PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA

MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH

UNIVERSITY OF SAAD DAHLEB BLIDA 1

INSTITUTE OF AERONAUTICS AND SPACE STUDIES

AIR NAVIGATION DEPARTMENT

FINAL DISSERTATION

Submitted to obtain the degree of

ACADEMIC MASTER

Option: CNS/ATM

THEME

Parallel Distributed Adaptive Order Statistics CFAR-Detector with Data Fusion Based PSO for Threshold Optimization

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YEAR 2024

ACKNOWLEDGMENT

First of all, we wish to express our thanks to the Almighty God who granted us

the strength and courage to successfully complete this modest work.

Our sincere thanks and deep gratitude go to our supervisor,

Ms. **DOUDOU FATMA ZAHRA**, for her invaluable assistance and for proposing this topic to us.

We are grateful to her for her insightful advice, good humour, and daily support which

greatly contributed to the progress of our work.

We also extend our respectful thanks to the members of the jury who agreed to evaluate our work.

DEDICATION 1

I wish to express my infinite gratitude to, my parents,

who have always supported me

with love and patience, and who have given me the strength to pursue my dreams.

Your wisdom and encouragement have been precious guides throughout my journey.

To my brothers, my two sisters, and to all my family,

To my friends, colleagues, and everyone who has helped me along this journey,

To my supervisor, Ms. **DOUDOU FATMA ZAHRA**, and to my partner,

Rezki Amine Boureghdad, and his family

AYOUB.

DEDICATION 2

I dedicate the fruit of my labor,

To my mother who has always supported and encouraged me throughout the journey of my studies;

her valuable advice and paternal guidance have greatly helped me overcome numerous obstacles.

To my father who has consistently shown unwavering support towards me.

To my dear brothers and my only sister.

To my friends whom I love and whose friendship I will cherish for a long time.

To my supervisor, Ms. **DOUDOU FATMA ZAHRA**, and to my partner,

ZAOUI AYOUB, and his family.

Finally, our thanks go to the students of our promotion.

AMINE.

Abstract :

In this master thesis, target detection in a non-homogeneous environment is studied, when the receiver uses multi-sensor data fusion with detection threshold optimization based on the PSO metaheuristic algorithm. The aim of this thesis is to improve the performance of the detection process in an inhomogeneous environment. The scheme used is based on the optimisation of the detection threshold in a parallel multi-sensor data fusion. The distributed systems used here are based on the OS-CFAR (ordered statistics constant false alarm rate) and CMLD (censored mean level detector) adaptive detectors. For detection threshold optimisation, the PSO (Particulate Swarm Optimization) algorithm with a linearly decreasing strategy is applied where the multi-sensor detection threshold is determined by maximising the global detection probability while keeping the global false alarm probability constant, employing two logical fusion rules for detection improvement in an non-homogeneous environment.

Keywords: Radar- parallel data fusion - order statistics detectors- PSO optimization

Résumé

Dans le cadre de cette thèse de master, la detection de cible dans un environnement non homogene est etudiée, quand le récepteur utilise une fusion de données multi-capteurs avec une optimization du seuil de detection basé sur l »algorithme methaheuristique PSO. . Le but recherché dans cette thèse, est d'améliorer les performances du processus de detection dans un environnement non homogene, le schéma utilisé est basé sur l'optimisation du seuil de détection dans une fusion de données multi-capteurs parallels. Les systèmes distribués utilisés ici sont à base des détecteurs adaptatifs OS-CFAR (ordered statistics constant false alarm rate) et CMLD (Censored mean level detector). Pour l'optimisation du seuil de detection, l'algorithme PSO (Particule Swarm Optimization) avec une stratégie linéairement décroissante est appliquée où le seuil de detection des multi capteurs est determiné en maximisant la probabilité de detection globale tout en maintenant la probabilité de fausse alarme globale constante, en employant deux règles de fusion logiques pour l'amélioration de la detection dans un environnement non homogene.

Mots clés : Radar- parallel data fusion – order statistics detectors- PSO optimization

ملخص

في رسالة الماستر هذه، تتم دراسة الكشف عن الهدف في بيئة غير متجانسة، عندما يستخدم جهاز الاستقبال دمج بيانات متعددة الهدف من هذه الأطروحة هو تحسين أداء .PSOأجهزة الاستشعار مع تحسين عتبة الكشف على أساس خوارزمية ميتاهوريست عملية الكشف في بيئة غير متجانسة. يعتمد المخطط المستخدم على تحسين عتبة الكشف في دمج بيانات متعددة أجهزة الاستشعار (معدل الإنذار الكاذب الثابت للإحصائيات OS-CFARالمتوازية. تستند الأنظمة الموزعة المستخدمة هنا إلى كاشفات التكيف PSO(كاشف المستوى المتوسط الخاضع للرقابة). من أجل تحسين عتبة الكشف، يتم تطبيق خوارزمية CMLDالمرتبة) و (تحسين سرب الجسيمات) مع استراتيجية تناقصية خطية حيث يتم تحديد عتبة الكشف متعدد أجهزة الاستشعار من خلال تعظيم احتمال الكشف العالمي مع الحفاظ على احتمال الإنذار الكاذب العالمي ثابتًا، باستخدام قاعدتي دمج منطقيتين لتحسين الكشف في بيئة غير متجانسة.

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LIST OF ABBREVEATIONS

RADAR The remote detection and localization of an object.

CFAR Constant False Alarm Rate

CA-CFAR CFAR average cell.

OS-CFAR CFAR statistical order.

Pdf Probability density function. .

P_d Probability of detection.

P_{fa} Probability of false alarm.

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

σ Noise Level

R1 Distance Antenna target

PSO Particle Swarm Optimization

T_{OS} OS-CFAR Scaling Factor

T_{CMLD} CMLDk-CFAR Scaling Factor

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GENERAL INTRODUCTON

Radar systems are crucial for detecting and tracking targets in various environments, whether homogeneous or non-homogeneous. Achieving high detection performance while maintaining a constant false alarm rate (CFAR) is a primary goal in radar signal processing. Traditional CFAR detectors often face challenges in non-homogeneous environments due to variations in noise and clutter levels. This necessitates the development of optimized CFAR techniques that can adapt to changing conditions while ensuring reliable target detection.

