers to the inability of a radar system to distinguish between two or more targets that are located at different ranges but are at the same angle relative to the radar. This can occur when the pulse repetition frequency (PRF) of the radar is too low, causing the transmitted pulses to overlap in time and the returned echoes to be ambiguous in range. The ambiguity can result in errors in the measurement of target range, as the radar system may report the range of the incorrect target. To overcome range ambiguity, radar engineers use a variety of techniques, such as increasing the PRF, using pulse compression, or using multiple frequencies. [11]

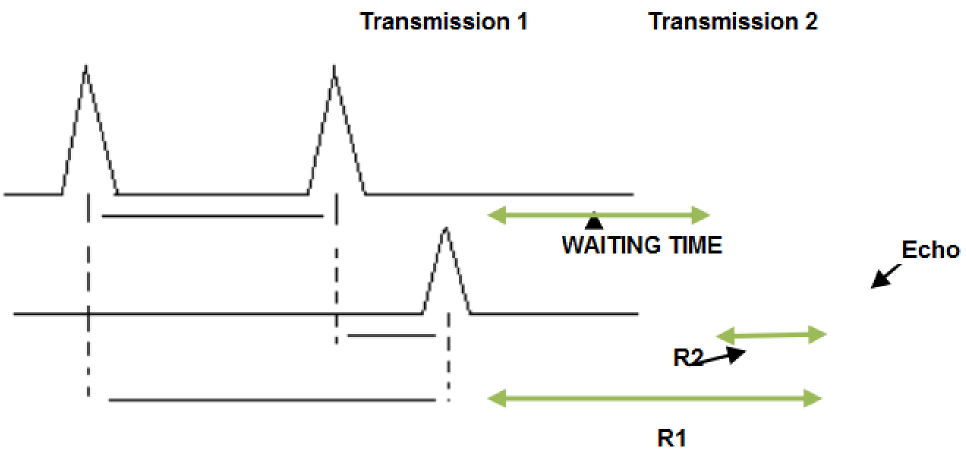


Figure 1.10 Illustration of distance ambiguity.

1.11 THE MODEL OF FLUCTUATING TARGETS

In a radar system, the model of fluctuating targets typically refers to the representation of radar returns from moving targets that exhibit variations over time due to factors such as motion, clutter, and environmental conditions. The modeling of fluctuating targets in radar systems is crucial for signal processing, target tracking, and detection algorithms. One commonly used model for fluctuating targets in radar systems is the Swerling models. These models were developed by Peter Swerling in the 1950s and are widely used to characterize the statistical behavior of radar returns from fluctuating targets. Swerling models assume different fluctuation patterns based on the target type and radar cross-section (RCS) characteristics.

From the distributions (1.6) and (1.7) as well as the degrees of fluctuation, the four

SWERLING models are defined as follows:

1.11.1 SWERLING I (SWI) Slowly fluctuating target whose signal envelope varies according to the law (1.6).

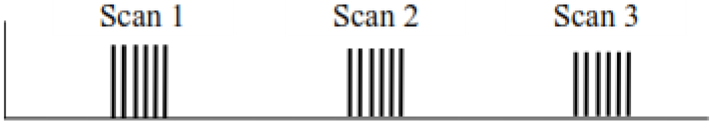


Figure1.11 fluctuation pattern pulses Swerling2

1.11.2 SWERLING II (SWII) Rapidly fluctuating target whose signal envelope varies according to the law (1.6)

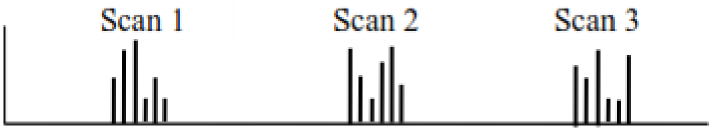


Figure1.12 fluctuation pattern pulses Swerling II

1.11.3 SWERLING III (SWIII) Slowly fluctuating target whose signal envelope varies according to the law (1.7).

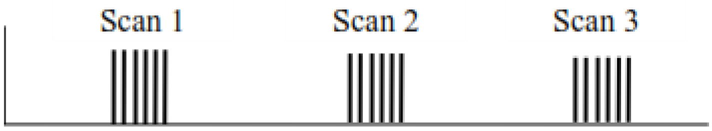


Figure1.13 fluctuation pattern pulses Swerling III

1.11.4 SWERLING IV (SWIV) Rapidly fluctuating target whose signal envelope varies according to the law (1.7).

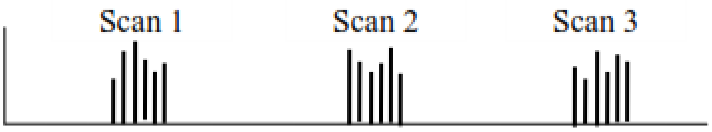


Figure1.14 fluctuation pattern pulses Swerling IV

The Swerling model is used to predict the probability distribution of the signal-to-noise ratio (SNR) of radar signals reflected from targets of different types. This is important for designing radar systems that can effectively detect and track targets of different sizes and types, and for optimizing the performance of radar systems in different environments. [12]

1.12 THE TYPICAL PHASES OF RADAR SIGNAL PROCESSING

Radar signal processing is a crucial aspect of radar systems that involves various techniques and algorithms to extract valuable information from received radar signals. Here are the key phases of radar signal processing along with references for further exploration:

1.12.1 Signal Transmission: The radar system emits electromagnetic signals, such as pulses or continuous waveforms, to illuminate the target area.

1.12.2 Signal Reception: The radar receiver captures the echoes reflected by targets in the environment.

1.12.3 Signal Preprocessing: This phase involves techniques such as filtering, sampling, and amplification to enhance the quality of the received signal.

1.12.4 Pulse Compression: Pulse compression techniques, such as matched filtering or pulse compression codes, are employed to improve the radar's range resolution and detection capabilities.

1.12.5 Doppler Processing: Doppler processing is used to measure the velocity of moving targets.

1.12.6 Target Detection: Various algorithms, including constant false alarm rate (CFAR) detection and adaptive thresholding, are employed to identify targets against background clutter and noise. [14]

CONCLUSION

In conclusion, radar technology has revolutionized many fields and continues to play a vital role in modern society. By using radio waves to detect and locate objects in the surrounding environment, radar systems have enabled advances in fields such as air traffic control, weather forecasting, military surveillance, and navigation. The study of radar targets and their behavior is essential for developing effective radar technology for a wide range of applications. Overall, radar is a crucial technology that has transformed the way we understand and interact with the world around us.

CHAPTER II:

RADAR DETECTION

2.1 INTRODUCTION

Detection theory plays a critical role in radar systems by providing the principles and tools necessary for detecting and extracting valuable information from radar signals. By using mathematical and statistical methods, detection theory allows for the analysis of radar signals to detect the presence of targets, estimate their characteristics, and make appropriate decisions.

The main objective of detection theory in radar systems is to separate useful signals from unwanted signals or noise. Radar signals can be weakened by various sources of noise, such as thermal noise, receiver noise, electromagnetic interference, and more. Detection theory provides algorithms and techniques to analyze the signals and detect targets in noisy and uncertain conditions.

In radar systems, detection theory often relies on statistical hypothesis testing. It compares observed data with reference models to decide whether a target is present or not. Measurements such as signal energy, correlation, coherence, or signal-to-noise ratio are used to assess the presence of targets.

Detection theory also allows for optimizing the performance of radar systems by determining appropriate detection thresholds and adjusting system parameters. It takes into account factors such as probability of detection, probability of false alarm, system sensitivity, and operational constraints to find the right balance between target detection and managing false alarms. [17]

2.2 DEFINITION OF RADAR DETECTION

Radar detection, also known as radar sensing, is a technology used to detect and track objects using radio waves. It employs the principle of sending out radio waves and then measuring the time it takes for those waves to bounce back after hitting an object. This information is used to determine the distance, speed, and direction of the detected object. Radar detection finds extensive applications in various fields, including aviation, maritime navigation, weather forecasting, and traffic control. It plays a crucial role in providing accurate and real-time information for effective monitoring and decision-making.

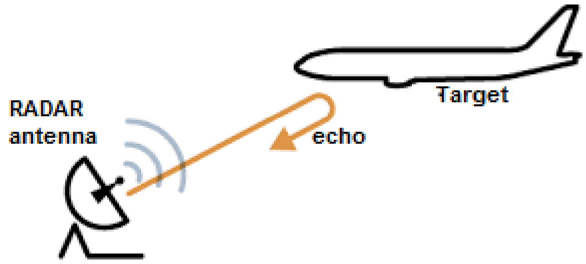


Figure 2.1 Radar detection

2.3 RADAR DETECTION THEORY

The theory of radar detection refers to the principles and techniques involved in detecting the presence and characteristics of objects using radar technology. Radar, which stands for "Radio Detection and Ranging," is a system that uses electromagnetic waves to detect, locate, and track objects such as aircraft, ships, vehicles, or weather phenomena. The basic principle of radar detection involves transmitting a radio signal, known as a radar pulse, and then measuring the time it takes for the signal to bounce back after hitting an object. By analyzing the properties of the returned signal, such as its time delay, frequency shift, and amplitude, it is possible to determine the presence, distance, velocity, and other characteristics of the object.

Detection is the operation which consists in making a decision on the existence or not of targets in the search space. The basic principle of target detection is based on the use of a comparison threshold to extract information from the received signal and to distinguish a fluctuation due to noise from that due to a useful signal [10].

• If the useful signal exceeds the threshold, the target is detected.

• If the noise exceeds the threshold in the absence of the echo signal, it is said to be a false alarm l a probability of false alarm is inversely proportional to the detection threshold. So if the threshold is too high, targets may not be detected, and if it is too low the probability alarm rate increases as shown in the figure (2.2) :

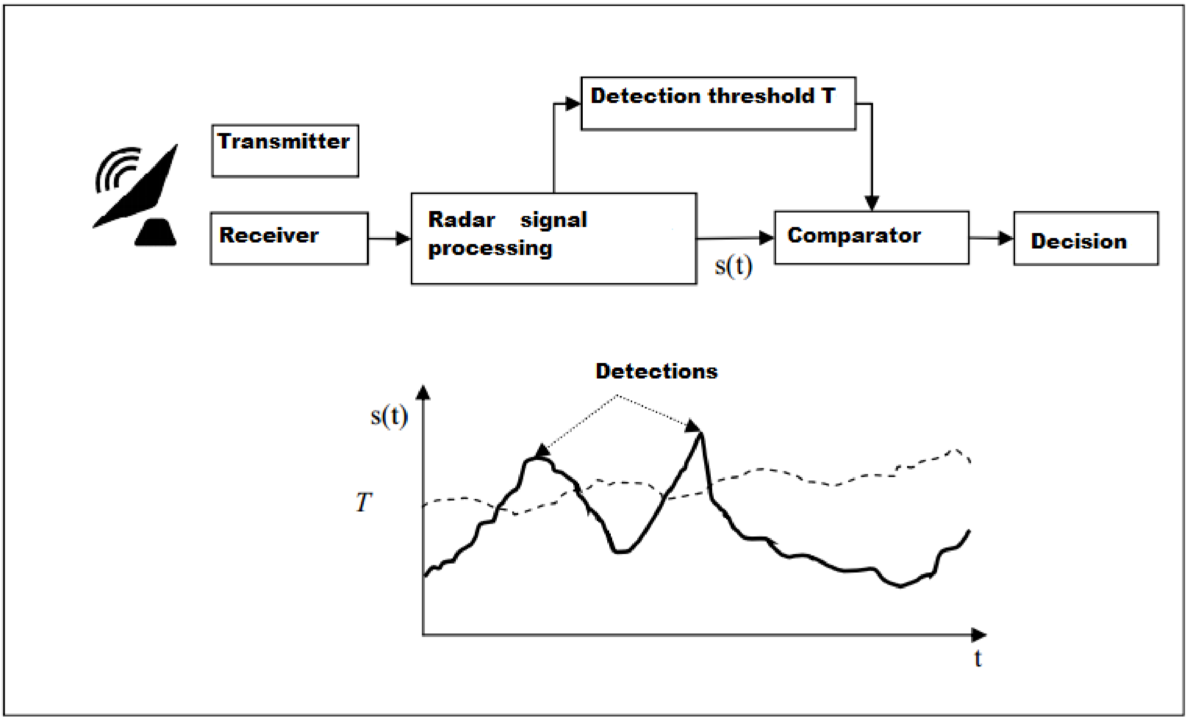


Figure 2.2 Basic functions of a radar detection system.

2.3 DECISION CRETERION

A decision criterion is a rule or principle used to evaluate different options or alternatives when making a decision. It provides a systematic framework for comparing and selecting the most suitable choice based on specific criteria or objectives**.** We suppose the receiver must make a decision based on a single observation of the received signal. The interval of values taken by the random variable Y constitutes the space observations Z. The latter is partitioned into two regions Z_0 and Z_1, as that if Y is in Z_0, the receiver decides in favor of H_0; by against, if Y is in Z_1, the receiver decides in favor of H_1.[15]

The observation space is the union of Z_0 and Z_1. In other words:

$$Z = Z_0 \cup Z_1 \qquad (2.1)$$

2.3.1 THE BAYES CRITERION

The use of the Bayes criterion suggests the use of two assumptions. In the first, we assume that the exit probabilities of the source are known. These are the prior probabilities $P(H_0)$and$P(H_1)$. $P(H_0)$is the probability of the occurrence of the hypothesis H_0, while $P(H_1)$ is the probability of the occurrence of hypothesisH_0. By denoting, respectively, by

P_0 and P_1 the prior probabilities $P(H_0)$ and $P(H_1)$and knowing that either hypothesis H_0or H_1 is always true, we can write:

$$P_0 + P_1 = 1 \qquad (2.2)$$

In the second, we assume that we know the costs associated with each decision. If we denote by $D_i, i = 0{,}1$, where D_0 denotes "Decide H_0" and D_1denote "Decide H_1," we defne C_{ij} , i=0,1, as the cost associated with the decision D_i , knowing that the hypothesis $H_j$is true. In other words, P(incurring the cost C_{ij})= P(deciding D_i , H_j true), i, j=0.1 Therefore, the costs for this hypothesis testing problem binary are C_{00} for case (1), C_{01} for case (2), C_{10} for case (3), and C_{11} for case (4). The purpose of the Bayes criterion is to determine the rule decision such as the average cost, E[C] also called risk, R is minimum. E[C] denotes the “Average Value” operator. We also assume that the cost of a wrong decision is greater than that of a wrong decision correct; that's to say:

$$C_{01} > C_{11} \text{ and } C_{10} > C_{00} \qquad (2.3)$$

Given P(D_i ,H_j) , the joint probability of deciding Di, knowing that the hypothesis Hj is true, the average cost is written:

$$R = E[C] = C_{00}P(D_0, H_0) + C_{01}P(D_0, H_1) + C_{10}P(D_1, H_0) + C_{11}P(D_1, H_1) \quad (2.4)$$

From Bayes rule we can write:

$$P(D_i, H_j) = P(D_i|H_j)P(H_j) \qquad (2.5)$$

I=0,1 and j=0,1

The conditional density functions P(D_i |H_j), i, j = 0.1, as a function of the regions Z_0 and $Z_1$are then:

$$P(D_0, H_0) \equiv P(\,Decide H_0|H_0 true) = \int_{Z_0} f_{y|H_0}(y|H_0)\,dy \qquad (2.6)$$

$$P(D_0, H_1) \equiv P(\,Decide H_0|H_1 true) = \int_{Z_0} f_{y|H_1}(y|H_1)\,dy \qquad (2.7)$$

$$P(D_1, H_0) \equiv P(\ DecideH_1|H_0true) = \int_{Z_0} f_{y|H_0}(y|H_0)\, dy \qquad (2.8)$$

And

$$P(D_1, H_1) \equiv P(\ DecideH_1|H_1true) = \int_{Z_0} f_{y|H_1}(y|H_1)\, dy \qquad (2.9)$$

In radar terminology, the probabilities P(D_0 | H_0), P(D_0 | H_1), P(D_1 | H_0), and P(D_1 | H_1), represent the probability of null P_{Null} , of non detection (probability of miss) P_M , false alarm (probability of false alarm) P_F, and of detection (probability of detection) P_D , respectively. We also notice that:

$$P_M = 1 - P_D \qquad (2.10)$$

And $$P_{Null} = 1 - P_F \qquad (2.11)$$

Therefore, the probability of a correct decision is:

$$\text{P(right decision)} = \text{P(c)} = \text{P}(D_0, H_0) + P(D_1, H_1)$$

$$= P(D_0|H_0)P(H_0) + P(D_1|H_1)P(H_1)$$

$$= (1 - P_F)P_0 +$$

P_D (2.12)

and the probability of an erroneous decision or probability of error is:

$$P(Wrong\ decision) = P(\varepsilon) = P(D_0, H_1) + P(D_1, H_0)$$

$$= (D_0|H_1)P(H_1) + (D_1 \setminus H_0)$$

$$= P_M P_1 + P_F P_0 \qquad (2.13)$$

The average cost given by (2.4) then becomes:

$$\text{R=E}[C] = c_{00}(1 - P_F)P_0 + c_{01}(1 - P_D)P_1 + C_{10}P_F P_0 + C_{11}P_D P_1 \qquad (2.14)$$

In terms of the decision regions defined in (2.6)-(2.9), the average cost can take the form:

$$R = P_0 C_{00} \int_{Z0} f_{y|H_0}(y|H_0)\, dy + P_1 C_{01} \int_{Z0} f_{y|H_0}(y|H_1)\, dy$$
$$+ P_0 C_{10} \int_{Z1} f_{y|H_0}(y|H_0)\, dy + P_1 C_{11} \int_{Z1} f_{y|H_1}(y|H_1)\, dy \qquad (2.15)$$

Using (2.1) and the fact that:

$$\int_{Z} f_{y|H_0}(y|H_0)\, dy = \int_{Z} f_{y|H_1}(y|H_1)\, dy = 1 \qquad (2.16)$$

this implies that:

$$\int_{Z1} f_{y|H_j}(y|H_j)\, dy = 1 - \int_{Z_0} f_{y|H_j}(y|H_j)\, dy\ , j = 0{,}1 \qquad (2.17)$$

where $f_{y|H_j}(y|H_j)$, j = 0.1, is the probability density function of Y corresponding to each hypothesis. Substituting (2.17) into (2.15), we get:

$$R = P_0 C_{10} + P_1 C_{11}$$
$$+ \int_{Z_0} \{[P_1(C_{01-} C_{11}) f_{y|H_1}(y|H_1)]$$
$$- [P_0(C_{10} - C_{00}) f_{y|H_0}(y|H_0)]\}\, dy \qquad (2.18)$$

We notice that the quantity $P_0 C_{10} + P_1 C_{11}$is a positive constant. Of (2.3), the terms $P_1(C_{01} - C_{11})$ $f_{y\,|\,H_1}(y\,|\,H_1)$ and $P_0(C_{10} - C_{00})$ $f_{y\,|\,H_0}(y\,|\,H_0)$, are both positive. Therefore, the risk is minimized by selecting the region Z_0including only values of Y for which the second term is greater than the first term. So this then gives an integrand negative. Specifically, we assign the Z_0 region the points for which :

$$P_1(C_{01-} C_{11}) f_{y|H_1}(y|H_1) < P_0(C_{10} - C_{00}) f_{y|H_0}(y|H_0) \qquad (2.19)$$

All values of Y for which the second term is less than the former are excluded fromZ_0 and assigned to Z_1 . The values for which the two terms are equal do not affect the risk and can be assigned to one or the other region. Therefore, we say that whether:

$$P_1(C_{01-} C_{11}) f_{y|H_1}(y|H_1) > P_0(C_{10} - C_{00}) f_{y|H_0}(y|H_0) \qquad (2.20)$$

then, we decide H_1. Otherwise, we decide H_0. So the rule of decision that results from the Bayes criterion (Likelihood Ratio Test or LRT) is:

$$\frac{f_{y|H_1}(y|H_1)}{f_{y|H_0}(y|H_0)} \underset{H_0}{\overset{H_1}{\lessgtr}} \frac{P_0(C_{10}-C_{00})}{P_1(C_{01}-C_{11})} \qquad (2.21)$$

We define the likelihood ratio (LR) as:

$$\Lambda(y) = \frac{f_{y|H_1}(y|H_1)}{f_{y|H_0}(y|H_0)} \qquad (2.22)$$

and the threshold as:

$$\eta = \frac{P_0(C_{10} - C_{00})}{P_1(C_{01}-C_{11})} \qquad (2.23)$$

If we have K observations where K denotes the number of samples $y_1, y_2, \dots \dots . . y_K$ of the received signal, the likelihood ratio can be expressed as following:

$$\Lambda(Y) = \frac{f_{Y|H_1}(Y|H_1)}{f_{Y|H_0}(Y|H_0)} \qquad (2.24)$$

where **Y** is the received vector $Y^T = [Y_1\ Y_2\ \ \dots\ \ Y_K]^T$ The likelihood statistic **Λ(Y)** is a random variable because it is a function of the random variable **Y**. Therefore, the Bayes criterion which minimizes the average cost leads to the likelihood ratio test following:

$$\Lambda(Y) \underset{H_0}{\overset{H_1}{\lessgtr}} \eta \qquad (2.25)$$

An important remark is related to the fact that the test of the ratio of likelihood is simply performed by considering the received vector to get the likelihood ratio so it can be compared threshold. Therefore, in real situations where the probabilities a priori and the cost can change, it is the threshold that changes only while the calculation of the likelihood ratio is not affected.