In the first chapter, we introduce the fundamental parameters and components of a radar system, including the transmitter, receiver, antenna, and detector. We explain the radar equation used for calculating range, and the Doppler effect for estimating target speed and distinguishing between moving and stationary targets. Additionally, we highlight the importance of limiting radar range to avoid distance ambiguity and introduce Swerling models for modelling fluctuating targets and estimating detector performance.

In the second chapter, we explore the basic concepts of decision criteria in radar detection and the techniques used in radar systems. We identify the limitations of fixed threshold detection in non-homogeneous environments, highlighting the need for adaptive threshold detection to maintain a constant false alarm rate.

Chapter three examines the evolution of CFAR (Constant False Alarm Rate) detection methods, focusing on their adaptation to varying environmental conditions. It explores distributed CFAR rules using AND and OR logic to optimize detection accuracy through sensor data integration. Additionally, the chapter investigates the use of Particle Swarm Optimization (PSO) to refine parameters like threshold T and K in OS-CFAR and CMLDk-CFAR detectors, aiming to enhance overall detection capabilities. We conclude this thesis with a comprehensive simulation study evaluating the effectiveness of these enhanced CFAR detection methods. The simulations are conducted in both homogeneous and non-homogeneous environments to assess the impact of using AND/OR fusion rules and PSO-optimized parameters T and K on detection performance. This empirical analysis aims to validate the practical utility and effectiveness of the proposed approaches in diverse operational settings [1].

CHAPTER 1

RADAR BASICS

Chapitre 1

1.1 Introduction

RADAR (radio detection and ranging) is one of the wonders of the twentieth century. It is an electromagnetic system used to detect the presence of moving objects and determine their trajectory, speed, closest point of contact, and other data, while transmitting radio waves, whose wavelength varies from a few centimetres to about 1 m. It then extracts the necessary information about the target from the echo signal.

Figure 1-1 Radar Antenna *[2]*.

The primary property of radar, namely high accuracy of distance measurements, has also made it possible to accurately measure the distance from the earth to various stars either with radio waves or with lasers. In the civilian field, radar has many important applications, ranging from air traffic control, which is so dense today, with long-range equipment, to landing control in conditions of very poor visibility. In meteorology, it can be used to track sounding balloons, measure cloud ceilings over aerodromes and warn crews of disturbances on their route, allowing them to avoid them. On the roads, it allows the monitoring of the speed of motorists, and therefore contributes to improving road traffic safety. Finally, it is widely used in space exploration as it makes it possible to study the ground of planets surrounded by clouds, for example, Venus. The word radar is therefore applied to a wide range of equipment and installations, from very small on-board equipment to very large assemblies served by hundreds of people. However, despite this extreme diversity of aspects and uses, the same basic principles are found in all types of equipment. Therefore, these principles are the main focus of the radar literature and their current extensions, i.e. modern radar.

1.2 HISTORY OF RADAR

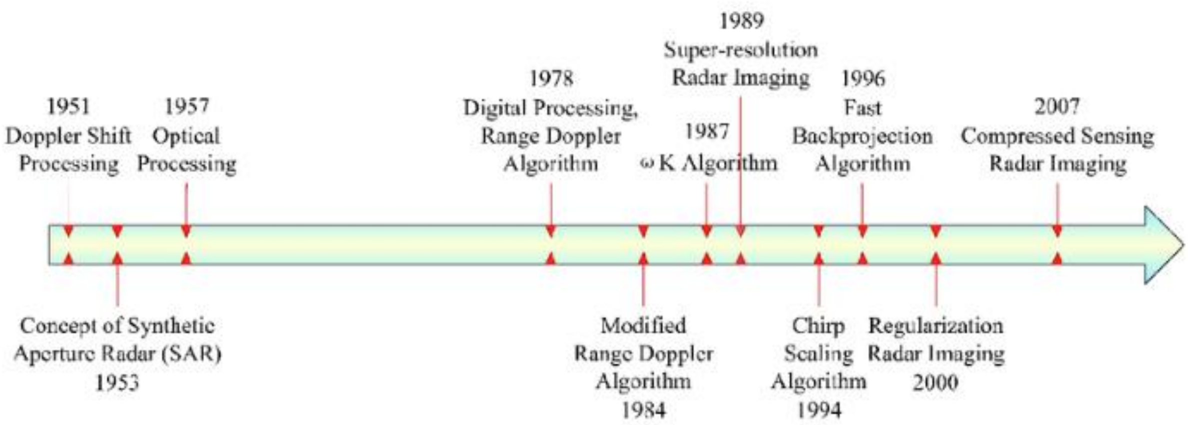

Figure 1-2 Development History of Radar Imaging *[3]*.

Radar is certainly one of the most useful inventions in modern aeronautics. One can no longer imagine an aircraft flying without this instrument, nor a control tower operating without its help. However, no one can claim sole credit for this discovery.

Radar (Radio Detection and Ranging) is the result of the research of many physicists and the work of many engineers throughout the world. Each of them took advantage of previous discoveries to advance their own research.

The source of the invention can be traced back to 1864. That year, the British physicist James Clerck Maxwell formulated the equations governing electromagnetic waves. Therefore, it was a British success story. Nevertheless, not for long.

In 1889, the German Heinrich Rudolph Hertz proved by experiment that electromagnetic waves were reflected on conductive surfaces. This was the first application.

In 1904, Christian Hülsmeyer, another German engineer, hypothesised that it would be possible to use this property to avoid ship collisions and worked on the development of an instrument.

After the 1914 war, many laboratories in Europe and the United States took a closer look at the discovery.

In 1922, the Italian Guglielmo Marconi invented a device more or less identical to that of the German Hülsmeyer. The real development of radar as we know it was to begin.

In 1924, in England, E.V. Appleton, winner of the Nobel Prize for Physics in 1914, and A. F. Barnett carried out several experiments on radar. F. Barnett carried out several experiments.