Since the natural logarithm is a strictly monotone function increasing, a decision rule equivalent to (2.25) is:

$$\ln \Lambda(Y) \underset{H_0}{\overset{H_1}{\lesseqgtr}} \ln \eta \qquad (2.26)$$

If we choose the cost of an erroneous decision equal to 1 and that of a correct decision equal to 0, then:

$C_{01} = C_{10} = 1$ and $C_{00} = C_{11} = 0$

(2.27)

The risk given by (14) becomes:

$$R = P_M P_1 + P_F P_0$$
$$= P(\varepsilon) \qquad (2.28)$$

That is, in this case, minimizing the average cost is equivalent to minimize the probability of error. Such receptors are called receivers (with minimum probability of error receivers)

The threshold given by (2.23) is reduced to:

$$\eta = \frac{P_0}{P_1} \qquad (2.29)$$

If, moreover, the prior probabilities are equal, η is equal to one and the logarithm of the threshold becomes zero.[18]

2.3.2 THE NEYMAN-PEARSON CRITERION

In several other applications such as radar detection, it is difficult to assign realistic costs and a priori probabilities so that we can use the Bayes criterion in situations where it is not possible to know the probabilities a priori. In such cases, we use the conditional probabilities PF and PD. The Neyman-Pearson (N-P) test sets the P_F to a value α and maximizes theP_D. As P_M=1-P_D; maximizing $P_D$is equivalent to minimizing P_M. To do this, we form the objective function J such that:

$$J = P_M + \lambda(P_F - \alpha) \tag{2.30}$$

where $\lambda(\lambda \geq 0)$denotes the Lagrange multiplier. Given the space observation Z, there are several decision regions Z_1 for which P_F=∝. The problem is to determine among these regions those which guarantee a minimum P_M. For this, let us write J as a function of the regions decision:

$$J = \int_{Z_0} f_{y|H_1}(y|H_1)\, dy + \lambda\left[\int_{Z_1} f_{y|H_0}(y|H_0)\, dy - \alpha\right] \tag{2.31}$$

Using (2.17), (2.31) can be put in the form

$$J = \int_{Z_0} f_{y|H_1}(y|H_1)\, dy + \lambda\left[1 - \int_{Z_0} f_{y|H_0}(y|H_0)\, dy - \alpha\right]$$

$$= \lambda(1-\alpha) + \int_{Z_0} f_{Y|H_1}(Y|H_1) - \lambda f_{Y|H_0}(Y|H_0)\, dy \tag{2.32}$$

Consequently, values that minimize J are assigned to the region of decision Z_0, guaranteeing $f_{y\,|\,H_1}(y\,|\,H_1) < \lambda\, f_{y\,|\,H_0}(y\,|\,H_0)$. The decision rule is then given by:

$$\Lambda(y) = \frac{f_{y|H_1}(y|H_1)}{f_{y|H_0}(y|H_0)} \underset{H_0}{\overset{H_1}{\lessgtr}} \lambda \tag{2.33}$$

The threshold η, derived from the Bayes criterion is equivalent to λ, the Lagrange multiplier in the Neyman-Pearson test which sets P_F to ∝ . If we defne $f_{\Lambda\,|\,H_0}(y\,|\,H_0)$ the probability density function of Λ knowing that H_0 is true, then $P_F = \propto$ can be rewritten as follows:

$$P_F = \int_{Z_1} f_{Y|H_0}(Y|H_0)\, dy = \int_{\lambda}^{\infty} f_{\Lambda(y)|H_0}[\lambda(y)|H_0] d\lambda \qquad (2.34)$$

Such a test is said to be the most powerful of level ∝ (most powerful test of level ∝) if its probability of rejecting the hypothesis H_0 is ∝.

2.4 EVALUATION OF THE PROBABILITY OF DETECTION AND FALSE ALARM

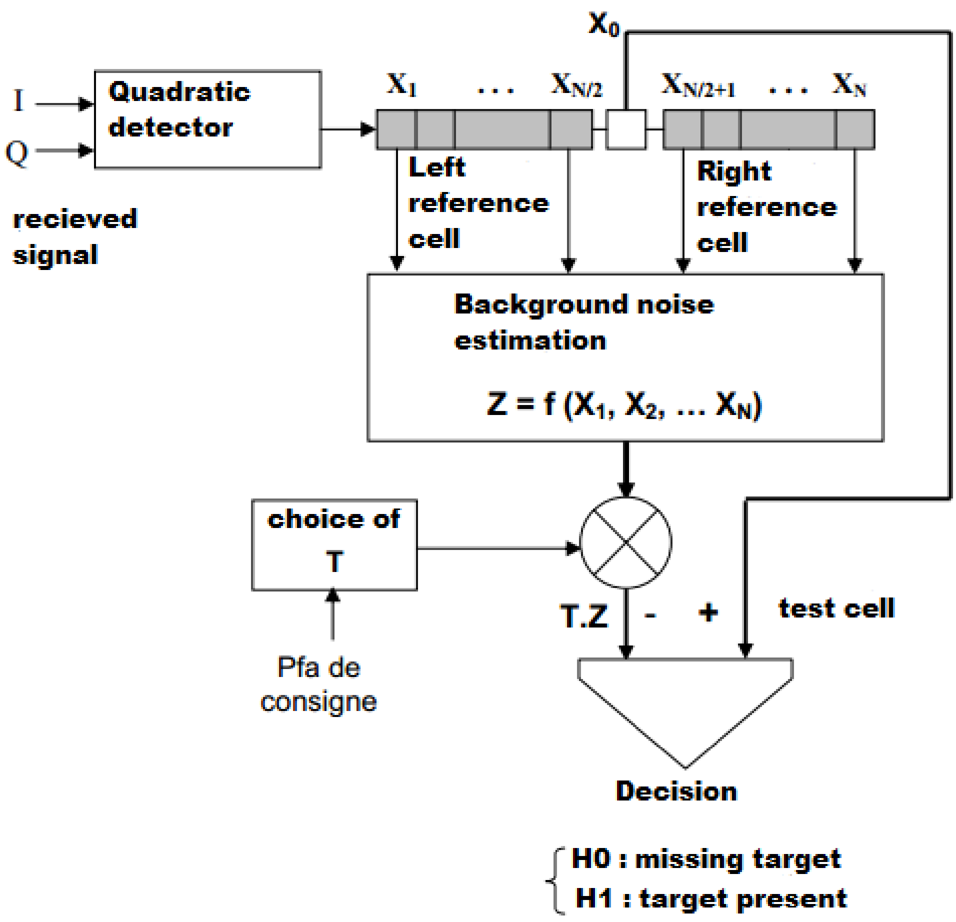


Figure 2.3 Block diagram of a constant false alarm rate detector.

The detection of the target signal, drowned in the background noise, is expressed in the form of a test of statistical hypotheses.

• The alternative hypothesis H1, where the target is considered present in the cell under test.

• The null hypothesis H0, where the test cell contains only background noise (noise thermal and/or clutter)

At the input of the quadratic detector, this test can be formulated taking into account the attenuation (Fading) and the phase shift of the received signal, x, with respect to the emitted wave. Thus, for the Jth emitted pulse, the complex modeling of the received signal will be:

H_0 : $x = u + iv$ (Target absence) (2.35)

H_1: $x = (s + u) + i(t + v)$ (Target presence) (2.36)

With $i^2 = -1$ In a homogeneous clutter of the Rayleigh type, u and v are variables random Gaussians, independent and identically distributed (IID), of mean zero and of unity variance. u and v correspond to the components in phase and in Phase quadrature of the clutter+noise signal.

The target echo is modeled by the signal complex :

$$s+it = A\exp(i\theta_j) \quad (2.37)$$

where A represents the amplitude of the signal and θj its phase shift with respect to the signal of reference:

$$\theta_j = \theta_0 + 2\pi f_d T_R \quad (2.38)$$

f_d and T_R correspond, respectively, to the Doppler frequency and to the period of pulse repetition. θ_0 is a random variable uniformly distributed over the interval [0, 2π].

At the output of the quadratic detector, the two statistical hypotheses become:

$$H_0 : x = \frac{1}{2}(u^2 + v^2) \quad (2.39)$$

$$H_1 : x = \frac{1}{2}((u + s)^2 + (v + t)^2) \quad (2.40)$$

where, the total signal-to-noise ratio of the target is

$$SNR = (s^2 + t^2)/2 \qquad (2.41)$$

This statistical test leads to two categories of error :

- We decide H_1 while H_0 is true, it is the probability of false alarm, Pfa.
- We decide H_0 while H_1 is true, it is the probability of non-detection, $P_m = 1 - P_d$.

Where, P_d represents the probability of detection (we decide H_1 while H_1 is true). The decision rule, not requiring a priori knowledge of the statistics of the target signal, is based on the Neyman-Pearson criterion. This criterion results in the maximization of P_d, maintaining a Pfa less than or equal to a value of set point α. The formulation of this criterion amounts to testing the likelihood ratio

$$\Lambda(X) = \frac{P_{X_{0/H_1}}(x)}{P_{X_{0/H_1}}(x)} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \qquad (2.42)$$

$P_{x0/H1}(x)$represents the conditional probability density (Pdf) of the cell under test x_0 in the presence of target, while $P_{X0/H0}(x)$is the conditional Pdf of X_0 in the absence of target. λ corresponds to the detection threshold obtained from the constraint Pfa= α , i.e. say :

$$\int_{\lambda}^{\infty} P_{\Lambda/H_0}(x)\mathrm{dx} = \alpha \qquad (2.43)$$

The resolution of equation (2.42) leads to a detection threshold which is a function of the environmental variance (noise+clutter). In reality, clutter is a process not stationary whose variance may vary as the reference window sweeps across the cells of range. Therefore, the use of a fixed threshold does not allow the regulation of the rate. false alarm. In order to guarantee control of the Pfa in the event of a change of the environment, the detection threshold is adapted to the background noise by multiplying the local estimator Z by the coefficient T, so as to maintain a set point Pfa constant (Fig.2.3). In this detection scheme, for a set point value α , the detection and false alarm probabilities are given by the probabilities conditional:

$$P_d = Prob(x_0 \geq {}^{TZ}/_{H_1}) \qquad (2.44)$$

$$P_{FA} = Prob(x_0 \geq {}^{TZ}/_{H_0}) \qquad (2.45)$$

Using the Pdf of the Z statistic, we get:

$$P_d = \int_0^\infty f_z(z) \int_{TZ}^\infty P_{X0}/_{H1}(x)dxdz \qquad (2.46)$$

$$P_{fa} = \int_0^\infty f_z(z) \int_{TZ}^\infty P_{X0}/_{H0}(x)dxdz \qquad (2.47)$$

where, Z represents the local estimator, TZ the adaptive threshold and $f_Z(Z)$the Pdf of the variable random Z. Using the residue theorem, the Pd and Pfa can be expressed in terms of moment generating functions (MGF), as follows:

$$P_d = -\sum_i Res\left[\omega^{-1}\Phi_{X0}/_{H1}(\omega)\Phi_z(-T\omega), \omega_i\right] \qquad (2.48)$$

$$P_{fa} = -\sum_i Res\left[\omega^{-1}\Phi_{X0}/_{H0}(\omega)\Phi_z(-T\omega), \omega_i\right] \qquad (2.49)$$

Where:

- ΦX0/H1(ω) corresponds to the MGF of the cell under test in the presence of target.
- ΦX0/H0(ω) corresponds to the FGM of the test cell in the absence of target.
- ΦZ(ω) is the MGF of the Z statistic.
- ωi and ωj represent, respectively, the negative real part poles of ΦX0/H1(ω) and ΦX0/Ho(ω).

The MGFs used in equations (2.48) and (2.49) are given by :

$$\Phi_z(\omega) = \int_0^\infty f_Z(z) \exp(-z\omega)\, dz \qquad (2.50)$$

$$\Phi_{X0}/_{H1}(\omega) = \int_0^\infty P_{X0}/_{H1}(x) \exp(-x\omega)\, dx \qquad (2.51)$$

$$\Phi_{X0}/_{H0}(\omega) = \int_0^\infty P_{X0}/_{H0}(x) \exp(-x\omega)\, dx \qquad (2.52)$$

Fig.2.3 shows that CFAR detectors differ only in the form of the estimator Z=f(X1, …, XN). On the other hand, equations (2.47) and (2.48) essentially depend of the MGF ΦZ(ω). In particular, they make it possible to size the detector, by calculating T for a given nominal Pfa. In fact, for Rayleigh clutters, the FGMs ΦX0/H1 and ΦX0/H0 are generally known and defined by the next unified relationship :

$$\Phi_{X0/_{H1}}(\omega) = \frac{(1+\omega)^{\eta-M}}{(1+b\omega)^{\eta}} \qquad (2.53)$$

$$b = 1 + \frac{M.SNR}{\eta} \qquad (2.54)$$

With :

M: number of integrated pulses,

SNR: signal-to-noise ratio per pulse and

η: target fluctuation parameter.

The interest of the relations (2.53) and (2.54) is that it brings together the four Swerling cases. Actually, the values η=1, M, 2, 2M correspond respectively to the models SWI, SWII, SWIII and SWIV. the case η=∞ describes so-called "non-fluctuating" targets. Note that FGM ΦX0/H0(ω) of the test cell under the hypothesis H_0 is deduced from (2.53) and (2.54), by setting SNR=0.

2.5 RADAR DETECTION TECHNICS

Radar detection techniques encompass a range of methods used to identify and track targets in radar systems. These techniques leverage the principles of radar technology and signal processing to extract valuable information from the received radar signals. Some common radar detection techniques include Pulse-Doppler radar, which analyzes frequency shifts caused by the Doppler effect to detect moving targets; Continuous Wave (CW) radar, which uses continuous wave transmission and analyzes frequency shifts for target detection; Synthetic Aperture Radar (SAR), which generates high-resolution images by combining multiple pulses and motion; Moving Target Indication (MTI), which filters out stationary clutter to focus on moving targets; Multiple-Input Multiple-Output (MIMO) radar, which employs multiple transmitters and receivers for improved target detection and localization; Frequency Modulated Continuous Wave (FMCW) radar, which measures range using the frequency difference between transmitted and received signals; and Passive radar, which utilizes existing electromagnetic radiation sources for target detection. These radar detection techniques offer diverse capabilities and find applications in fields such as aviation, surveillance, navigation, and weather monitoring. Through continuous advancements in radar technology, these techniques continue to evolve, enabling more accurate and efficient target detection and tracking.

2.5.1 Optimal detection

Refers to the process of designing a detection system that maximizes its performance in terms of correctly identifying the presence or absence of a specific signal or target. It aims to minimize the probability of detection errors, such as false positives (incorrectly detecting a signal when it is not present) and false negatives (failing to detect a signal when it is present).

In optimal detection theory, the goal is to find a decision rule that maximizes a specified criterion, such as the likelihood ratio test, the Neyman-Pearson criterion, or the minimum probability of error criterion. These criteria are designed to optimize the trade-off between detection performance and the associated costs or risks.

Optimal detection techniques take into account factors such as noise characteristics, signal-to-noise ratio, prior knowledge, and the statistical properties of the signals and backgrounds. These factors are used to determine appropriate decision thresholds or criteria that optimize the detection performance based on the specific application requirements.

The development of optimal detection techniques involves mathematical modeling, statistical analysis, and optimization algorithms. It finds applications in various fields, including radar systems, communications, signal processing, biomedical engineering, and many others.

Overall, the goal of optimal detection is to design systems that achieve the highest possible detection accuracy, reliability, and efficiency while considering the specific constraints and requirements of the given application.

2.5.2 Fixed threshold detection

Fixed threshold detection is a common approach in signal processing and detection theory. It involves comparing the measured or observed signal against a predetermined threshold to make a binary decision about the presence or absence of a desired signal.

In fixed threshold detection, a threshold value is set in advance based on the characteristics of the signal and the noise. The observed signal is then compared to this fixed threshold to determine if it exceeds or falls below the threshold. The decision is made based on whether the observed signal is greater than or equal to the threshold (indicating signal presence) or less than the threshold (indicating signal absence).

The choice of the threshold is crucial in fixed threshold detection. If the threshold is set too high, it may lead to missed detections (false negatives), where the signal is present but not detected. Conversely, if the threshold is set too low, it may result in false alarms (false positives), where noise or interference is mistaken for the desired signal.

The performance of fixed threshold detection can be evaluated using metrics such as probability of detection (Pd), probability of false alarm (Pfa), and receiver operating characteristic (ROC) curves. The threshold can be adjusted to achieve a desired balance between detection probability and false alarm rate, depending on the specific application requirements and trade-offs.

Fixed threshold detection is commonly used in various domains, including telecommunications, radar systems, image processing, and biomedical signal analysis. It provides a simple and efficient means of detecting signals in scenarios where the signal characteristics and noise statistics are reasonably well-known.[]

2.5.3 Adaptive threshold detection

Automatic detection consists of deciding on the absence or presence of a target by comparing the echo received with a detection threshold. In decision theory statistics, it is a question of choosing between two statistical hypotheses: H0 for the hypothesis null (absence of the useful signal) or H1 for the alternative hypothesis (presence of target). Each echo received results, in the most general case, from the superposition of the noise thermal, clutter reflections and a possible target echo. Thus, the choice of a fixed detection threshold (pre-calculated) leads to an intolerable increase in the number false alarms when the noise level, in the vicinity of the cell under test (C.T.), undergoes a significant change in clutter. In order to circumvent this problem, we have to use methods of adaptive thresholding where the detection threshold is directly related to the noise level in the span cells surrounding the cell under test. As shown in Fig.2.4, these cells adjacent lines, the number of which is quite small for reasons of calculation time, form what is called "Reference window". They provide an estimate local level of noise and clutter. Fig.2.2 gives the block diagram of a CFAR (Constant False Alarm Rate) detector, performing, for each range cell, comparing the cell under test with an adaptive threshold T.Z. The multiplication factor T is calculated in such a way as to maintain a constant false alarm probability equal to a setpoint value (Design pfa). The mathematical form of the estimator Z=f (X1, X2, … XN) represents the main difference between the various CFAR detectors proposed in the radar literature. The class detectors at "average level" (Mean level) is by far the most approached and the one that best suited for homogeneous environments. The CA-CFAR detector (Cell Averaging) , whose adaptive threshold is obtained by calculating the average of the cells of reference, represents the precursor of this category of detectors.

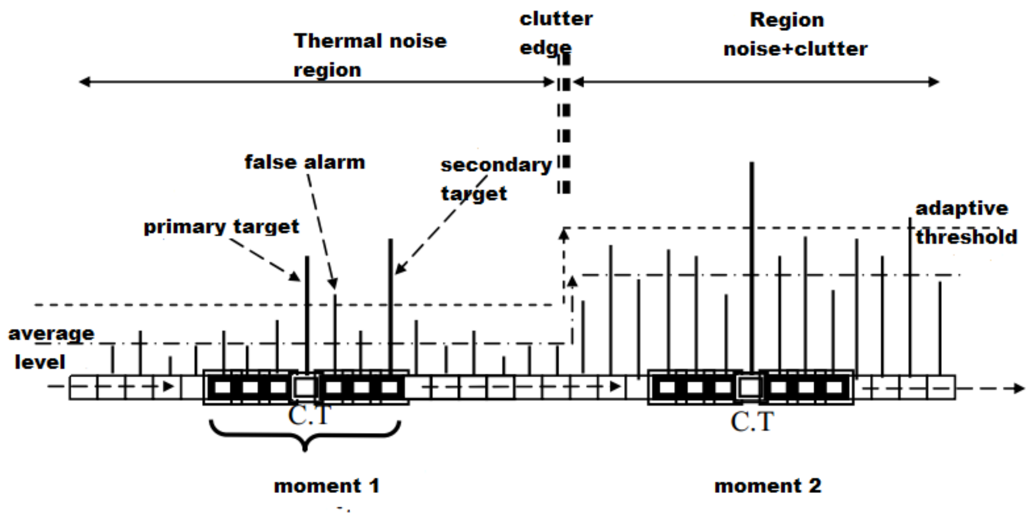


Figure 2.4 Reference cell scanning an inhomogeneous environment.

CONCLUSION

In conclusion, radar detection techniques have evolved to meet the diverse needs of various applications. From pulse radar and continuous wave radar to advanced techniques like SAR, phased array radar, and cognitive radar, each technique offers unique advantages and capabilities. The integration of radar with other sensor modalities and the application of artificial intelligence further enhance the performance and versatility of radar detection systems. As technology continues to progress, we can expect further advancements in radar detection techniques, leading to more accurate, efficient, and intelligent systems.

CHAPTER 3:

ANALYSIS OF DETECTORS

CA CFAR AND OS CFAR

3.1 INTRODUCTION

Constant False Alarm Rate (CFAR) is a technique used in radar signal processing to maintain a consistent probability of false alarms in the presence of changing clutter and noise levels. CFAR algorithms dynamically adjust the detection threshold based on the statistical properties of the background clutter and noise, ensuring accurate target detection while minimizing false alarms.

In radar systems, clutter refers to unwanted signals caused by stationary or slowly moving objects, while noise stems from electronic components and environmental factors. CFAR techniques overcome the challenge of setting a fixed threshold by using nearby reference cells to estimate the local noise level or clutter distribution. This estimation helps determine an appropriate threshold that adapts to the specific clutter and noise conditions.

CFAR algorithms are essential for reliable target detection in various radar applications, including surveillance, tracking, and navigation. By maintaining a constant false alarm rate, CFAR techniques enable radar systems to effectively detect targets while minimizing false alarms caused by environmental factors.

3.2 DETECTION OF CFAR

3.2.1 Definition

CFAR stands for Constant False Alarm Rate. It is a signal processing technique used in radar systems to detect and track targets while maintaining a consistent level of false alarms

3.2.2 The Principle Of Detection In CFAR

The Constant False Alarm Rate (CFAR) principle is widely used in radar systems for target detection. CFAR is based on the idea of setting a threshold for detecting targets while maintaining a constant false alarm rate in the presence of varying clutter conditions.

To elaborate on the principle of detection in CFAR, it is essential to understand how the statistical properties of the clutter are estimated and how the threshold is computed. The clutter properties are typically estimated assuming that the clutter is stationary and follows a known statistical distribution, such as Gaussian or Rayleigh. These properties can be estimated from neighboring Regions of Interest (ROIs) or from a training dataset collected during a period when no targets are present. The training dataset is used to estimate the clutter distribution, and the threshold is then set based on the desired false alarm rate.

The threshold plays a critical role in CFAR, as it determines the tradeoff between the probability of detection and the probability of false alarms. The threshold can be set based on a fixed false alarm rate, such as 1%, or it can be adaptive, adjusting to changes in the clutter level. Adaptive CFAR algorithms utilize feedback from the detections to update the clutter statistics and adjust the threshold accordingly. [20]

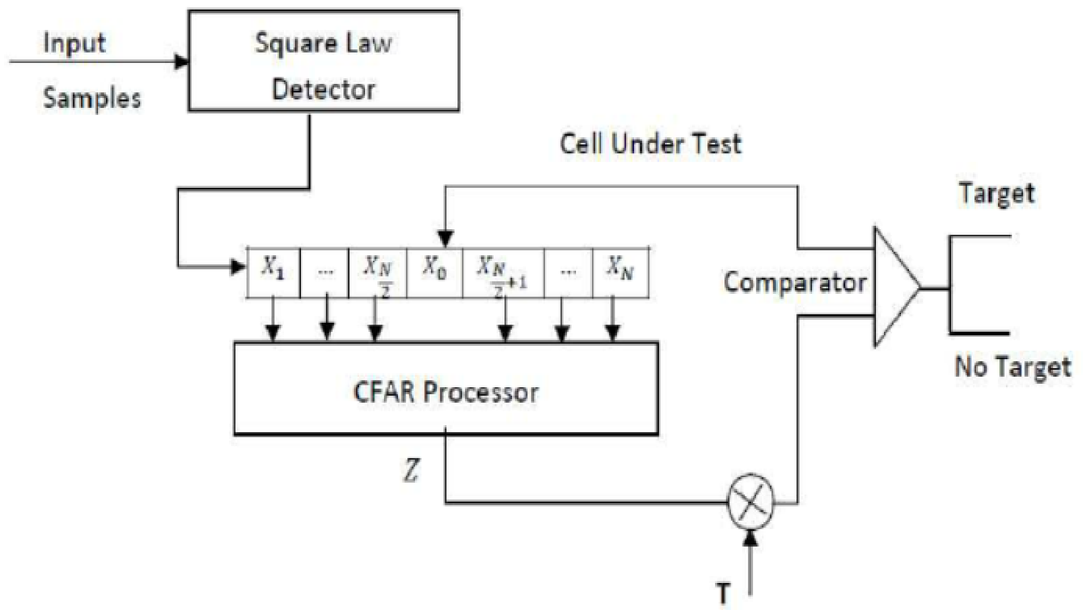


Figure3.1 The Bloc Diagram Of a Typical CFAR Detector

CFAR is commonly used in radar systems to detect targets in environments with high levels of clutter and noise, such as in air traffic control, weather monitoring, and military applications. The performance of CFAR algorithms depends on various factors, including the clutter properties, the signal-to-noise ratio, the target characteristics, and the choice of algorithm. As such, the design and optimization of CFAR algorithms is an active area of research in radar signal processing.

The CFAR principle can be summarized as follows:

Reference Cell Selection: A group of reference cells surrounding the cell under test is selected. These reference cells should ideally contain only clutter and noise, without any significant target signals.

- Statistical Estimation: The statistical properties of the reference cells are calculated, such as the mean, median, or order statistic. These statistics serve as estimates for the expected level of clutter and noise.
- Threshold Determination: The detection threshold is set based on the estimated statistical properties of the reference cells. The threshold is adjusted to maintain a desired false alarm rate, considering the variability of clutter and noise levels.
- Target Detection: The radar signal in the cell under test is compared to the detection threshold. If the signal exceeds the threshold, a target is declared present; otherwise, it is considered clutter or noise.
- Adaptation: The CFAR algorithm continuously updates the reference cells and adjusts the detection threshold as the clutter and noise levels change. This ensures that the false alarm rate remains constant despite variations in the background environment

3.2.3 The Radar Environment

3.2.3.1 Homogeneous Radar Environment

In a radar system, the environment in which it operates can have a significant impact on its performance and the ability to detect and track targets accurately. One such environment is a homogeneous radar environment, where the clutter properties and statistical characteristics remain relatively constant throughout the surveillance area.

In a homogeneous radar environment, the clutter exhibits similar statistical behavior across the entire radar coverage region. This means that the clutter's characteristics, such as its amplitude distribution, spatial correlation, and temporal variations, remain consistent over time and space. The clutter may arise from various sources, including terrain features, buildings, vegetation, and atmospheric effects.

When the clutter properties are homogeneous, it simplifies the task of clutter estimation and threshold setting in radar signal processing. The statistical properties of clutter can be estimated accurately by analyzing a representative sample of clutter returns obtained from different regions within the surveillance area. These regions are assumed to have similar clutter characteristics, allowing for the estimation of a common clutter model.

The knowledge of the clutter properties in a homogeneous environment enables the radar system to distinguish between target echoes and clutter returns effectively. By characterizing the clutter, the radar system can set an appropriate threshold for target detection, maintaining a constant false alarm rate while maximizing the probability of detecting true targets.

It is important to note that achieving a truly homogeneous radar environment may be challenging in practice, as there can be variations and non-uniformities in clutter properties due to factors such as changes in terrain, weather conditions, and man-made structures. However, in scenarios where the clutter properties can be considered relatively stable and consistent over the surveillance area, the assumption of a homogeneous radar environment can provide a useful framework for radar signal processing. |[21]

3.2.3.2 A Non-Homogeneous Radar Environment

In a radar system, the environment in which it operates can vary significantly, leading to non-homogeneous radar environments. In such environments, the clutter properties and statistical characteristics can change spatially and temporally, posing challenges for radar signal processing and target detection.

A non-homogeneous radar environment is characterized by variations in clutter behavior across different regions within the surveillance area. These variations can arise due to diverse terrain features, vegetation density, atmospheric conditions, and man-made structures. As a result, the clutter exhibits different statistical properties, such as varying amplitude distributions, spatial correlations, and temporal fluctuations.

Detecting targets accurately in a non-homogeneous radar environment becomes more complex. Estimating clutter properties and setting an appropriate detection threshold become challenging tasks. The traditional approach of assuming a common clutter model across the entire surveillance area may not be valid in such scenarios.

To address the non-homogeneity of clutter, advanced radar signal processing techniques are employed. These techniques involve adaptive algorithms that dynamically estimate the clutter properties within localized regions and adjust the detection threshold accordingly. By considering the local clutter characteristics, these algorithms aim to maintain a constant false alarm rate while maximizing the probability of target detection.

Adaptive clutter estimation algorithms utilize techniques such as spatial filtering, temporal averaging, and adaptive thresholding to account for the non-homogeneity in the radar environment. These methods use feedback from the radar returns and adaptively update the clutter statistics and detection thresholds based on the observed clutter variations.

Dealing with a non-homogeneous radar environment requires sophisticated signal processing algorithms and techniques to handle the spatial and temporal variations in clutter. These approaches enable the radar system to effectively differentiate between target echoes and clutter returns, improving the overall detection and tracking performance. [22]

- **Borderline clutter**

Borderline clutter refers to radar returns that lie on the boundary between clutter and potential targets. It represents a challenging scenario where distinguishing between genuine targets and clutter becomes difficult. Borderline clutter can arise due to various factors such as weak or partially obscured targets, clutter with similar characteristics to targets, or radar system limitations in differentiating between the two.

In the presence of borderline clutter, radar signal processing techniques need to carefully handle the uncertainty associated with these returns. Advanced algorithms and decision criteria are employed to minimize false alarms while maintaining high detection probabilities for genuine targets. These techniques often involve the use of adaptive thresholding, statistical modeling, and pattern recognition methods to differentiate between borderline clutter and true targets.

Handling borderline clutter is crucial in radar systems to ensure accurate target detection and minimize false alarms. By employing sophisticated signal processing techniques, the radar system can mitigate the challenges posed by borderline clutter and enhance its overall performance. [21]

. Multiple targets

In radar systems, the scenario of multiple targets refers to the presence of more than one object within the surveillance area that reflects radar signals. Dealing with multiple targets poses challenges in accurately detecting and tracking each individual target and distinguishing them from clutter and interference.

In such scenarios, radar signal processing algorithms need to handle the complexity of overlapping returns from multiple targets. Techniques such as pulse-Doppler processing, adaptive beamforming, and advanced tracking algorithms are employed to separate and track individual targets based on their unique characteristics such as range, velocity, and direction.

The detection and tracking of multiple targets are essential in various radar applications, including air traffic control, surveillance, and military operations. Effective processing algorithms enable radar systems to detect and track multiple targets simultaneously, providing valuable information for situational awareness and decision-making. [21]

3.3 The CFAR TECHNIQUE

The CFAR (Constant False Alarm Rate) technique is a signal processing method used in radar and other detection systems to detect and track targets in noisy environments while maintaining a constant probability of false alarms. It is particularly useful in situations where there is a significant amount of clutter or noise that can cause false detections.

The basic principle of the CFAR technique is to adaptively adjust the detection threshold based on the local statistics of the received signal. Instead of using a fixed threshold, the CFAR algorithm estimates the statistical characteristics of the background clutter and noise and sets a threshold above which a signal will be considered a target.

There are several variations of the CFAR technique, each with its own algorithm and approach. Some common CFAR techniques include:

- Cell Averaging CFAR (CA-CFAR): This method calculates the average power of neighboring cells surrounding the cell of interest. The threshold is then set above the estimated clutter level.

- Order Statistic CFAR (OS-CFAR): This technique ort the power levels of surrounding cells and selects the power level at a specific rank, such as the median or the 70th percentile, as the threshold.
- Greatest of CFAR (GO-CFAR): In this approach, the maximum power level among the surrounding cells is used as the threshold.
- Smallest of CFAR (SO-CFAR): This method sets the threshold to the minimum power level among the surrounding cells.

These CFAR variations provide flexibility in adapting to different signal and clutter conditions, and the choice of technique depends on the specific application and system requirements.

By using the CFAR technique, radar systems can maintain a constant probability of false alarms while effectively detecting and tracking targets in challenging environments. It is widely employed in various applications such as air traffic control, weather monitoring, target tracking, and military surveillance.

The CFAR technique estimates the statistical properties of clutter by assuming it is stationary and follows a known probability distribution, such as Gaussian or Rayleigh. These clutter properties are estimated either from neighboring Regions of Interest (ROIs) or from a training dataset collected during clutter-only periods. Based on these estimated clutter properties, a detection threshold is set to achieve the desired false alarm rate.

One popular CFAR algorithm is the Cell Averaging CFAR (CA-CFAR), which estimates the clutter power by averaging the signal power from surrounding cells or windows. This adaptive thresholding approach enables the CFAR algorithm to effectively handle varying clutter levels and maintain a consistent false alarm rate. [22]

3.4. The CA-CFAR algorithm

3.4.1 Definition

CA-CFAR, or Cell Averaging Constant False Alarm Rate, is a signal processing algorithm used in radar systems to detect targets in the presence of clutter or interference. It is a type of threshold-based detection scheme that is designed to maintain a constant false alarm rate over a wide range of clutter levels.

The CA-CFAR algorithm works by dividing the radar signal into cells, each containing a certain number of samples. The algorithm calculates the average power level of the samples within each cell and compares it to the average power level of neighboring cells. If the power level in a cell exceeds a certain threshold, it is considered a potential target.

The threshold is chosen based on the desired false alarm rate and the number of samples in the cell, and it is adjusted to maintain a constant false alarm rate over a wide range of clutter levels. The algorithm is designed to adapt to changes in the clutter level, allowing for reliable target detection and tracking in cluttered environments.