To detect objects using radio waves. These same experiments were carried out in the United States, notably by Taylor and Young on buildings with a metal structure.

In 1927, in France, Camille Gutton and Pierret experimented with wave echoes in the courtyard of the Faculty of Science in Nancy. The matter remained in the family since Camille Gutton's son, Henri, was one of those who really developed radar. At the same time, we must also remember the name of Maurice Ponte who worked with Maurice de Broglie on the association of waves with the electron. The elements were falling into place. We are close to the discovery that will really take place a few months later.

In 1931 in France, two technical advisers of the military radiography, Mesny and David, noticed that the passage of aeroplanes created disturbances in the communications.

In 1935, they developed a device to locate these aircraft. However, 1934 can be considered as the date of the actual birth of radar. During tests to adjust a magnetron transmitter in the courtyard of the SFR factory in Levallois, the engineers noticed a parasitic reception. They looked for the origin of the interference in the equipment; the cause was much more surprising: the gusts of wind that made the wheels of bicycles suspended under a shelter turn. After a long observation, they conclude that the echo turns at the same time and at the same rhythm as the bicycles.

This was all it took to decide on the direction of the research. A steering committee decided to build special echo detection equipment. However, they had to choose the right waves. They decided on centimetre waves.

This was fortunate because the entire future of the new detector, which was not yet called a radar but an obstacle detector, would depend on it. Teams from the Compagnie General de T.S.F. and the Société Française de Radio-électrique (C.S.F.R.) therefore developed the first device. It will be installed on the cargo ship Oregon in November 1934 and will equip from August 1935 the liner Normandie... Honour to the French!

Radar was born. It was to take its place everywhere on land, at sea and in the sky.

In 1935 in England, the Committee for the Study of Air Defence received from Sir Robert Watson-Watt, then head of the radio section of the National Physical Laboratory, a project for the remote signalling of aircraft by electromagnetic detection.

On 5 December 1935, the British Air Ministry decided to build a system on the east coast of England to protect the Thames estuary. It was reinforced in the spring of 1937 by 15 stations installed on the east and south-east coasts. The American naval authorities also looked into the matter. Admiral Bowens obtained a credit of 100,000 dollars from Congress.

In April 1937, the Americans carried out the first radar tests on board the destroyer Leary at the mouth of the Cheasepeake. At the same time, the War Department and the Parliamentary Committee on the Army witnessed aircraft detection experiments at Fort Monmouth.

The war was to lead to considerable development of radar. And even today, laboratories all over the world are still working on its daily improvement [2].

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:

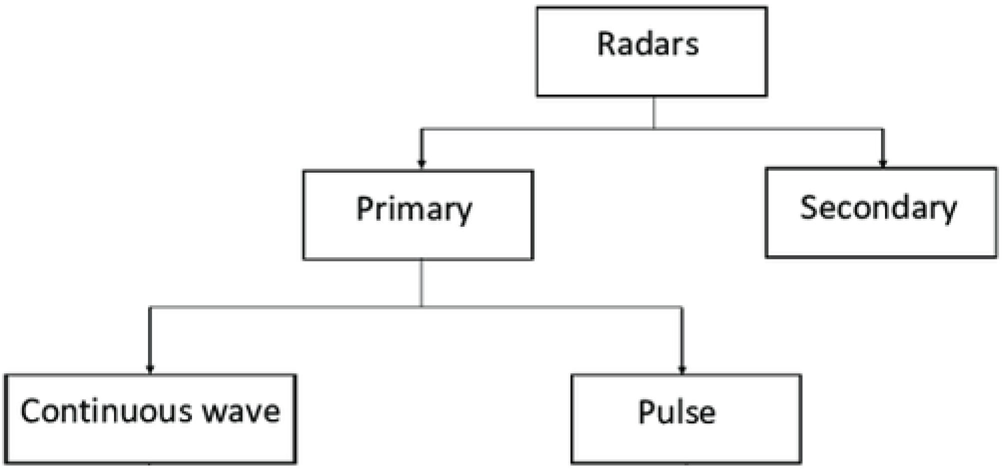

Figure 1-3 CLASSIFICATION OF RADAR *[4]*.

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 [4].

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 [5].

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 [6].

1.3.4 Continuos 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. [5]

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. [7]

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 [5].

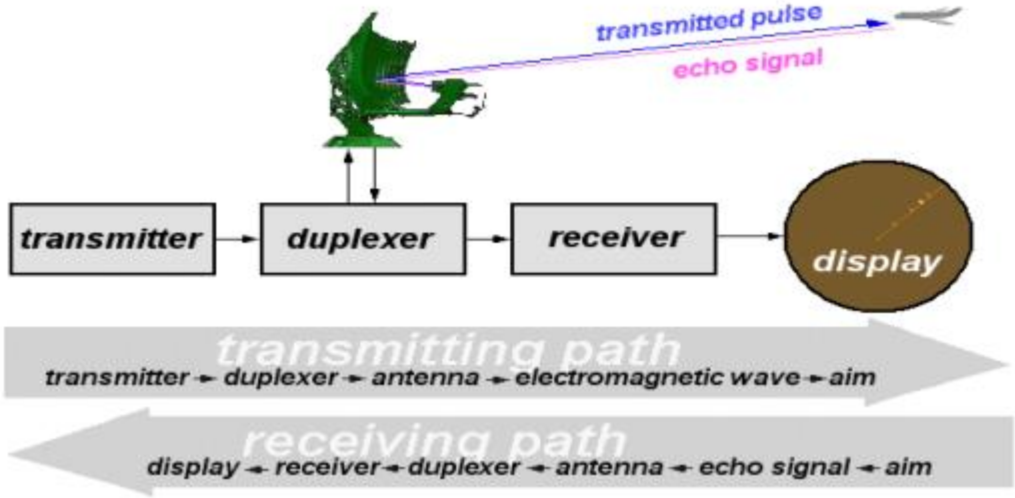

Figure 1-4 THE RADAR COMPONENT *[5]*.

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].

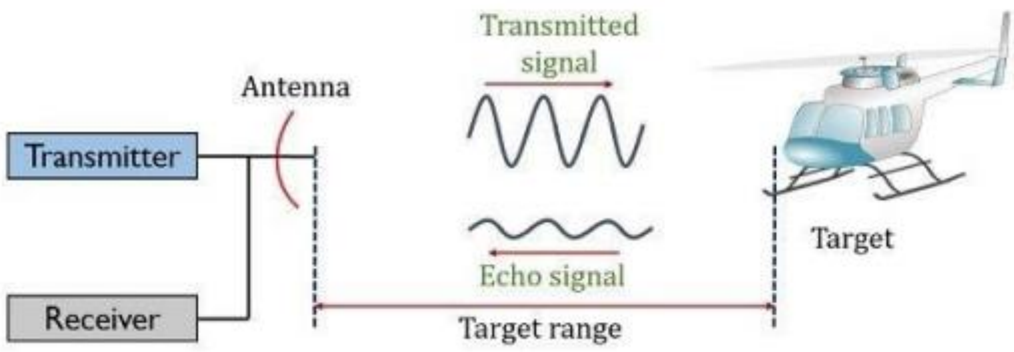

Figure 1-5 THE PRINCIPLE OF RADAR OPERATION *[7]***.**

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 [7].

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

$$f_d = \frac{v_r}{\lambda} \tag{1.1}$$

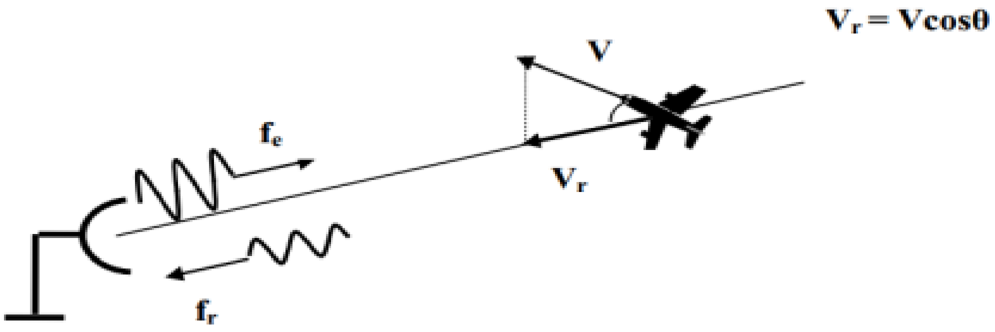

Figure 1-6 Doppler Shift *[7]*.

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:

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

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:

$$\Delta f = \left(\frac{2v}{c}\right) \cdot F_0 \tag{1.3}$$

Where:

Δf = Doppler shift

v = velocity of the target

c = speed of light

F_0 = frequency of the transmitted signal [8]

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.

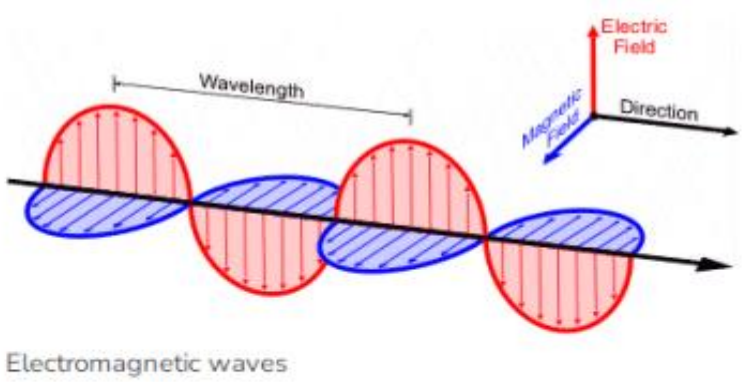

Figure 1-7 The electromagnetic waves.

$\vec{E}$: Electric field.

$\vec{B}$: 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 [5].

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 [5].

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:

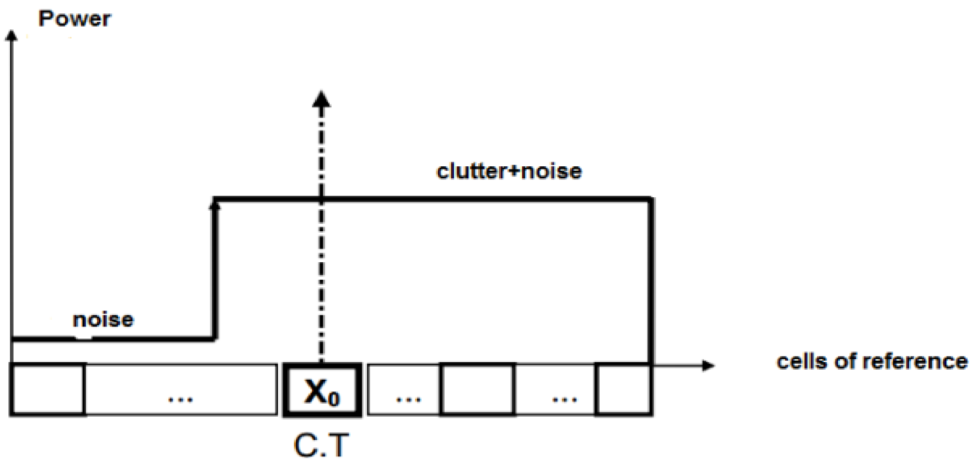

Figure 1-8 cell under test embedded in the clutter region.