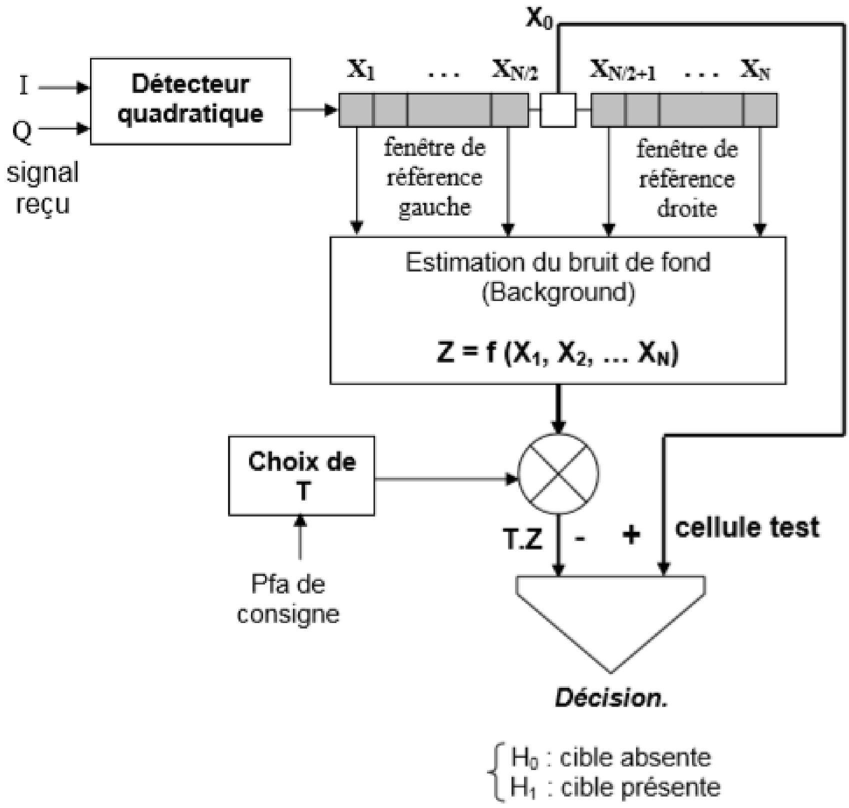
In summary, CA-CFAR is a useful technique for detecting targets in cluttered environments and is widely used in modern radar systems. Its ability to maintain a constant false alarm rate over a wide range of clutter levels makes it a valuable tool for real-time target detection and tracking.

3.4.2 The principle of detection of CA-CFAR

The principle of detection in CA-CFAR, or Cell Averaging Constant False Alarm Rate, is based on the assumption that the noise or clutter in the radar signal is statistically homogeneous across the range of cells. The algorithm works by dividing the range of the radar signal into cells, each containing a certain number of samples.

The principle of detection in CA-CFAR can be explained in the following steps:

- Divide the radar signal into cells: The algorithm divides the radar signal into a grid of cells, each containing a certain number of samples.
- Calculate the average power level of each cell: The algorithm calculates the average power level of the samples within each cell, excluding the samples at the edges of the cell to avoid the influence of neighboring cells.
- Calculate the threshold: The algorithm calculates the threshold based on the desired false alarm rate and the number of samples in the cell. The threshold is chosen to maintain a constant false alarm rate over a wide range of clutter levels.
- Compare the power level of each cell to the threshold: The algorithm compares the power level of each cell to the threshold. If the power level in a cell exceeds the threshold, it is considered a potential target.



Figur3.2 Schéma bloc d'un détecteur à taux de fausse alarme constant (CFAR).

Example of a medium level detector: the CA-CFAR

In the case of CA-CFAR ,$Z = \sum_{i=1}^{N} X_i$. In single-pulse processing and in the presence of a Rayleigh clutter, the Xi are independent and identically distributed according to the exponential law $f_{xi}(x) = (1/_{\mu}).exp(-x/_{\mu})$ The parameter µ depends on the content of each reference cell Xi. In general, when Xi is embedded in the clutter and contains an interfering target of the SWI or SW2 type, µ is given by:

$$\mu = \mu_t(1 + CNR + INR) \text{ (3.1)}$$

where, µt represents the normalized variance of thermal noise. CNR and INR are the Clutter-Noise and Interference-Noise ratios, respectively.

The test cell X0 is also distributed according to the exponential law with parameter

$$\mu = \mu_t\,(1 + SNR) \text{ (3.2)}$$

In a homogeneous Rayleigh clutter, the estimator Z being the sum of N random IID variables with an exponential law, it follows that its distribution is a Gamma law with parameters (N, μ), which gives:

$$f_Z\,(Z) = \frac{Z^{N-1}\,exp(-Z/\mu)}{\Gamma(\mathrm{N})_\mu} \quad (3.3)$$

by replacing f Z(z) by its expression in (2.20.a), we obtain the MGF of Z**:**

$$\phi_Z\,(\omega) = \frac{1}{(1+\omega)^N} \quad (3.4)$$

For a single pulse treatment, the SWI and SWII models are combined (η= M=1) and the MGF of the test cell, under hypothesis H1 will be**:**

$$\Phi X0/H1(\omega) \;= \frac{1}{(1+b\omega)} \quad (3.5)$$

Substituting (3.5) and (3.4) into (3.3) and evaluating the residue at the simple pole –1/b, we find for the CA-CFAR

$$Pd = (1 + \frac{T}{1+SNR})^{-N} \quad (3.6)$$

the Pfa is easily deduced from (3.6) by setting SNR=0:

$$Pfa = (1+T)^{-N} \quad (3.7)$$

equation (3.7) allows us to calculate T which maintains a constant setpoint Pfa

3.5. OS-CFAR

3.5.1 Definition

OS-CFAR, or Ordered Statistic Constant False Alarm Rate, is a signal processing algorithm used in radar systems to detect targets in the presence of clutter or interference. It is a type of threshold-based detection scheme that is designed to maintain a constant false alarm rate over a wide range of clutter levels.

The OS-CFAR algorithm works by dividing the radar signal into cells, each containing a certain number of samples. The algorithm then sorts the samples within each cell in ascending order and selects the middle sample as the "test" sample.

The algorithm calculates the average power level of the "reference" samples, which are the samples in the neighboring cells that do not contain the test sample. It then applies a threshold to the power level of the test sample based on the desired false alarm rate and the number of reference samples.

If the power level of the test sample exceeds the threshold, it is considered a potential target. The algorithm then applies additional tests, such as Doppler filtering or phase correction, to further refine the detection and eliminate false alarms.

The key advantage of the OS-CFAR algorithm is that it is less affected by the presence of strong targets in the neighboring cells compared to other CFAR algorithms. This is because the algorithm uses the middle sample, which is less likely to be influenced by the presence of strong targets.

In summary, OS-CFAR is a useful technique for detecting targets in cluttered environments and is widely used in modern radar systems. Its ability to maintain a constant false alarm rate over a wide range of clutter levels and its robustness to strong targets in neighboring cells make it a valuable tool for real-time target detection and tracking. [23]

3.5.2 The Detection Principle Of OS-CFAR

The principle of detection in OS-CFAR (Ordered Statistic Constant False Alarm Rate) is based on the assumption that the noise or clutter in the radar signal is statistically homogeneous across the range of cells. The algorithm works by dividing the range of the radar signal into cells, each containing a certain number of samples.

The principle of detection in OS-CFAR can be explained in the following steps:

- Divide the radar signal into cells: The algorithm divides the radar signal into a grid of cells, each containing a certain number of samples.
- Sort the samples within each cell: The algorithm sorts the samples within each cell in ascending order and selects the middle sample as the "test" sample.
- Calculate the average power level of the reference samples: The algorithm calculates the average power level of the "reference" samples, which are the samples in the neighboring cells that do not contain the test sample.
- Calculate the threshold: The algorithm applies a threshold to the power level of the test sample based on the desired false alarm rate and the number of reference samples.
- Compare the power level of the test sample to the threshold: The algorithm compares the power level of the test sample to the threshold. If the power level in a cell exceeds the threshold, it is considered a potential target.
- Apply additional tests: The algorithm applies additional tests, such as Doppler filtering or phase correction, to further refine the detection and eliminate false alarms.

The principle of detection in OS-CFAR is based on the idea of thresholding the power level of the test sample, which is selected as the middle sample in each cell. The algorithm adapts to changes in the clutter level by adjusting the threshold based on the number of reference samples and the desired false alarm rate. [24]

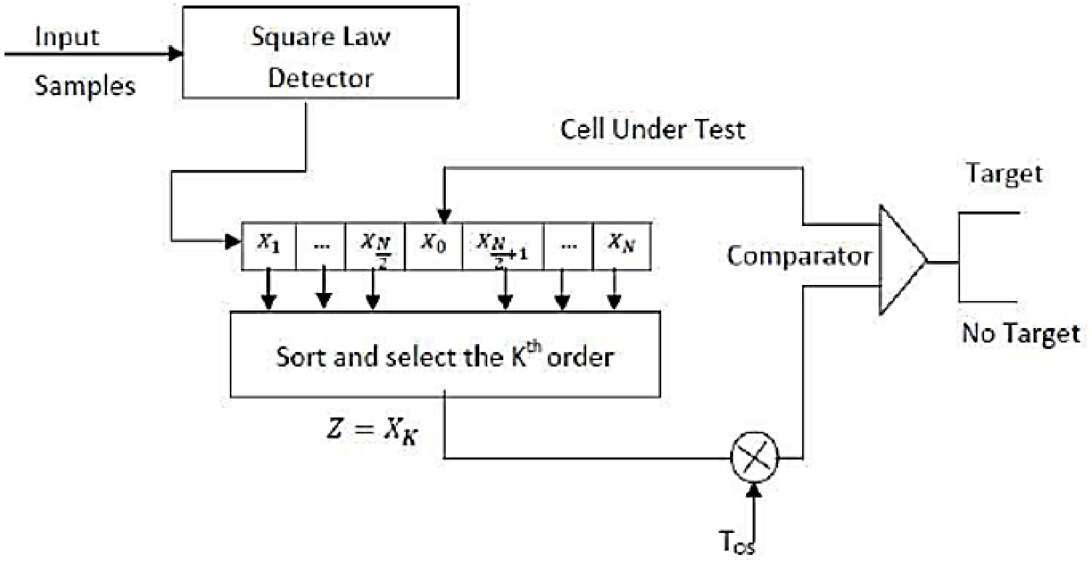


Figure3.3 Block Diagram of OS CFAR Detector

• Example of a detector using order statistics: OS-CFAR

In detectors based on order statistics, the reference cells are ranked in ascending order: X(1) ≤ X(2) ≤...≤ The OS-CFAR detector [5] uses the k-order statistic to estimate the background noise: Z=X(k). Although the reference random variables (the Xi) are IID, the order statistics X(k) are neither independent nor identically distributed. If f(x) and F(x) respectively represent the Pdf and the Cdf (cumulative density) of the N reference cells, then the ordered variable X(k) is distributed according to the law H. A. **David**:

$$f_k(X) = k\binom{N}{K}[1 - F(X)]^{N-k}F(X)^{k-1}f(X) \quad (3.9)$$

If, in addition, f(x) is an exponential law with normalized parameter (μ=1), then the Pdf of X(k) becomes:

$$f_k(X) = k\binom{N}{K}(1 - e^{-X})^{k-1}e^{-(N-k+1)x} \quad (3.10)$$

Using (2.20.a), we evaluate the MGF of Z:

$$\Phi_Z(\omega) = k\binom{N}{K}\int_0^\infty e^{-\omega X}(1 - e^{-X})^{k-1}(e^{-X})^{N-k}e^{-X}dx \quad (3.11)$$

by setting t=e-x, (3.11) becomes:

$$\Phi_Z(\omega) = k\binom{N}{K}\int_0^1 t^{\omega+N-k}(1 - t)^{k-1}dt \quad (3.12)$$

The evaluation of the usual integral (3.12), gives [30]:

$$\boldsymbol{\Phi_Z(\omega)} = \prod_{j=1}^{k}\left[1+\frac{\omega}{N+1-j}\right]^{-1} \quad (3.13)$$

The substitution of (2.33) and (2.26) in (2.18), as well as the calculation of the residue at the pole –1/b, makes it possible to obtain the Pd of the OS-CFAR [5,6], in the presence of a SWI or SWII target:

$$Pd = \prod_{j=0}^{k-1}\frac{(N-j)}{(N-j+\frac{T}{1+SNR})} \quad (3.14)$$

With $Pfa = Pd_{SNR=0}$

3.6 Distributed CA-CFAR and OS-CFAR Detection Using Fuzzy Fusion Rules

3.6.1 Introduction

Distributed Constant False Alarm Rate (CA-CFAR) and Order Statistic Constant False Alarm Rate (OS-CFAR) detection techniques are widely used in radar signal processing to detect targets in the presence of clutter or noise. These techniques can be further enhanced by incorporating fuzzy spaces and fuzzy fusion rules, which provide a flexible framework to handle uncertainty and imprecision in radar measurements.

In this approach, each detection cell or sensor computes its local CFAR statistic based on the received radar signal and its local clutter statistics. The CFAR statistic represents the likelihood of a target being present in the respective cell. These local CFAR statistics from all cells are then fused using fuzzy fusion rules, which consider the uncertain nature of the measurements.

Fuzzy fusion rules combine the local CFAR statistics, taking into account their uncertainty, and generate a global decision about target presence. By incorporating fuzzy logic principles, the fusion process effectively combines the information from multiple sensors or cells, providing a more accurate and reliable detection result. The use of fuzzy spaces allows for modeling the distribution of clutter or noise, as well as the potential presence of targets, which further enhances the detection performance.

One reference cell or sensor is chosen as a reference for comparison. The reference cell represents a region of interest that is expected to have minimal or no target presence.

The fused result from the fuzzy fusion process is compared with the CFAR statistic of the reference cell. If the fused result exceeds a certain threshold relative to the reference statistic, a target is declared to be present; otherwise, it is considered as clutter or noise

In recent years, the area of decentralized detection has gained importance because it offers better performance in terms of reliability, speed and the capacity to handle large quantities of data. In this paper, we extend the concept of using fuzzy spaces to adaptive threshold based detectors, namely CA-CFAR and OS-CFAR detectors. We consider a distributed system in which the local sensors do not produce a binary decision but a value (between 0 and 1) of the membership to the false alarm space.

We analyses the fuzzy CA-CFAR and OS-CFAR detectors and derive their appropriate membership functions which map the observations to the false alarm space. We examine a two-sensor network with the fuzzy AND and fuzzy OR fusion rules for different operators, and we derive the thresholds corresponding to the desired probability of false alarm for each case [25]. Some simulation results are presented for homogeneous and non-homogeneous backgrounds in the next chapter .

3.6.2 Analysis of Fuzzy CA-CFAR and OS-CFAR Detectors

3.6.2.1 Fuzzy CA-CFAR Detector

The CA-CFAR detector is an adaptive processor which consists of comparing the output of the cell under test (CUT) to an adaptive threshold equal to the sum of the content of the reference cells scaled by a factor T to achieve the desired probability of false alarm (pfa). This binary detector produces a binary output $\mu(\boldsymbol{Q})$

Where $\boldsymbol{Q} = [q_1, q_2, \dots, q_{N/2}, q_{CUT}, q_{N+1}, \dots, q_N]$ as shown in Fig (3.4)

$$\mu : Q \to \begin{Bmatrix} 1 & q_{cut} & > & T \cdot \sum_{i=1}^{N} q_i \\ 0 & q_{cut} & < & T \cdot \sum_{i=1}^{N} q_i \end{Bmatrix} \quad (3.15)$$

Or equivalently

$$\mu : Q \to \begin{Bmatrix} 1 & \frac{q_{cut}}{\sum_{i=1}^{N} q_i} > T \\ 0 & \frac{q_{cut}}{\sum_{i=1}^{N} q_i} < T \end{Bmatrix} \quad (3.16)$$

In the fuzzy detector proposed in [3.1], the membership function m is defined so that it maps the observation space to a value between 0 and 1 indicating the degree to which the test is indicative to the hypothesis 'no signal' and 'signal'.

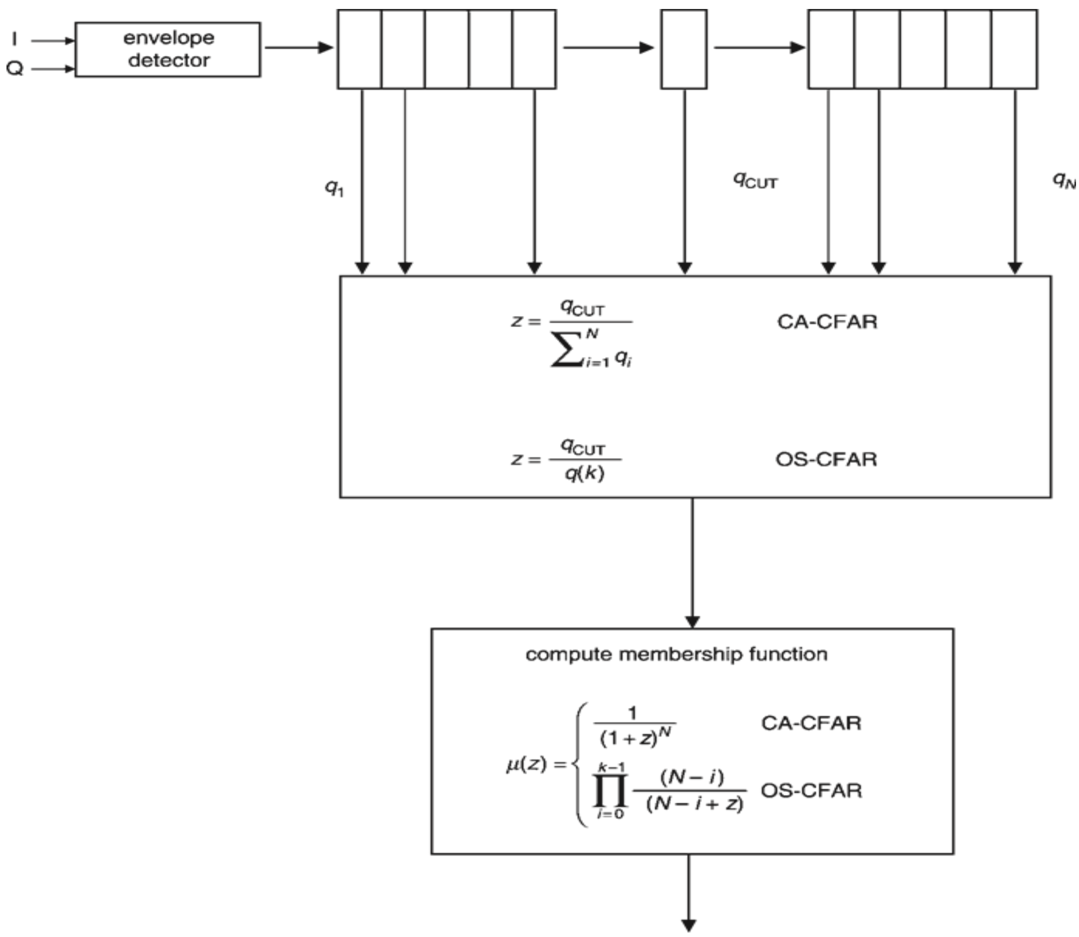


Figure3.4 Fuzzy CA-CFAR and OS-CFAR Detectors

The membership function corresponding to the false alarm space was defined as

$$\mu(y_i) = Pr\big(Z > Y_I \big| Z \sim N(0, \sigma^2)\big) \qquad (3.17)$$

where $y_i$is the observation, which is Gaussian. The membership function monotonically decreases ensuring that stronger observations are assigned smaller membership to the 'no target' hypothesis. The fuzzy CFAR criterion adapts the decision rule by declaring a target present if

$$\mu(y_i) < Pfa \qquad (3.18)$$

In our case, since the threshold is adaptive, we propose an alternative definition of the membership function corresponding to the false alarm space for the CA-CFAR detector.