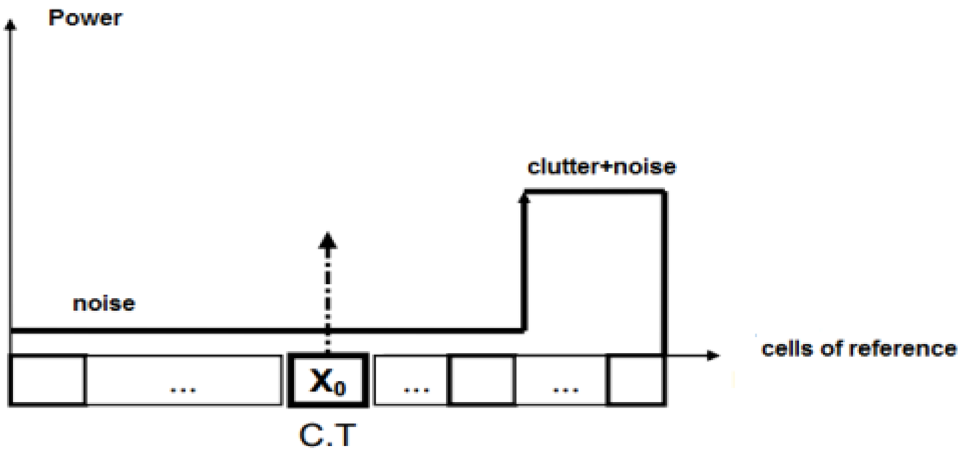

Figure 1-9 cell under test drowned in thermal noise.

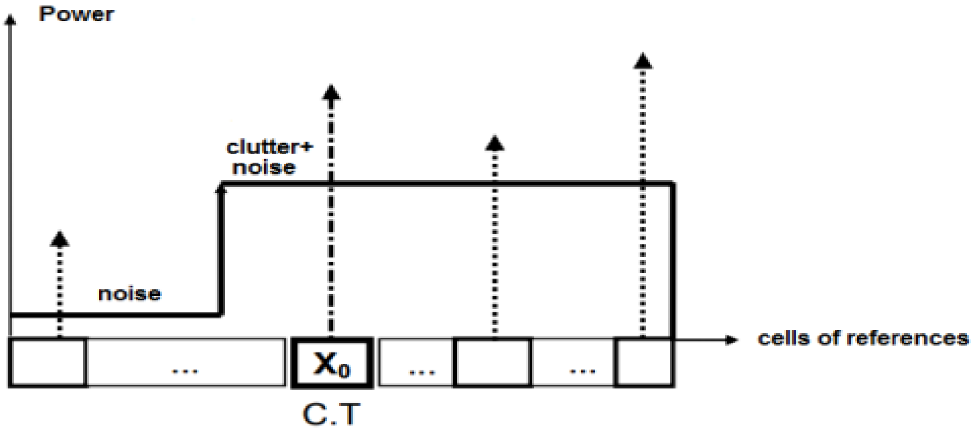

Figure 1-10 Presence of clutter edge and interfering targets.

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 [5].

1.9.1.2 Clutter Statistical 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.

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

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

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

If, at the output of the quadratic detector, the video signal undergoes a nonintegrating 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):

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

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.

1.9.1.3Target 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 Rayleig.

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

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:

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

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 (defull pulse-to-pulse correlation) [9].

1.9.2 Noise 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-todigital converters, as well as digital signal processing techniques such as averaging and filtering. [6]

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. [5]

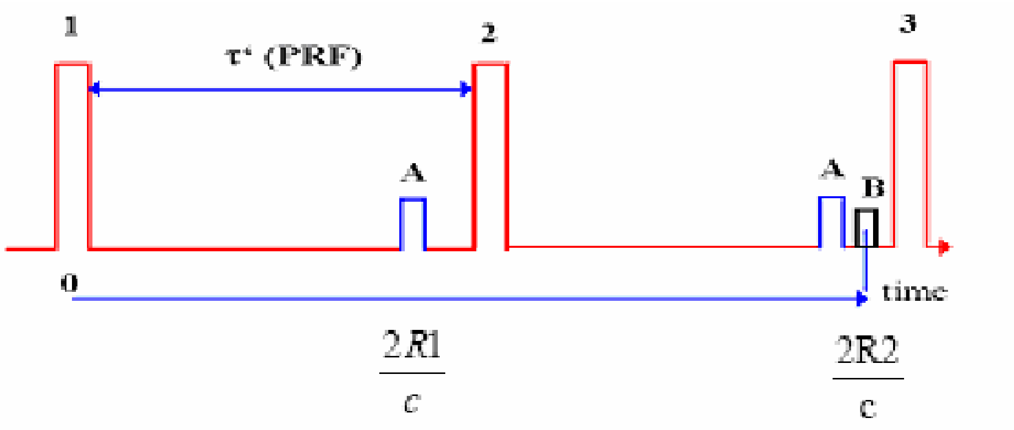

Figure 1-11 Illustration of distance ambiguity *[10]*.

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)

Figure 1-12 Fluctuation Pattern Pulses Swerling I.

1.11.2 SWERLING II (SWII)

Rapidly fluctuating target whose signal envelope varies according to the law (1.6)

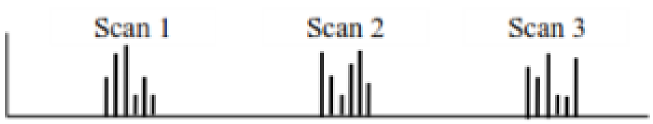

Figure 1-13 Fluctuation Pattern Pulses Swerling II.

1.11.3 SWERLING III (SWIII)

Slowly fluctuating target whose signal envelope varies according to the law (1.7).

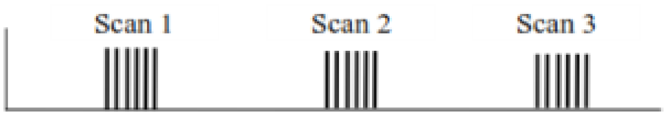

Figure 1-14 Fluctuation Pattern Pulses Swerling III.

1.11.4 SWERLING IV (SWIV)

Rapidly fluctuating target whose signal envelope varies according to the law (1.7).

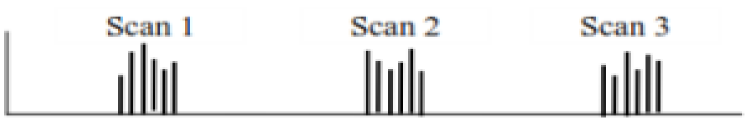

Figure 1-15 Fluctuation Pattern Pulses Swerling IV**.**

The Swerling model is used to predict the probability distribution of the signal-tonoise 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 [11].

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 [12].

1.13 CONCLUSION

In conclusion, radar technology has revolutionized various fields, from military applications to civilian uses such as air traffic control, meteorology, and road traffic safety. Its development is a result of the collaborative efforts of scientists and engineers worldwide, building upon each other's discoveries over decades. From its early beginnings with Maxwell's equations and Hertz's experiments to the practical implementations by pioneers like Marconi and subsequent advancements by researchers in France, England, and the United States, radar has evolved into a vital tool for modern society.

Understanding the principles of radar operation, including the Doppler shift phenomenon and radar equations, is fundamental to its effective use. Moreover, the study of electromagnetic waves, clutter, noise, and target models provides insights into the challenges faced in radar signal processing and target detection.

Overall, radar continues to play a crucial role in enhancing safety, security, and efficiency across various sectors, with ongoing research and development aimed at further improving its capabilities and expanding its applications. As technology advances, radar systems are likely to become even more sophisticated, contributing to advancements in fields such as autonomous vehicles, space exploration, and defense systems.

CHAPTER 2

RADAR DETECTION

CHAPTER 2

2.1 Introduction

The primary functions of a radar signal processor are detection, tracking, and imaging, with detection being a crucial focus. In radar, detection involves deciding whether a radar measurement results from a target echo or merely interference. Once a target presence is confirmed, further processing like tracking through precise range, angle, or Doppler measurements typically follows.

Detection can occur at various stages of radar signal processing, from raw echoes to highly processed data such as Doppler spectra or synthetic aperture radar images. At its simplest, each range bin (fast-time sample) for each pulse can be tested individually to determine if a target is present at the corresponding range and spatial angles. Given the high number of range bins and pulse repetition frequencies, radars can make millions of detection decisions per second.

Both interference and echoes from complex targets are best described by statistical signal models. Thus, deciding whether a measurement indicates a target or interference is a statistical hypothesis testing problem. This decision strategy leads to the concept of threshold testing, which is the most common detection logic in radar, with performance curves derived for basic signal and interference models.

Clutter, such as ground echoes, can serve as interference or a target depending on the context. For instance, when detecting a moving vehicle, ground clutter is interference, whereas, in imaging a region of the earth, the same terrain becomes the target. [6]

2.2 RADAR DETECTION THEORY

In our daily life, we are constantly making decisions. Given some hypotheses, a criterion is selected, upon which a decision has to be made. For example, in engineering, when there is a radar signal detection problem, the returned signal is observed and a decision is made as to whether a target is present or absent. In a digital communication system, a string of zeros and ones may be transmitted over some medium. At the receiver, the received signals representing the zeros and ones are corrupted in the medium by some additive noise and by the receiver noise. The receiver does not know which signal represents a zero and which signal represents a one, but must make a decision as to whether the received signals represent zeros or ones. The process that the receiver undertakes in selecting a decision rule falls under the theory of signal detection.

The situation above may be described by a source emitting two possible outputs at various instants of time. The outputs are referred to as *hypotheses*. The *null hypothesis* H_0 represents a zero (target not present) while the *alternate hypothesis* H_1 represents a one (target present). [9]

Each hypothesis corresponds to one or more observations that are represented by random variables. Based on the observation values of these random variables, the receiver decides which hypothesis (H_0 or H_1) is true. Assume that the receiver is to make a decision based on a single observation of the received signal. The range of values that the random variable Y takes constitutes the observation space Z. The observation space is partitioned into two regions Z_0 and Z_1, such that if Y lies in Z_0, the receiver decides in favor of H_0; while if Y lies in Z_1, the receiver decides in favor of H_1. The observation space Z is the union of Z_0 and Z_1; that is,

$$Z = Z0\ U\ Z1 \qquad (2.1)$$

2.2.1 THE BAYES CRITERION

In using Bayes' criterion, two assumptions are made. First, the probability of occurrence of the two source outputs is known [9]. They are the a priori probabilities $P(H_0)$ and $P(H_1)$. $P(H_0)$ is the probability of occurrence of hypothesis H_0, while $P(H_1)$ is the probability of occurrence of hypothesis $H1$. Denoting the a priori probabilities $P(H_0)$ and $P(H_1)$ by P_0 and P_1 respectively, and since either hypothesis H_0 or H_1 will always occur, we have

$$P0 + P1 = 1 \qquad (2.2)$$

The second assumption is that a cost is assigned to each possible decision. The cost is due to the fact that some action will be taken based on a decision made. The consequences of one decision are different from the consequences of another. For example, in a radar detection problem, the consequences of miss are not the same as the consequences of false alarm. If we let D_i, i = 0, 1, where D_0 denotes "decide H_0" and D_1 denotes "decide H_1," we can define C_{ij} , i, j = 0, 1, as the cost associated with the decision D_i, given that the true hypothesis is H_j. That is,

$$P \text{ (incurring cost } C_{ij}) = P \text{ (decide } D_i, H_j \text{ true)}), i, j = 0,1 \quad (2.3)$$

In particular, the costs for this binary hypothesis testing problem are C00 for case (1), C01 for case (2), C10 for case (3), and C11 for case (4). The goal in Bayes' criterion is to determine the decision rule so that the average cost E[C] , also known as risk $\mathfrak{R}$, is minimized. The operation E[C] denotes expected value. It is also assumed that the cost of making a wrong decision is greater than the cost of making a correct decision. That is,

$$C01 > C11 \quad and \, C10 > C00 \quad (2.4)$$

Given P (D_i, H_j) , the joint probability that we decide Di, and that the hypothesis Hj is true, the average cost is

$$\mathfrak{R} = E[C] = C_{00}P(D_0, H_0) + C_{01}P(D_0, H_1) + C_{10}P(D_1, H_0) + C_{11}P(D_1, H_1) \quad (2.5)$$