To be a meaningful definition, we define the membership function for the CA-CFAR detector for the observation vector Q as

$$\mu(Q) = Pr\left(Z > \frac{q_{CUT}}{\sum_{i=1}^{N} q_i} \middle| H_0\right) \quad (3.19)$$

$$Z = \left(\frac{q_{CUT}}{\sum_{i=1}^{N} Q_i}\right) \quad (3.20)$$

Intuitively, if q_{CUT} is too much greater than $\sum_{i=1}^{N} q_i$ then, the ratio in (3.20) is too much greater than T and therefore, $\mu(Q)$ tends to zero which means that Q is likely to correspond to a detection.

In order to derive the expression of the membership function, we shall first derive the probability density function (pdf) of Z under hypothesis H0:

Since qi are exponentially distributed, we have

$$Z = \frac{X}{Y} \quad \text{where } X = Q_{CUT} \text{ and } Y = \sum_{i=1}^{N} Q_i$$

It follows that

$$f_{x(y)=}e^{-x} \quad (3.21)$$

And

$$f_y(y) = \frac{1}{\mathrm{T}(N)} \cdot y^{N-1} \cdot e^{-y} \quad (3.22)$$

we have

$$f_z(Z) = \int_0^{\infty} f_x(z \cdot y) \cdot f_y(y) \cdot |y| d_y \quad (3.23)$$

Substituting (3.22) and (3.23) into (3.21), we find $f_z(Z)$ to be

$$f_z(Z) = \frac{N}{(z+1)^{N+1}} \quad (3.24)$$

Now, using (3.5), we find the membership function $\mu_{(z)}$to be

$$\mu_{(z)} = \int_{z}^{\infty} \frac{N}{(u+1)^{N+1}} \cdot du = \frac{1}{(z+1)^{N}} = 1 - F_{z}(z) \qquad (3.25)$$

where $f_{z}(Z)$ is the cumulative distribution function (CDF) of Z.

It is worth noting from (3.11) that if $F_{z}(z)$; we find the expression of thePfa of a CA-CFAR detector. A target is then declared present if This $\mu(z) > T$definition ensures also the following rules .

$$\mu(z) \in [0,1] \quad \forall_{Z} > 0$$

$$Z_{1} \geq Z_{2} \Rightarrow \mu(Z_{1}) \leq \mu(Z_{2})$$

$$\lim_{z \to 0} Z_{1} = 1$$

$$\lim_{z \to \infty} Z_{2} = 0$$

It is shown in (3.25) that the random variable formed by applying the cumulative distribution function to any continuous random variable is uniformly distributed on [0,1]. Therefore the distribution of the membership function $\mu(Z)$is uniformly distributed on [0,1].

3.6.2.2 Fuzzy OS-CFAR detector

The OS-CFAR detector is a modified version of the CACFAR detector, which was first proposed by Rohling to deal with multiple target situations. It consists of rank ordering the samples of the reference window according to their magnitudes and the kth largest sample is taken as the estimate of the noise power. In order to derive the membership function relative to the OS-CFAR detector under hypothesis H0; we follow the same reasoning as for the CA-CFAR detector. In this case, the sample of rank (k) , $q_{(k)}$has the following pdf:

$$f_{Q(K)}(q_k) = K\binom{N}{k} \cdot (1 - e^{-y})^{K-1} . e^{(-(N-k+1)y)} \qquad (3.26)$$

Using (3.26), the pdf of $Z = {Q_{CUT}}/{Q_{(k)}}$ is

$$f_z(z) = \int_0^\infty k\binom{N}{k} \cdot y \cdot e^{(-Zy)} \times \left(1 - e^{(-y)^{k-1}}\right) \cdot e^{(-(N-k+1)\cdot y)}\, dy$$

(3.27)

After some manipulation (see the Appendix), we find the membership function corresponding to the OS-CFAR detector to be

$$\mu_{(z)} = \prod_{i=1}^{k-1} \frac{(N-1)}{(N-i+z)}$$

(3.28)

We note from (3.28) that if we substitute z by the threshold T, we find the expression of the Pfa of the OS-CFAR detector. Next, we will analyse distributed CA-CFAR and OSCFAR detection using fuzzy fusion rules.[26]

3.6.3 Distributed CA CFAR AND OS CFAR Detection Using Fuzzy Fusion Rules

Let us consider a distributed system consisting of two detectors and a fusion center as shown in Fig. 2. Each detector receives a vector Q and then computes the value of the membership function of the false alarm space. These values (between 0 and1) are sent to the fusion center to produce a global membership function according to a fuzzy fusion rule. This membership function is compared to a threshold to achieve the desired global probability of false alarm. In our work, we consider the fuzzy fusion rules which are the counterparts of the logical AND and the logical OR in fuzzy set theory. In fuzzy set theory, the truth of any statement is a matter of degree. The operator that preserves the results of the AND truth table and also extends to all real numbers between 0 and 1 is the MIN function [9]. That is, the statement A and B where A and B are limited to the range (0,1) is replaced by the function min(A, B). This is also known as the fuzzy intersection or conjunction. Hence, the membership function of the intersection of two fuzzy sets D1 and D2 (where D1 and D2 represent, respectively, detector 1 and detector 2) with membership functions mD1 and mD2 is defined as the minimum of the two individual membership functions

$$\mu_{D1\cap D2} = min(\mu_{D1},\mu_{D2}) \quad (3.29)$$

Using the same reasoning, the OR operation is replaced by the MAX function also known as the fuzzy union or disjunction. That is, the membership function of the union of two fuzzy sets D1 and D2 is defined as the maximum of the two individual membership functions

$$\mu_{D1\cap D2} = max(\mu_{D1},\mu_{D2}) \quad (3.30)$$

The MIN and MAX functions mentioned above are not the only operators that could model the intersection and union, respectively. Additional fuzzy operators are also used and are defined to meet the basic requirements of the boundary monotonicity, commutability and associativity (3.30).In our study, we will restrict ourselves to the algebraic product operator for the intersection and the algebraic sum operator for the union which are defined, respectively, as

$$\mu_{product} = \mu_{D1} \cdot \mu_{D2}$$

(3.31)

$$\mu_{sum} = \mu_{D1} + \mu_{D2} - \mu_{D1} \cdot \mu_{D2}$$

(3.32)

We shall now derive the thresholds at the fusion center corresponding to the fuzzy operators considered earlier.[27]

- Union

For simplicity, let us denote μ_{FC} and TFC; the membership function and the threshold, respectively, at the fusion center. We have then

$$\mu_{FC} = max(\mu_{D1}, \mu_{D2}) \quad (3.33)$$

The pdf $\mu_{FC}$is given as (3.33)

$$f_{\mu FC}(m) = F_{\mu D1}(m) \cdot f_{\mu D2}(m) + F_{\mu D2}(m) \cdot f_{\mu D1}(m)$$

Since $\mu_{D1}$and μ_{D2} are uniformly distributed in [0,1]

$$f_{\mu FC}(m) = 2 \cdot m \quad 0 \leq m \geq 1$$

The Pfa is then obtained as follows:

$$Pfa = \int_0^{T_{FC}} 2 \cdot m \cdot dm = T^2{}_{FC} \Rightarrow T_{FC} = \sqrt{Pfa} \tag{3.34}$$

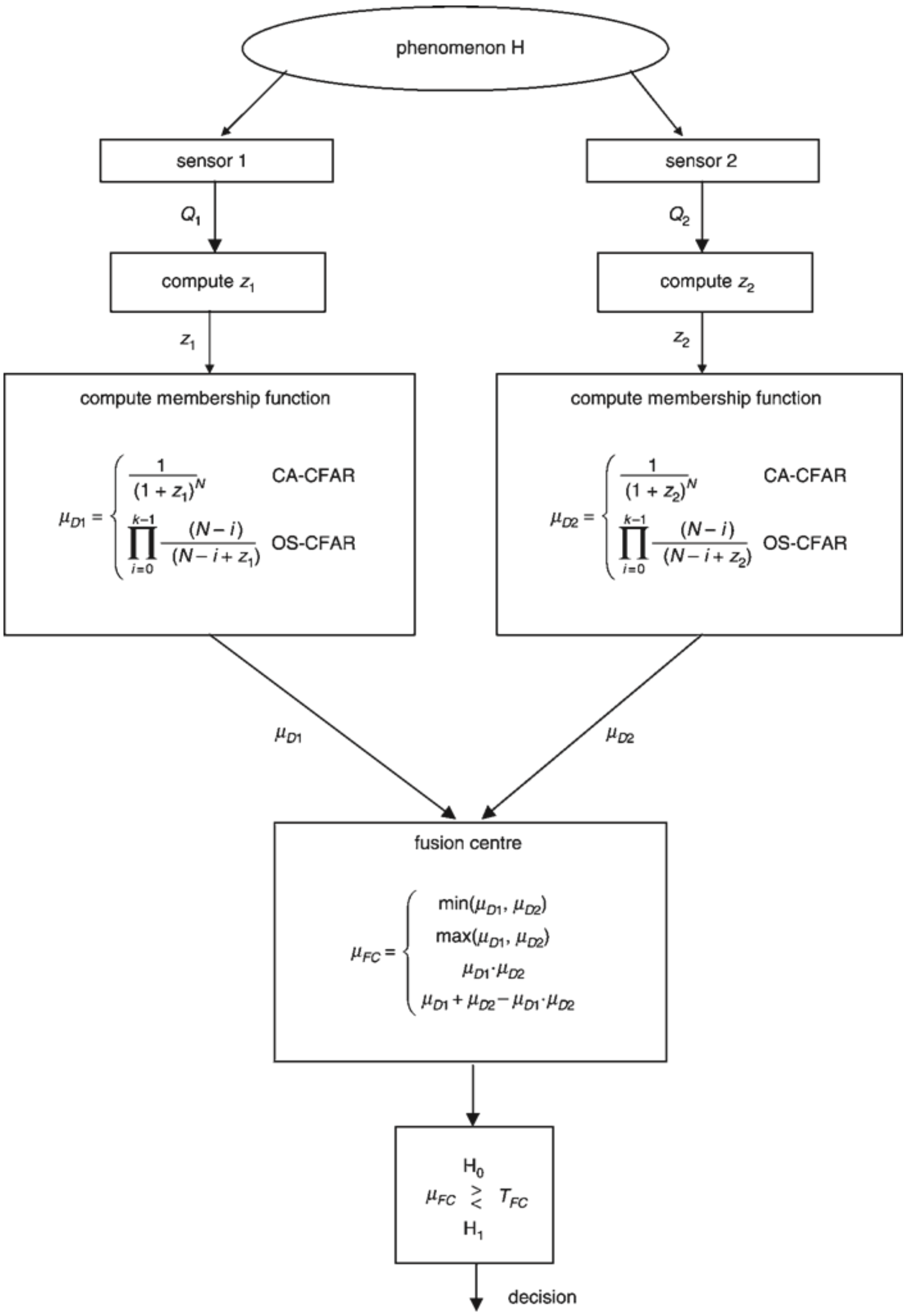


Figure3.5 Phenomena H

We shall show that the MAX fusion rule is equivalent to the binary AND. First, we recall that for identical local detectors and for the binary AND, the probability of false alarm at the fusion center is expressed in terms of the individual probabilities of false alarm of each detector$(Pfa)_L$ by

$$Pfa = (Pfa)_L^2 \Rightarrow (Pfa)_L = \sqrt{Pfa}$$

(3.35)

So, if the MAX fusion rule declares that there is a detection, this means that

$$max(\mu_{D1}\mu_{D2}) < \mu_{D1} \Leftrightarrow max(\mu_{D1}\mu_{D2}) < \sqrt{Pfa}$$

$$\Leftrightarrow \mu_{D1} < \sqrt{Pfa} \text{ and } \mu_{D2} < \sqrt{Pfa}$$

$$\Leftrightarrow \mu_{D} < (Pfa) \quad \text{and } \mu_{D2} < (Pfa)_L$$

From (3.30), we conclude that the binary AND fusion rule declares also that there is a detection.

- Intersection

$$\mu_{FC} = min(\mu_{D1}, \mu_{D2})$$

$$f_{uFC}(m) = f_{\mu D1}(m) \cdot \left(1 - F_{\mu D2}(m)\right) + F_{\mu D2}(m) \cdot \left(1 - F_{\mu D1}(m)\right) = 2 \cdot (1 - m)$$

$$\Longrightarrow Pfa = \int_0^{T_{FC}} 2(1 - m)dm = 1 - (1 - T_{FC})^2$$

$$\Longrightarrow T_{FC} = 1 - \sqrt{1 - Pfa}$$

(3.36)

As for the MAX fusion rule, we shall show that the MIN

Fusion rule is equivalent to the binary OR. In this case, the terms of the local probability of false alarm at the fusion center is expressed in terms of the local probabilities of false alarm as

$$Pfa = 2 \cdot (Pfa)_L - (Pfa)_L^2 \Rightarrow (Pfa)_L = 1 - \sqrt{1 - Pfa} \qquad (3.37)$$

If the MIN fusion rule declares that there is a detection, this means that

$$min(\mu_{D1,}\mu_{D2}) < T_{FC}$$

$$\Leftrightarrow min(\mu_{D1,}\mu_{D2}) < 1 - \sqrt{1 - Pfa}$$

$$\Leftrightarrow \mu_{D1} < 1 - \sqrt{1 - Pfa} \quad \text{or} \quad \mu_{D2} < 1 - \sqrt{1 - Pfa}$$

From (3.22), it follows that

$$\mu_{D1} < (Pfa)_L \ \text{ OR } \mu_{D2} < (Pfa)_L$$

Using (3.4), it is clear that the binary OR fusion rule declares

that there is a detection

- $Algebraic\ product$

$$\mu_{FC} = \mu_{D1} \cdot \mu_{D2}$$

we have

$$f_{\mu FC}(m) = \int_m^1 \frac{du}{u} = -\ln m$$

Integrating by parts, we findPfa to be

$$Pfa = \int_0^{T_{FC}} \ln(u) \cdot du = T_{FC}(1 - \ln(T_{FC})) \qquad (3.38)$$

- $Algebraic\ sum$

We have

$$\mu_{FC} = \mu_{D1} + \mu_{D2} - \mu_{D1} \cdot \mu_{D2}$$

Which can also be written as

$$\mu_{FC} = 1 - (1 - \mu_{D1})(1 - \mu_{D2})$$

Since μ_{D1} and $\mu_{D1}$are uniformly distributed on [0, 1], the random variables $(1 - \mu_{D1})$ and $(1 - \mu_{D2})$ are also uni- formally distributed on [0, 1]. From [3.6] and integrating by parts, we find

$$f_{\mu FC}(m) = -\ln(1 - m)$$

It follows that:

$$Pfa = -\int_{0}^{T_{FC}} \ln(1 - m) \cdot dm = T_{FC} + (1 - T_{FC}) \cdot \ln(1 - T_{FC})$$

(3.39)

3.7 Distributed CFAR (D-CFAR)

3.7.1 Introduction

Distributed CFAR (D-CFAR) is a signal processing algorithm used in radar systems to detect targets in the presence of clutter or interference. It is a type of CFAR algorithm that is designed to operate in a distributed network of sensors or receivers.

The D-CFAR algorithm works by dividing the range of the radar signal into cells, each containing a certain number of samples. The algorithm calculates the average power level of the samples within each cell and shares this information with neighboring sensors or receivers.

Each sensor or receiver then calculates the local threshold based on the average power level of the samples within its own cell and the average power levels of the neighboring cells. If the power level in a cell exceeds the local threshold, it is considered a potential target.

The key advantage of the D-CFAR algorithm is that it allows for distributed target detection and tracking in large-scale radar systems, where centralized processing may not be feasible or efficient. By sharing information and calculating thresholds locally, the algorithm is able to adapt to changes in the clutter level and maintain a constant false alarm rate over a wide range of clutter levels.

In summary, D-CFAR is a useful technique for detecting targets in cluttered environments in large-scale radar systems. Its ability to operate in a distributed network of sensors or receivers and maintain a constant false alarm rate over a wide range of clutter levels makes it a valuable tool for real-time target detection and tracking in complex scenarios.

3.7.2 Distributed CFAR (D-CFAR) with Data Fusion

Distributed CFAR (D-CFAR) with data fusion is an approach that combines the benefits of distributed target detection and collaborative decision-making. In this technique, the CFAR algorithm is implemented across multiple sensor nodes in a wireless sensor network, and the detection results from each node are fused to make a collective decision.

The process involves the following steps:

Local CFAR detection: Each sensor node independently performs CFAR processing on its local measurements to detect potential targets. The CFAR algorithm compares the power of the cell of interest with the average power of surrounding reference cells.

Local detection decision: Based on the CFAR processing, each sensor node makes a local detection decision, determining if the cell of interest contains a target or not.

- Data fusion: The local detection decisions from all the sensor nodes are shared and fused. Various fusion algorithms, such as majority voting, weighted averaging, or consensus-based methods, can be employed to combine the individual decisions.
- Global decision: The fused detection results are analyzed to make a global decision about the presence or absence of targets. This decision takes into account the collective information from multiple nodes and improves the overall detection accuracy.

By leveraging data fusion, D-CFAR with data fusion enhances the robustness and reliability of target detection. It enables collaboration among sensor nodes, allowing them to exchange information and collectively make more informed decisions. This approach is particularly valuable in scenarios where individual nodes may have limited sensing capabilities or face varying noise and clutter conditions.

Overall, Distributed CFAR with data fusion improves the performance of target detection in wireless sensor networks by combining the strengths of distributed processing and collaborative decision-making. [29]

3.7.3. Rule Fusion AND

Rule fusion, also known as decision fusion, is a technique used to combine multiple decision rules or classifiers to make a collective decision or prediction. It is widely used in various domains, including machine learning, pattern recognition, and decision-making systems, to improve accuracy, robustness, and overall performance.

The process of rule fusion involves the following steps:

Individual rule generation: Multiple decision rules or classifiers are independently developed using different algorithms, models, or feature sets. Each rule provides its own decision or prediction based on the input data.

Individual rule evaluation: The performance of each individual rule is assessed using appropriate evaluation metrics, such as accuracy, precision, recall, or F1 score. This evaluation helps determine the strengths and weaknesses of each rule.

Fusion strategy selection: A fusion strategy is chosen to combine the decisions or predictions from the individual rules. The fusion strategy can be based on majority voting, weighted averaging, Dempster-Shafer theory, Bayesian methods, or other fusion techniques. The choice of fusion strategy depends on the specific application and the characteristics of the individual rules.

Fusion of decisions: The decisions or predictions from the individual rules are combined using the selected fusion strategy. This fusion process aims to integrate the diverse information provided by the individual rules and generate a final decision or prediction.

Final decision or prediction: The fused decision or prediction is obtained as the output of the rule fusion process. It represents the collective decision that benefits from the combined knowledge of the individual rules, leading to improved accuracy and robustness.