From Bayes' rule, we have

$$P\ (Di, H\ j) = P\ (Di \mid H\ j)\ P\ (H\ j) \quad (2.6)$$

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:

$$P(D_0, H_0) \equiv P(\text{ Decide } H_0 \mid H_0 \text{ true }) = \int_{z_0} f_{y|H_0}(y \mid H_0) dy \quad (2.7a)$$

$$P(D_0, H_1) \equiv P(\text{ Decide } H_0 \mid H_1 \text{ true }) = \int_{z_0} f_{y|H_1}(y \mid H_1) dy \quad (2.7b)$$

$$P(D_1, H_0) \equiv P(\text{ Decide } H_1 \mid H_0 \text{ true }) = \int_{Z_1} f_{y|H_0}(y \mid H_0)dy \tag{2.7c}$$

And

$$P(D_1, H_1) \equiv P(\text{ Decide } H_1 \mid H_1 \text{ true }) = \int_{Z_1} f_{y|H_1}(y \mid H_1)dy \tag{2.7d}$$

The probabilities $P\ (D_0 \mid H_1)$, $P\ (D_1 \mid H_0)$, and $P\ (D_1, H_1)$ represent the *probability of miss*, *PM,* the *probability of false alarm*, P_F, and the *probability of detection*, P_D, respectively. We also observe that

$$PM = 1 - PD \tag{2.8}$$

And

$$P\ (D0 \mid H0) = 1 - PF \tag{2.9}$$

Consequently, the probability of a correct decision is given by

$$\begin{aligned} P(\text{ correct decision }) &= P(c) = P(D_0, H_0) + P(D_1, H_1) \\ &= P(D_0 \mid H_0)P(H_0) + P(D_1 \mid H_1)P(H_1) \\ &= (1 - P_F)P_0 + P_D P_1 \end{aligned} \tag{2.10}$$

and the probability of error is given by

$$\begin{aligned} P(\text{ error }) &= P(\varepsilon) = P(D_0, H_1) + P(D_1, H_0) \\ &= P(D_0 \mid H_1)P(H_1) + P(D_1 \mid H_0)P(H_0) \\ &= P_M P_1 + P_F P_0 \end{aligned} \tag{2.11}$$

The average cost now becomes

$$\Re = E[C] = C_{00}(1 - P_F)P_0 + C_{01}(1 - P_D)P_1 + C_{10}P_F P_0 + C_{11}P_D P_1 \tag{2.12}$$

In terms of the decision regions defined in (2.8a) to (2.9b), the average cost is

$$\Re = P_0 C_{00} \int_{Z_0} f_{Y|H_0}(y \mid H_0) dy + P_1 C_{01} \int_{Z_0} f_{Y|H_1}(y \mid H_1) dy$$
$$+ P_0 C_{10} \int_{Z_1} f_{Y|H_0}(y \mid H_0) dy + P_1 C_{11} \int_{Z_1} f_{Y|H_1}(y \mid H_1) dy \qquad (2.13)$$

Using (5.1) and the fact that

$$\int_{Z} f_{Y|H_0}(y \mid H_0) dy = \int_{Z} f_{Y|H_1}(y \mid H_1) dy = 1 \qquad (2.14)$$

it follows that

$$\int_{Z_1} f_{Y|H_j}(y \mid H_j) dy = 1 - \int_{Z_0} f_{Y|H_j}(y \mid H_j) dy, j = 0,1 \qquad (2.15)$$

Where $f_{Y|H_j}(y \mid H_j)$, *j* 0, 1, = is the probability density function of *Y* corresponding to each hypothesis. Substituting for (2.15) in (2.13), we obtain

$$\Re = P_0 C_{10} + P_1 C_{11} + \int_{Z_0} \{[P_1(C_{01} - C_{11}) f_{Y|H_1}(y \mid H_1)] - [P_0(C_{10} - C_{00}) f_{Y|H_0}(y \mid H_0)]\} dy \qquad (2.16)$$

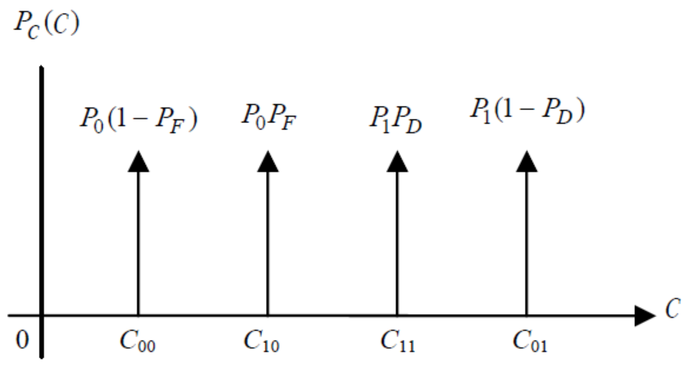

Figure 2-1 Density function of cost.

We observe that the quantity $P_0C_{10} + P_1C_{11}$ is constant, independent of how we assign points in the observation space, and that the only variable quantity is the region of integration Z_0. From (2.7a, b), the terms inside the brackets of (2.16) $[P_1(C_{01} - C_{11}) f_{Y|H_1}(y \mid H_1)$ and $P_0(C_{10} - C_{00}) f_{Y|H_0}(y \mid H_0)]$, are both positive. Consequently, the risk is minimized by selecting the decision region Z_0 to include only those points of Y for which the second term is larger, and hence the integrand is negative. Specifically, we assign to the region Z_0 those points for which

$$P_1(C_{01} - C_{11}) f_{Y|H_1}(y \mid H_1) < P_0(C_{10} - C_{00}) f_{Y|H_0}(y \mid H_0) \tag{2.17}$$

All values for which the second term is greater will be excluded from Z_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 either Z_0 or Z_1. Consequently, we say if

$$P_1(C_{01} - C_{11}) f_{Y|H_1}(y \mid H_1) > P_0(C_{10} - C_{00}) f_{Y|H_0}(y \mid H_0) \tag{2.18}$$

then we decide H_1. Otherwise, we decide H_0. Hence, the decision rule resulting from the Bayes' criterion is

$$\frac{f_{Y|H_1}(y \mid H_1)}{f_{Y|H_0}(y \mid H_0)} > \underset{H_0}{\overset{H_1}{<}} > \frac{P_0(C_{10} - C_{00})}{P_1(C_{01} - C_{11})} \tag{2.19}$$