3.7.4. Rule Fusion OR

Rule fusion, also known as decision fusion, is a technique used to combine multiple decision rules or classifiers to make a collective decision or prediction. It aims to leverage the strengths of different individual rules or classifiers and improve overall system performance, accuracy, and robustness.

The process of rule fusion involves the following steps:

- Individual rule generation: Multiple decision rules or classifiers are independently created using different algorithms, models, or feature sets. Each rule provides its own decision or prediction based on the input data.
- Individual rule evaluation: The performance of each individual rule is evaluated using appropriate metrics such as accuracy, precision, recall, or F1 score. This evaluation helps assess the quality and effectiveness of each rule.
- Fusion strategy selection: A fusion strategy is chosen to combine the decisions or predictions from the individual rules. The fusion strategy can vary based on the specific application and can include approaches such as majority voting, weighted averaging, Dumpster-Shafer theory, Bayesian methods, or other fusion techniques.
- Fusion of decisions: The decisions or predictions from the individual rules are combined using the selected fusion strategy. The fusion process aims to aggregate the outputs of the individual rules and generate a final decision or prediction that benefits from the collective knowledge and diversity of the rules.
- Final decision or prediction: The fused decision or prediction is obtained as the output of the rule fusion process. This decision represents the combined consensus or integration of the individual rule outputs and can lead to improved accuracy, robustness, and generalization. [30]

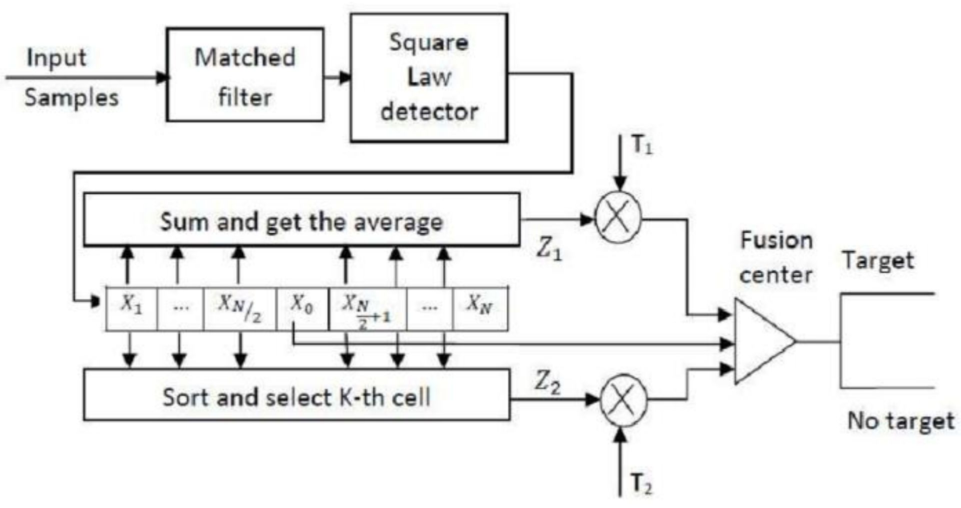


Figure3.7 The Bloc Diagram of the OR-CFAR and AND-CFAR Detectors

3.8 CFAR LOSS

CFAR loss, or Constant False Alarm Rate loss, is a loss function used in machine learning models for object detection in images or videos. It is based on the principle of CFAR algorithms used in radar systems, which aim to maintain a constant false alarm rate over a wide range of clutter levels.

The CFAR loss function works by dividing the input image or video into a grid of cells, each containing a certain number of pixels or frames. The algorithm then calculates the average confidence score of the pixels or frames within each cell and applies a threshold to this score.

If the confidence score of a pixel or frame exceeds the threshold, it is considered a potential object or target. The algorithm then applies non-maximum suppression (NMS) to eliminate duplicate detections and refine the bounding boxes of the objects.

The CFAR loss function is designed to balance the trade-off between detection accuracy and false alarm rate. It penalizes false positives and encourages the model to focus on detecting objects in the presence of clutter or noise.

In summary, CFAR loss is a useful loss function for object detection in images or videos, which takes inspiration from CFAR algorithms used in radar systems. Its ability to maintain a constant false alarm rate over a wide range of clutter levels makes it a valuable tool for real-time object detection and tracking in complex scenarios.

3.9 THE MONTE CARLO METHOD

The Monte Carlo method is a computational technique that uses random sampling to solve problems in various fields, such as physics, engineering, finance, and computer science. The method involves generating a large number of random samples from a probability distribution to estimate the numerical value of an unknown quantity or to simulate complex systems.

The Monte Carlo method is particularly useful for problems that involve multiple variables or complex systems where analytical solutions are difficult or impossible to obtain. The method can provide accurate estimates of the unknown quantity with high confidence levels, given enough random samples.

The Monte Carlo method has found numerous applications in diverse fields, such as:

- Physics: Monte Carlo simulations are used to study the behavior of physical systems at the atomic and subatomic level, such as particle collisions and quantum mechanical systems.
- Engineering: Monte Carlo simulations are used for reliability and risk analysis in engineering systems, such as structural design and safety assessments of nuclear power plants.
- Finance: Monte Carlo simulations are used for option pricing, risk management, and portfolio optimization in finance.
- Computer Science: Monte Carlo methods are used for algorithmic analysis, optimization, and machine learning.

The Monte Carlo method was first introduced by Stanislaw Ulam and John von Neumann in the 1940s, and its name originates from the famous casino in Monaco. The method has since become an essential tool in various fields, and its applications continue to expand. [31]

CONCLUSION

The CA-OS CFAR algorithm combines the advantages of the Cell Averaging (CA) and Order Statistics (OS) approaches to achieve robust target detection in various noise environments. By estimating the local background level through the CA technique and utilizing the statistical properties of the surrounding cells with the OS method, the CA-OS CFAR provides reliable target detection while adapting to changing clutter and noise conditions

In conclusion, the analysis of CA-OS CFAR detectors, guided by a professor, offers valuable insights into radar signal processing, enhancing target detection by mitigating false alarms and adapting to changing clutter and noise conditions.

CHAPITRE 4

Simulation and interpretation

4.1 INTRODUCTION

In this thesis, multiple scenarios are analyzed using the concept of using fuzzy spaces to adaptive threshold based detectors, namely CA-CFAR and OS-CFAR detectors. We consider a distributed system in which the local sensors do not produce a binary decision but a value (between 0 and 1) of the membership to the false alarm space. We analyze the fuzzy CA-CFAR and OS-CFAR .We examine a two-sensor network with the fuzzy **AND** and fuzzy OR fusion rules for different operators, and we derive the thresholds corresponding to the desired probability of false alarm for each case. In our simulation, we will be presenting the variation of the probability of detection for the CA-CFAR and OS-CFAR detectors as a function of the SNR by varying the number of N cells. These representations are made for the two CFAR types studied in the previous chapter CA and OS–CFAR. The simulation results are presented for homogeneous and non-homogeneous backgrounds. [32]

The detection probabilities are simulated from Monte Carlo trials using Matlab tools.

We are using the following hypothesis:

K = (3/4)×N.

The noise variance is normalized to 1.

SNR signal to noise Ratio : 0 : 2.5 : 30 dB.

N represents the reference window size .

Pfa defined the probability of false alarm fixed to 10-4.

T is the threshold and is derived from probabilities of false alarm expression of each detector:

N	T CACFAR	T OSCFAR
16	0.778	11
24	0.467	9.3

Table 4.1 Values of T with different N.

4.2 BINARY DECISION CA AND OS CFAR SIMULATION

4.2.1 The case of homogeneous environment

In this case we will be studying the performance of a CA CFAR detector assuming the number of reference cells to be 16 and 24 and pfa=10^-4.

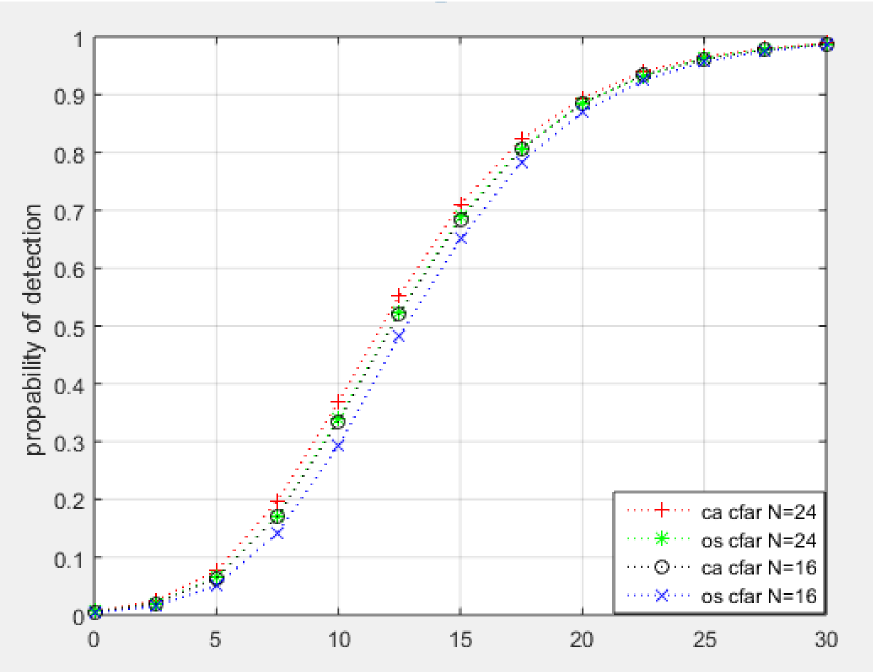


Figure 4.1 the probability of detection of the two detectors CA and OS CFAR plotting SNR in an homogeneous background where pfa=10^-4.

Interpretation of figure 4.1

In the previous figure algorithms have been developed for calculating detection probabilities and plotting SNR function of the two techniques used (CA and OS-CFAR). the simulation was carried out for a probability of false alarm pfa=10−4 and a number of reference cells N= 16 and 24. we note that the detectors of CA and OS CFAR give probabilities of detection closer and the more we increase the number of cell references the higher probability of detection gets.

4.2.2 The case of non-homogeneous environment

In this case the detection is difficult because there are interfering targets we did the simulation to see which is the capable detector that gives us greater detection in this environment. And the results are shown in the following figures.

In (N,k) configuration related to OSCFAR algorithm the number of interference targets must not exceed N-k in other words the OSCFAR algorithm maintains its robustness as long as the number of interferences is close to or equal to N-k

For the number of cells N=16,pfa =10^-4 and changing the number of the interference targets between 1 and 3 the results are shown in the next figures .

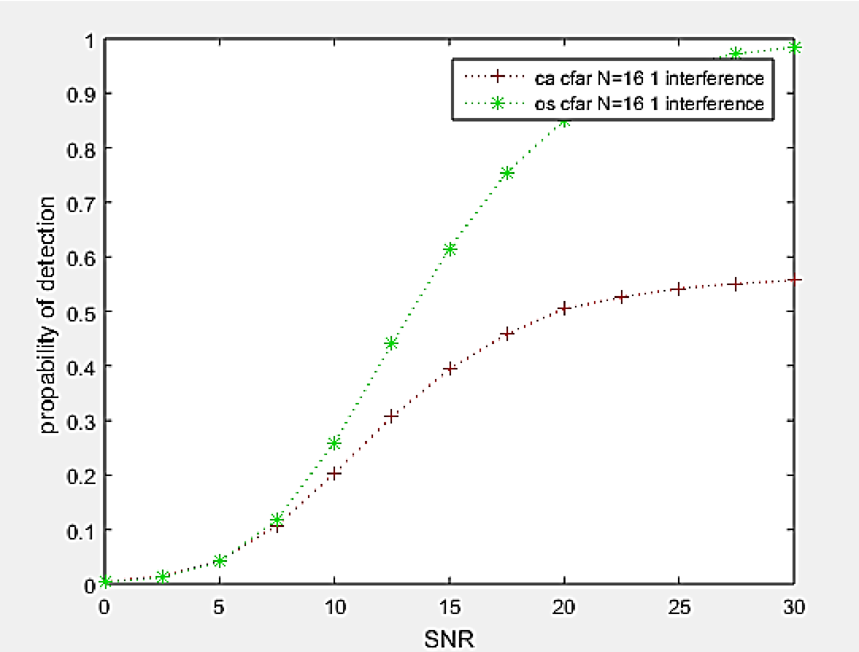


Figure 4.2: the probability of detection of the two detectors CA CFAR and OS CFAR plotting SNR in non-homogeneous background with one interfering target at the cell [8].

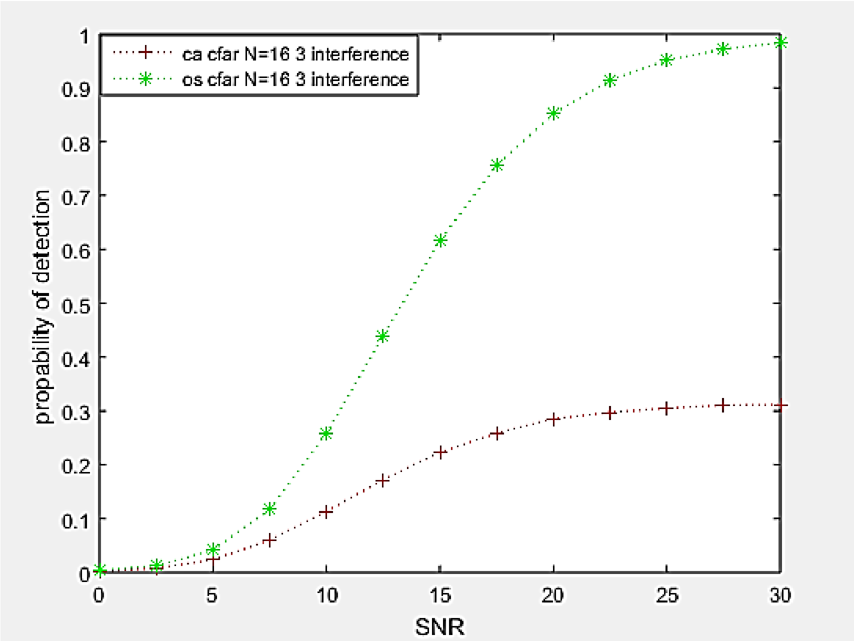


Figure 4.3 The probability of detection of the two detectors CA CFAR and OS CFAR plotting SNR in non-homogeneous background with three interfering targets at the cells [8, 10, 23].

Interpretation of figures 4.2 and 4.3

We have on the graphs of figures 4.2 and 4.3, the representations of the probabilities of detection as a function of the SNR ratio for a false alarm probability (Pfa = 10−4) and N=16.the results shows a decrease in the CA-CFAR and OS-CFAR curve. Which is due to the interfering targets.

As the number of interfering targets increases, the probability of detection decreases, and each time we notice that the CA curve decreases considerably.

Next simulation we assume the number of cells N=24,pfa =10^-4 and changing the number of the interference targets between 2 and 4 the results are shown in the following figures .

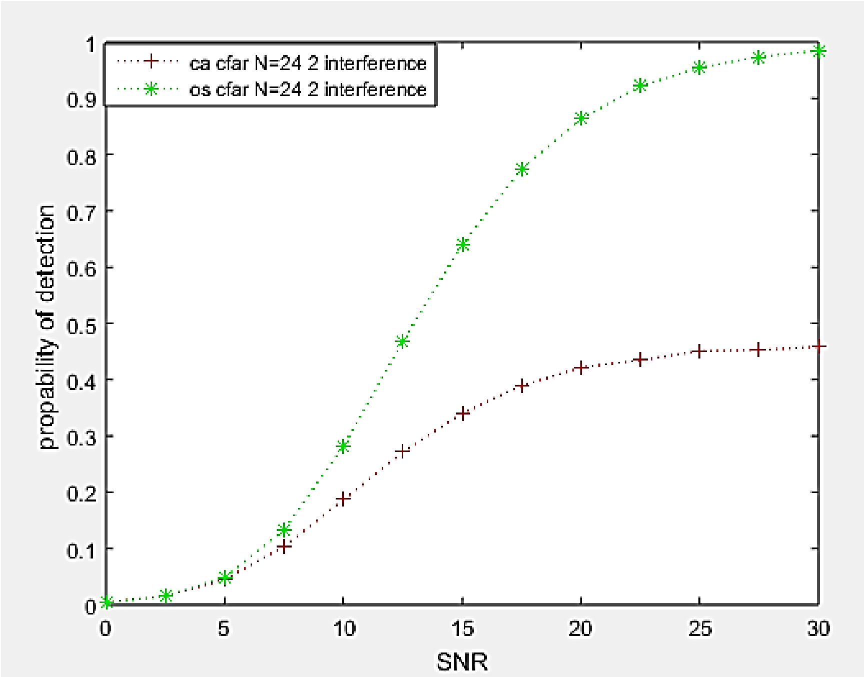


Figure 4.4 the probability of detection of the two detectors CA and OS CFAR plotting SNR in non-homogeneous background N=24 with two interfering targets in the cells [1,17].

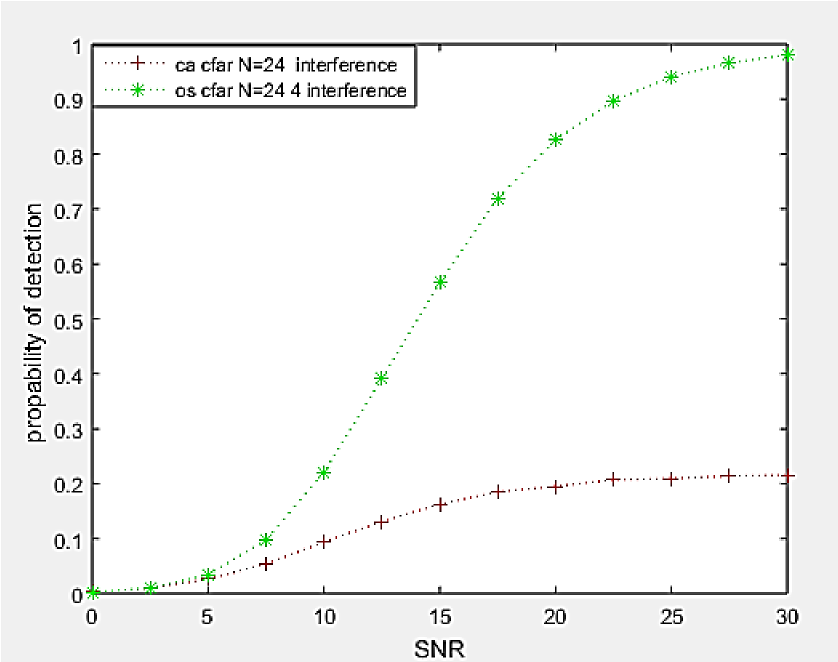


Figure 4.5 the probability of detection of the two detectors CA and OS CFAR plotting SNR in non-homogeneous background N=24 with 4 interfering targets in the cells[5,9,16,21].

Interpretation of figure 4.4 and 4.5

We have on the graphs of figures 4.4 and 4.5, the representations of the probabilities of detection as a function of the SNR ratio for a false alarm probability (Pfa = 10−4) and N=24. It is easily noted from the results that the higher the number of cells, the greater the probability of detection gets, and if the number of interfering targets is less, the probability of detection is greater big and vice versa the more we add the interferences the more the probability of detection gets. In these examples, the number of reference cells is large and we be adding interference targets. It is noted that the probability of detection of CA-CFAR has been reduced.

For (N,k) configuration the number N=16 avec 4 interferences et N=24 avec 6 interference

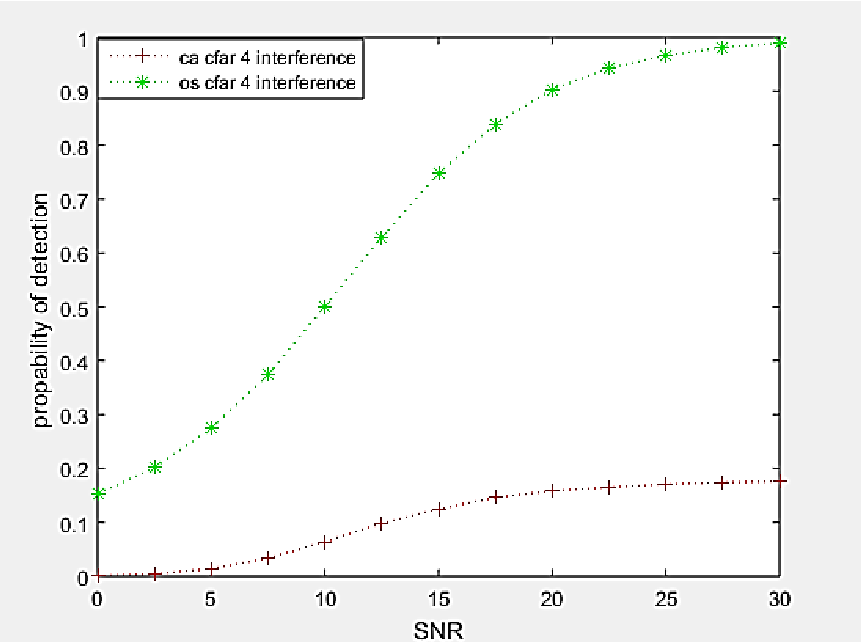


Figure 4.6 the probability of detection of the two detectors CA and OS CFAR plotting SNR in non-homogeneous background N=16 with 4 interfering targets in the cells [8, 10,21,23].

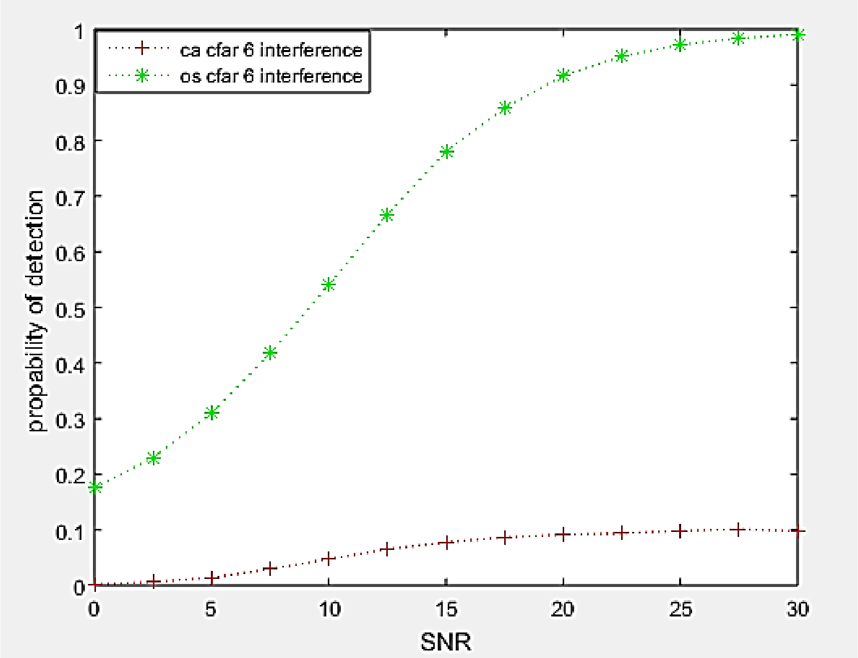


Figure 4.7 The probability of detection of the two detectors CA and OS CFAR plotting SNR in non-homogeneous background N=24 with 6 interfering targets in the cells [1,8,10,17,21,23].

In the last 2 figures we experienced the worst case when we put the maximum number of interferences for N=16 we added 4 interference and N=24 we put 6 interferences and from all the simulation we have done we conclude that the algorithm CA-CFAR gives the best performance in a homogeneous environment, the detector CA CFAR was observed to be growing faster than the algorithm OS CFAR. So both of them detectors give us good detection. Remarkably, in the presence of interference, OS CFAR is still better than CA CFAR that lose its performances in a non-homogeneous environment. The probability of detection depends on the number of the cell of references and the number of the interfering targets in the case of the non-homogeneous background.

4.3 DISTRIBUTED CA-CFAR DETECTION USING FUZZY FUSION RULES

To illustrate the performance of the distributed CACFAR and OS-CFAR detection using fuzzy spaces and fuzzy fusion rules in homogeneous and non-homogeneous backgrounds. We simulated the probability of detection. we assume that pfa=10^-4 and changing the number of the cells of reference between 16 and 24 we got the following results in both homogeneous and non-homogeneous backgrounds.

4.3.1 The case of homogeneous background

We will now study the performance of CA CFAR detector by simulating the probability of detection for the case of a two-sensor network. we assume that N=16 in the first one and N=24 for the second and pfa=10^-4 for both simulations.

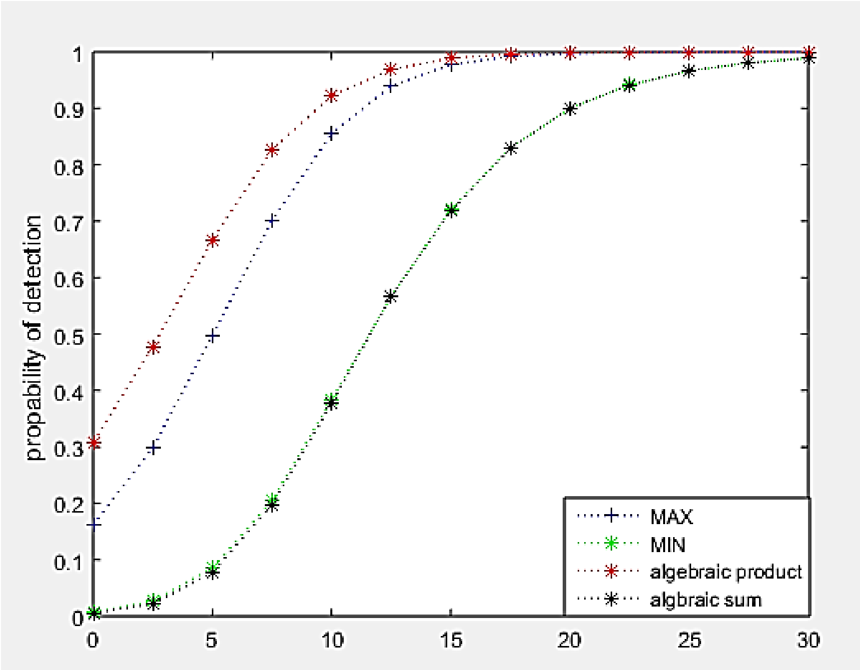


Figure4.8 Distributed CA-CFAR for two sensors with MIN, MAX, Algebraic sum and algebraic product fusion rules in homogeneous background N=16.

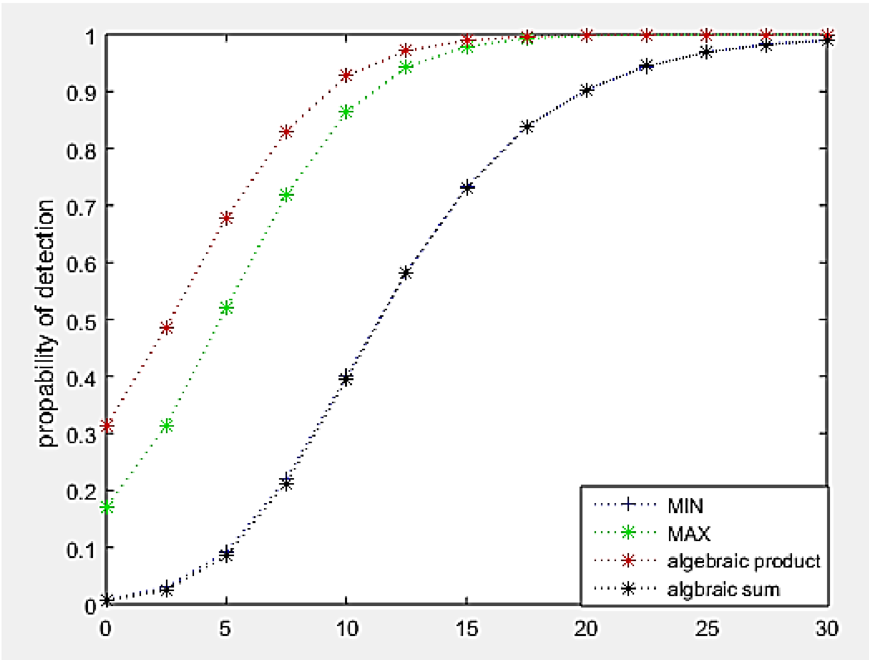


Figure4.9 Distributed CA-CFAR for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in homogeneous background N=24.

Interpretation of figure 4.8 and 4.9

By comparing the performances of the four fusion rules considered for the CA-CFAR detector and a homogeneous background. This comparison demonstrates the superiority of the algebraic product fusion rule over all the others. And by taking the length of the cells of reference as a variable parameter and fixing the probability of false alarm, according to the simulation results it is interesting to note that in order to ensure a high probability of detection use a higher length of the cells of reference.

4.3.2 The case of non-homogeneous background

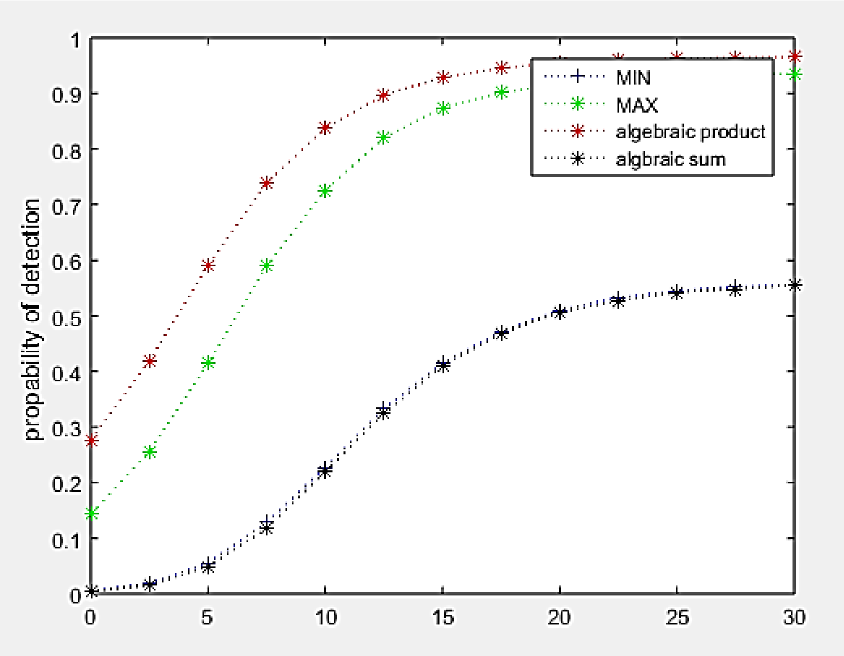


Figure4.10 Distributed CA-CFAR for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in non-homogeneous background N=16 with 1 interfering target in detector 1 and 2.

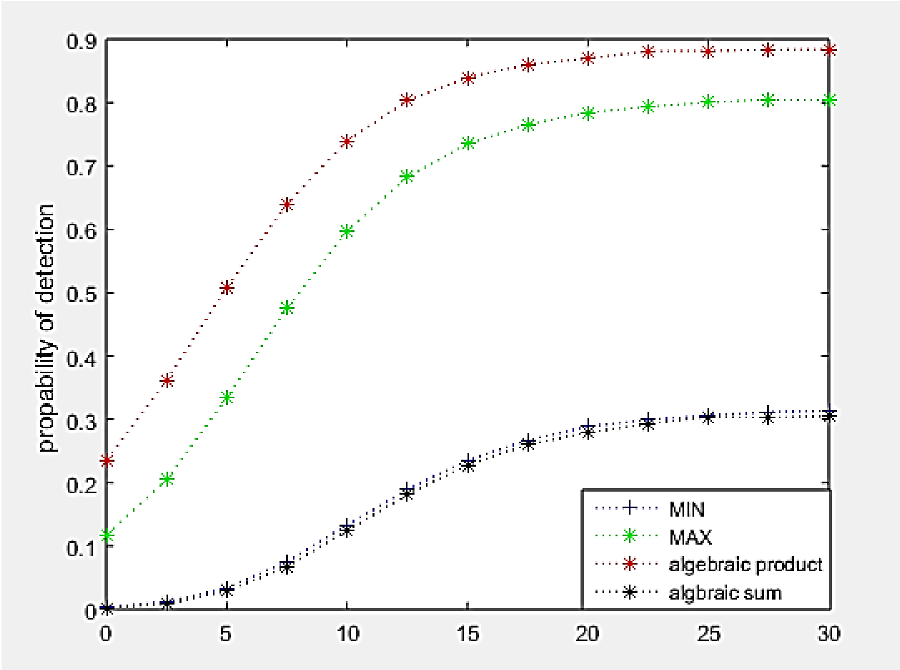


Figure4.11 Distributed CA-CFAR for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in non-homogeneous background N=16 with 2 interfering targets in detector 1 and 2 interfering targets in detector 2.

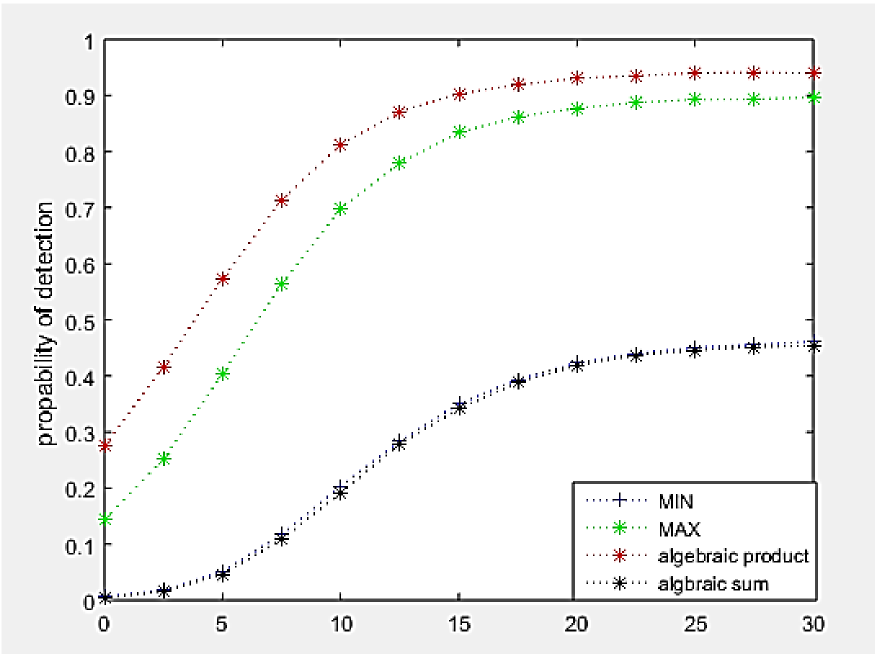


Figure4.12 Distributed CA-CFAR for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in non-homogeneous background N=24 with 2 interfering targets in detector 1 and 2 interfering targets in detector 2.

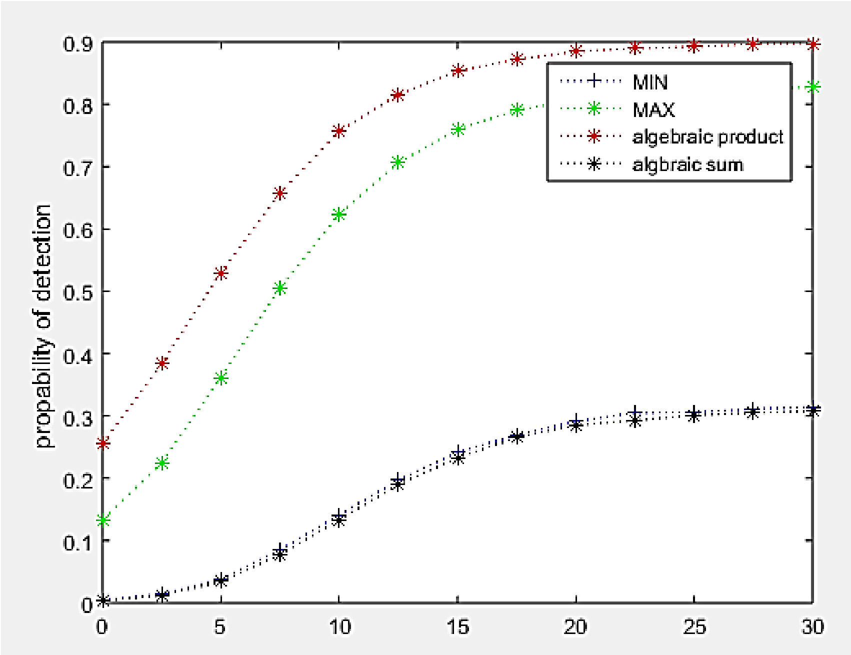


Figure4.13 Distributed CA-CFAR for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in non-homogeneous background N=24 with 2 interfering targets in detector 1 and 4 interfering targets in detector 2.

Interpretation of figures 4.10, 4.11, 4.12 and 4.13

In this case we illustrate the performance of the CA CFAR in non-homogeneous background and by changing the length of the cells of reference between 16 and 24 and adding more interfering targets each simulation to get the following results that shows that the probability of detection is seriously degraded for all the fuzzy fusion rules (MIN, MAX, algebraic sum and algebraic product). This is due to the mismatch of the environment.

4.4 DISTRIBUTED OS-CFAR DETECTION USING FUZZY FUSION RULES

4.4.1 The case of homogeneous background

We plot the probability of detection of the distributed OS-CFAR against the signal-to-noise ratio (SNR) for a homogeneous and non-homogeneous background .by taking N=16 and N=24 and pfa of 10^-4.

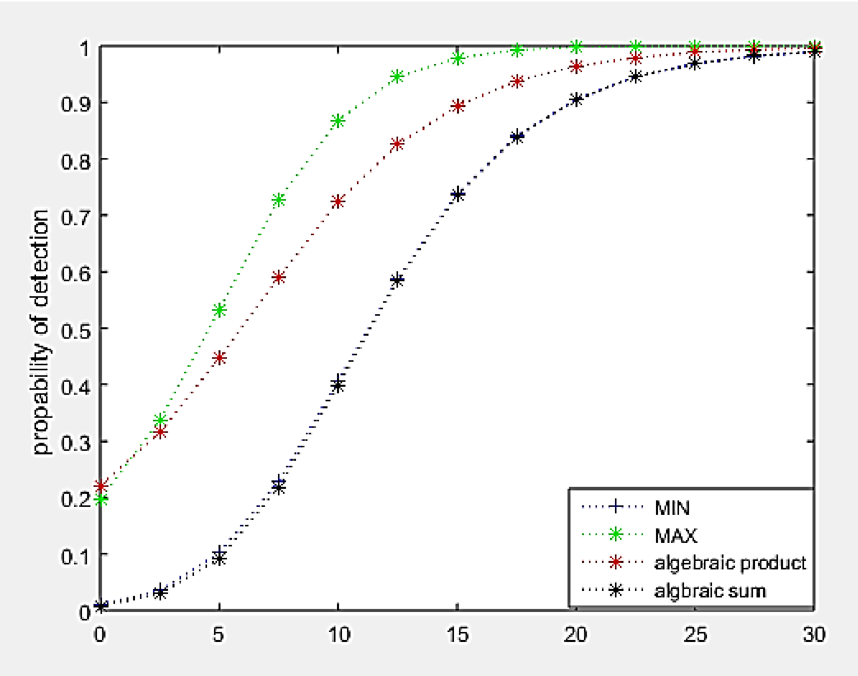


Figure4.14 Distributed OS-CFAR for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in homogeneous background N=16.

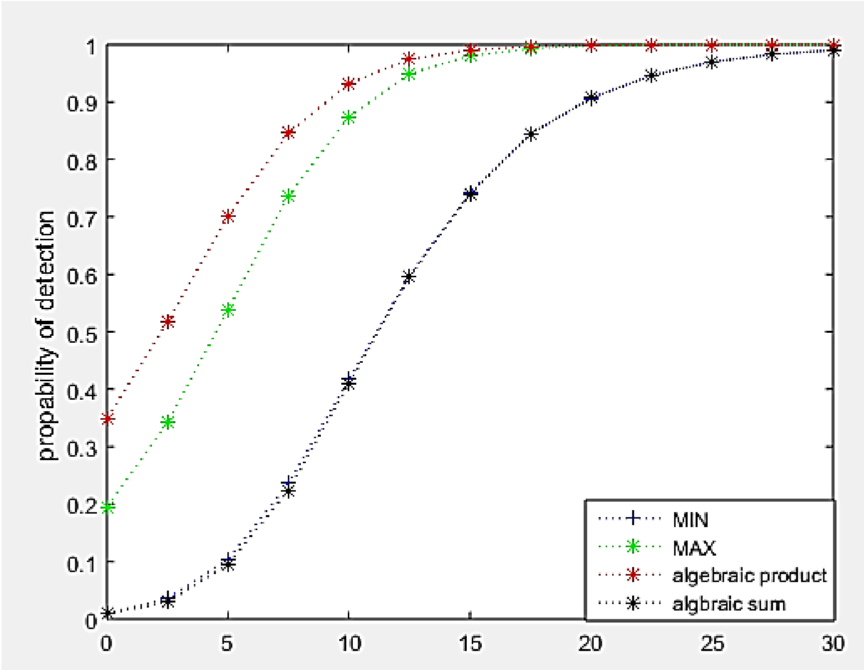


Figure4.15: Distributed OS-CFAR for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in homogeneous background N=24.

Interpretation 4.14 and 4.15

These last two simulation results show the performance of the distributed system where the local detectors are OS CFAR detectors in a homogeneous background. And as an observation it is the same as the one of the CA CFAR simulation results.

4.4.2 The case of non-homogeneous background

In the next simulation we will be testing the fusion rules of OS CFAR with two detectors in the non-homogeneous background to see the effect of interfering targets on its performances.

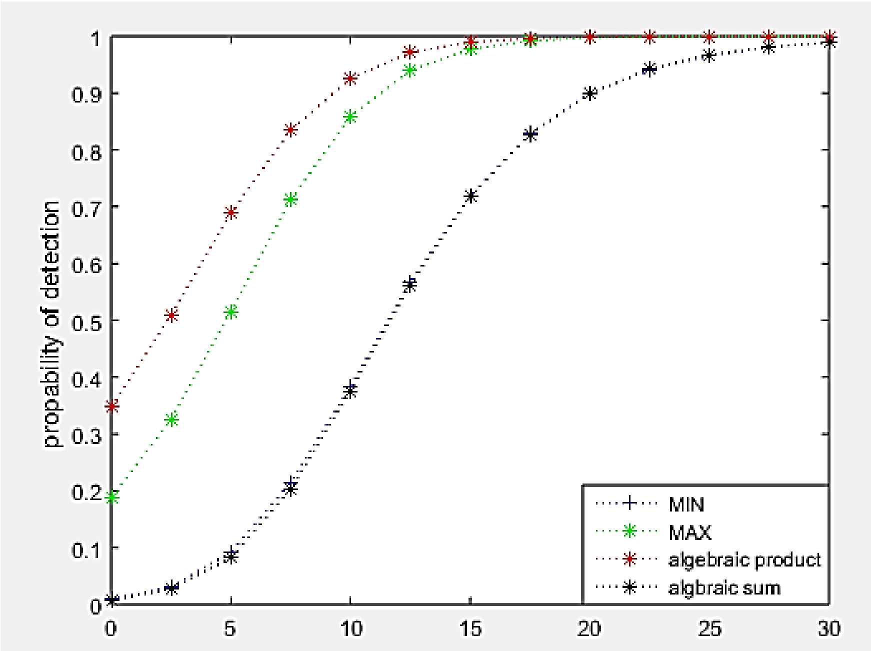


Figure4.16 Distributed OS-CFAR for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in non-homogeneous background N=16 with 1 interfering targets in detector 1 and 2.

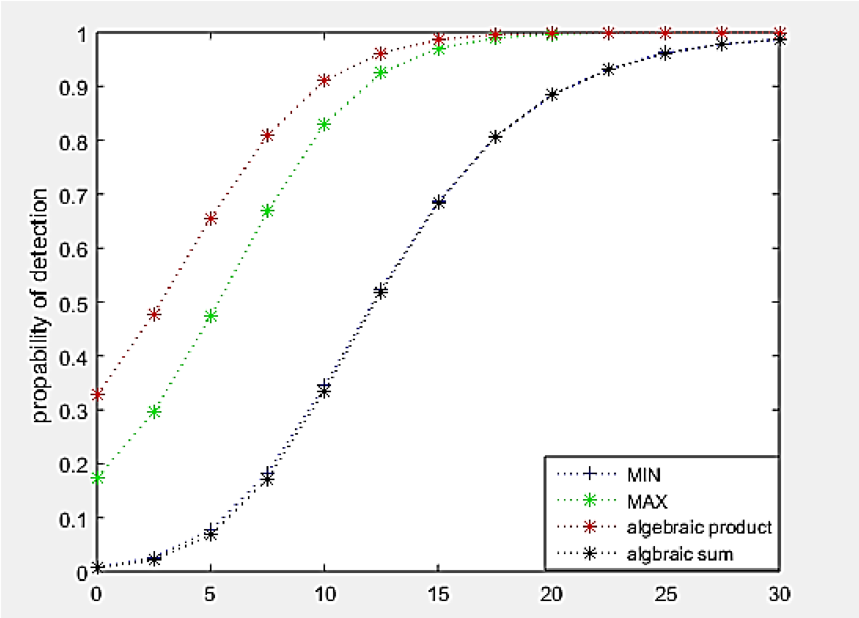


Figure4.17 Distributed OS-CFAR algorithm for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in non-homogeneous background N=16 with 2 interfering targets in detector 1 and 2 interfering targets in detector 2.

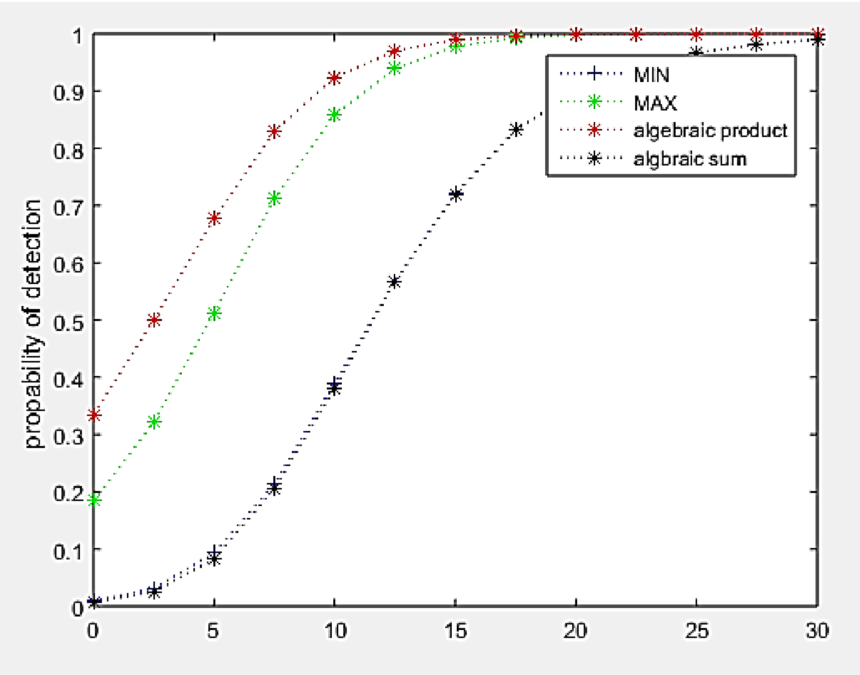


Figure4.18 Distributed OS-CFAR algorithm for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in non-homogeneous background N=24 with 2 interfering targets in detector 1 and 2.

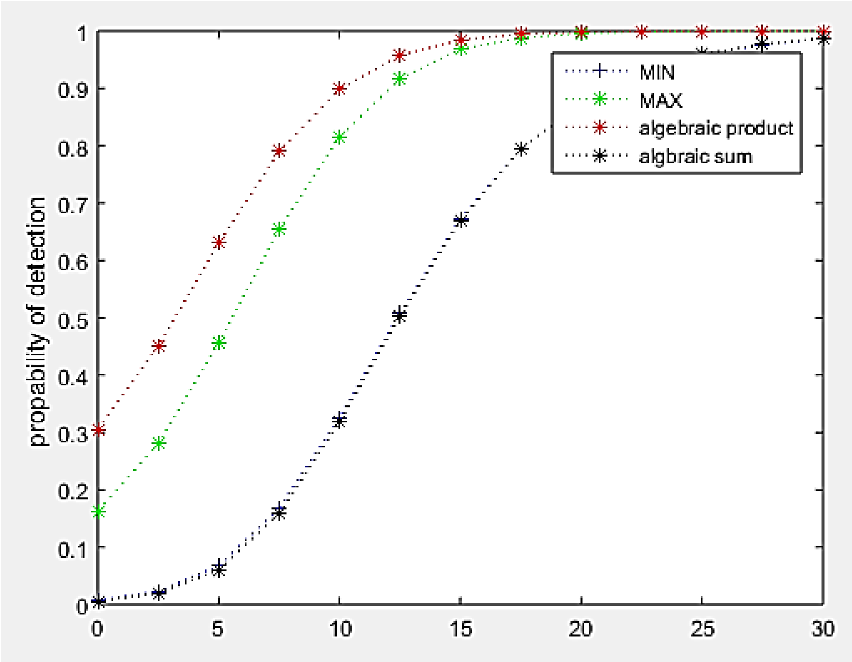


Figure4.19 Distributed OS-CFAR algorithm for two sensors with MIN, MAX, algebraic sum and algebraic product fusion rules in non-homogeneous background N=24 with 3interfering targets in detector 1 and 3 interfering targets in detector 2.

Interpretation of figures 4.16, 4.17, 4.18 and 4.19:

From the performance curves, it is very clear to notice again that the algebraic product operator gives the highest probability of detection with a small degradation by adding more and more interfering targets each simulation and it is helping when putting some length for the reference cells to higher the probability of detection.

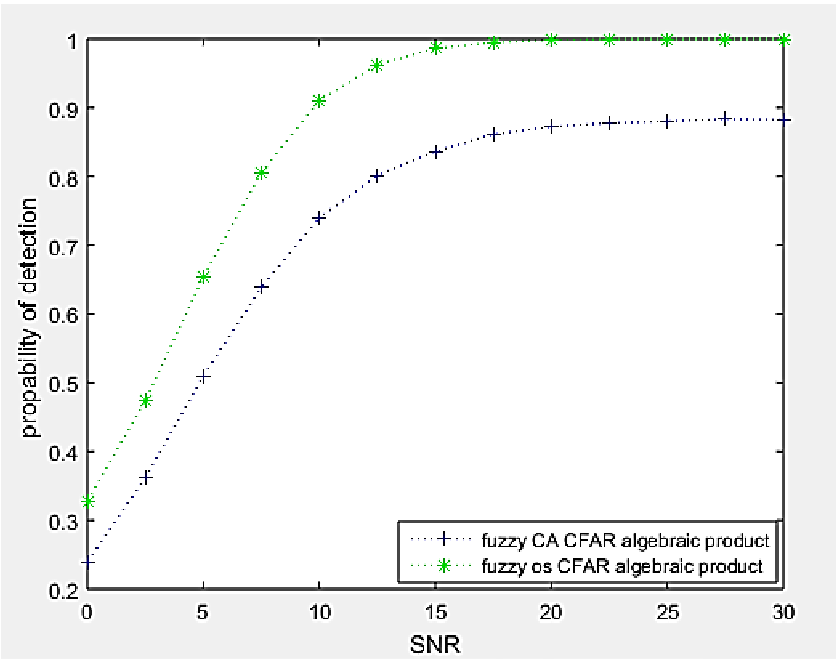


Figure 4.20 Distributed CA CFAR and OS CFAR algorithms for two sensors with algebraic product fusion rules in non-homogeneous background N=16 with 2 interfering targets in detector 1 and 2 interfering targets in detector 2.

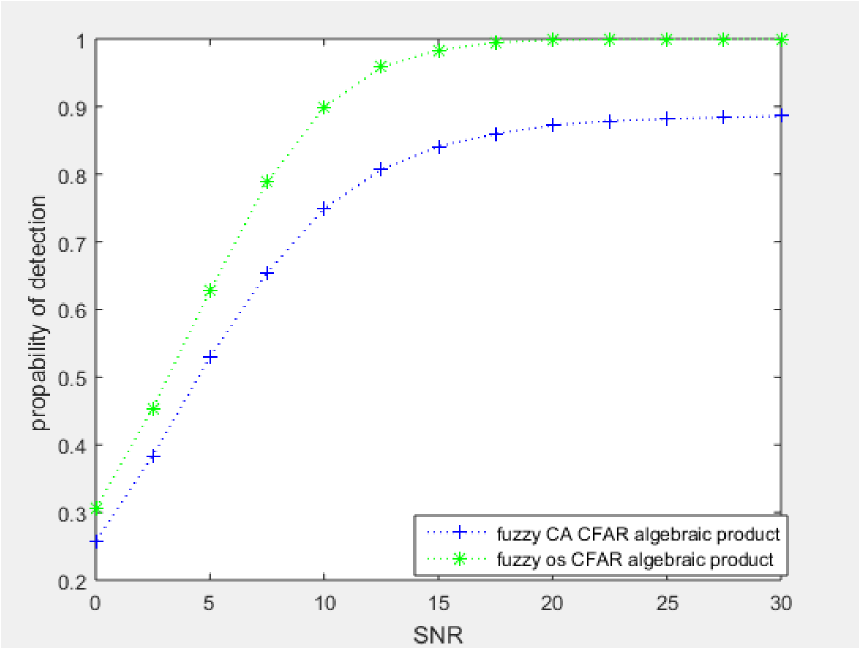


Figure 4.21 Distributed CA CFAR and OS CFAR algorithms for two sensors with algebraic product fusion rules in non-homogeneous background N=24 with 3 interfering targets in detector 1 and 3 interfering targets in detector 2.

Interpretation of Figures 4.20 and 4.21

Just like we notice earlier from comparing the results that the algebraic product gives the best performances for both algorithms but still the OS CFAR algorithm more efficient than the CA CFAR algorithm in the non-homogeneous background.

CONCLUSION

In this simulation we have extended the concept of radar CFAR detection by fuzzy logic to adaptive threshold detectors. We have provided a detailed derivation of the probability of false alarm as well as its corresponding threshold at the fusion center for different fuzzy fusion rules we come to conclude that in multiple-target situations, the algebraic product fusion rule is more robust than the others. And each detector loses some of its ability of detection in the non-homogeneous background no matter which detector and the kind of detection we use.

GENARAL

CONCLUSION

GENARAL CONCLUSION

CFAR (Constant False Alarm Rate) and OS CFAR (Order Statistic CFAR) detectors, using fuzzy logic, have demonstrated robust performance in the homogeneous background. By exploiting the flexibility of fuzzy logic, these detectors are able to adapt to variations in noise and dynamically adjust their detection thresholds.

In homogeneous environments, these detectors allow precise detection of targets while maintaining a constant false alarm rate. They are able to model uncertainty and adjust for environmental conditions, which improves their robustness and ability to distinguish target signals from random variations in noise.

In non-homogeneous background, the OS CFAR detectors also can perform well. Fuzzy logic allows it to adapt to background changes, account for spatial and temporal noise variations, and detect targets even in complex environments.

The use of fuzzy logic in these detectors makes it possible to optimize the detection performance by taking into account the uncertainty and ambiguity present in the radar data. It offers a flexible approach for modeling imperfect knowledge and allows detection thresholds to be adjusted adaptively based on target characteristics and environmental conditions.

CA CFAR and OS CFAR detectors using fuzzy logic provide reliable and robust performance in homogeneous environment, OS CFAR seems to perform better than CA CFAR in terms of target detection in non-homogeneous environment this detector is able to adapt to variations in noise and other interfering targets.

Their ability to adapt to variations in noise and model uncertainty makes them valuable for target detection in complex environments. Fuzzy logic thus offers a powerful approach to improve detection performance and reduce false alarms, contributing to more efficient and reliable detection systems.

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