The ratio of $f_{Y|H_1}(y \mid H_1)$ over $f_{Y|H_0}(y \mid H_0)$ is called the *likelihood ratio* and is denoted Λ(y). That is,

$$\Lambda(y) = \frac{f_{Y|H_1}(y \mid H_1)}{f_{Y|H_0}(y \mid H_0)} \tag{2.20}$$

It should be noted that if we have K observations, for example, K samples of a received waveform, Y_1, Y_2, …, Yk, based on which we make the decision, the likelihood ratio can be expressed as

$$\Lambda(y) = \frac{f_{Y|H_1}(\boldsymbol{y} \mid H_1)}{f_{\boldsymbol{Y}|H_0}(\boldsymbol{y} \mid H_0)} \tag{2.21}$$

where ***Y***, the received vector, is

$$Y^{\mathrm{T}} = [Y1 \quad Y2 \quad \dots \quad Y_K] \tag{2.22}$$

The *likelihood statistic* Λ (***Y)*** is a random variable since it is a function of the random variable ***Y***. The threshold is

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

Therefore, Bayes' criterion, which minimizes the average cost, results in the *likelihood ratio test*

$$\boldsymbol{\Lambda}(\mathbf{y}) \underset{H_0}{\overset{H_1}{\gtrless}} \eta \tag{2.24}$$

An important observation is that the likelihood ratio test is performed by simply processing the receiving vector to yield the likelihood ratio and comparing it with the threshold. Thus, in practical situations where the a priori probabilities and the cost may change, only the threshold changes, but the computation of likelihood ratio is not affected. Because the natural logarithm is a monotonically increasing function as shown in Figure 5.4, and since the likelihood ratio Λ(y) and the threshold η are nonnegative, an equivalent decision rule to (2.24) is

$$ln\boldsymbol{\Lambda}(\mathbf{y}) \underset{H_0}{\overset{H_1}{\gtrless}} \ln \eta \tag{2.25}$$

We note that if we select the cost of an error to be one and the cost of a correct decision to be zero; that is,

$$C01 = C10 \; and \; C00 \; = C11 \tag{2.26}$$

T hen the risk function of (2.12) reduces to

$$\Re = P_M P_1 + P_F P_0 = P(\varepsilon) \tag{2.27}$$

Thus, in this case, minimizing the average cost is equivalent to minimizing the probability of error. Receivers for such cost assignment are called *minimum probability of error receivers*. The threshold reduces to

$$\eta = \frac{P_0}{P_1} \tag{2.28}$$

If the a priori probabilities are equal, η is equal to one, and the log likelihood ratio test uses a zero threshold.

2.2.2 NEYMAN-PEARSON CRITERION

In the previous sections, we have seen that for the Bayes' criterion we require knowledge of the a priori probabilities and cost assignments for each possible decision. Then we have studied the minimax criterion, which is useful in situations where knowledge of the a priori probabilities is not possible. In many other physical situations, such as radar detection, it is very difficult to assign realistic costs and a priori probabilities. To overcome this difficulty, we use the conditional probabilities of false alarm, P_F, and detection P_D. The *Neyman-Pearson* test requires that P_F be fixed to some value α while P_D is maximized. Since P_M = 1− P_D, maximizing P_D is equivalent to minimizing P_M. [9]

In order to minimize P_M (maximize P_D) subject to the constraint that P_F = α, we use the calculus of extrema, and form the objective function *J* to be

$$J = P_M + \lambda(P_F - \alpha) \tag{2.29}$$

where λ (λ ≥ 0) is the *Lagrange multiplier*. We note that given the observation space Z, there are many decision regions Z_1 for which P_F = α. The question is to determine those decision regions for which P_M is minimum. Consequently, we rewrite the objective function J in terms of the decision region to obtain

$$J = \int_{Z_0} f_{Y|H_1}(y \mid H_1)dy + \lambda\left[\int_{Z_1} f_{Y|H_0}(y \mid H_0)dy - \alpha\right] \quad (2.30)$$

Using (2.10), (2.30) can be rewritten as

$$\begin{aligned} J &= \int_{Z_0} f_{Y|H_1}(y \mid H_1)dy + \lambda\left[\int_{Z_0} f_{Y|H_0}(y \mid H_0)dy - \alpha\right] \\ &= \lambda(1-\alpha) + \int_{Z_0} \left[f_{Y|H_1}(y \mid H_1) - \lambda f_{Y|H_0}(y \mid H_0)\right]dy \end{aligned} \quad (2.31)$$

Hence, J is minimized when values for which $f_{Y|H_1}(y \mid H_1) > f_{Y|H_0}(y \mid H_0)$ are assigned to the decision region Z_1. The decision rule is, therefore,

$$\Lambda(y) = \frac{f_{Y|H_1}(y \mid H_1)}{f_{Y|H_0}(y \mid H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \quad (2.32)$$

The threshold η derived from the Bayes' criterion is equivalent to λ, the Lagrange multiplier in the Neyman-Pearson (*N-P*) test for which the probability of false alarm is fixed to the value α. If we define the conditional density of Λ given that *H*0 is true as $f_{\Lambda|H_0}(\lambda \mid H_0)$, then P_F = α may be rewritten as

$$P_F = \int_{Z_1} f_{Y|H_0}(y \mid H_0)dy = \int_{\lambda}^{\infty} f_{\Lambda(y)|H_0}[\lambda(y) \mid H_0]d\lambda \quad (2.33)$$

The test is called *most powerful of level* α if its probability of rejecting H_0 is α.

2.3 Detection Techniques

Radar detection techniques are typically divided into classical and adaptive categories. In classical detection, the detection threshold remains constant, whereas in adaptive detection, the threshold adjusts continuously based on the noise level. This discussion focuses on adaptive detection, but let's first explore the traditional detection method, also known as detection with a fixed threshold. We'll revisit its operational principle and highlight its main drawback before delving into adaptive detection, which forms the basis of our discussion.

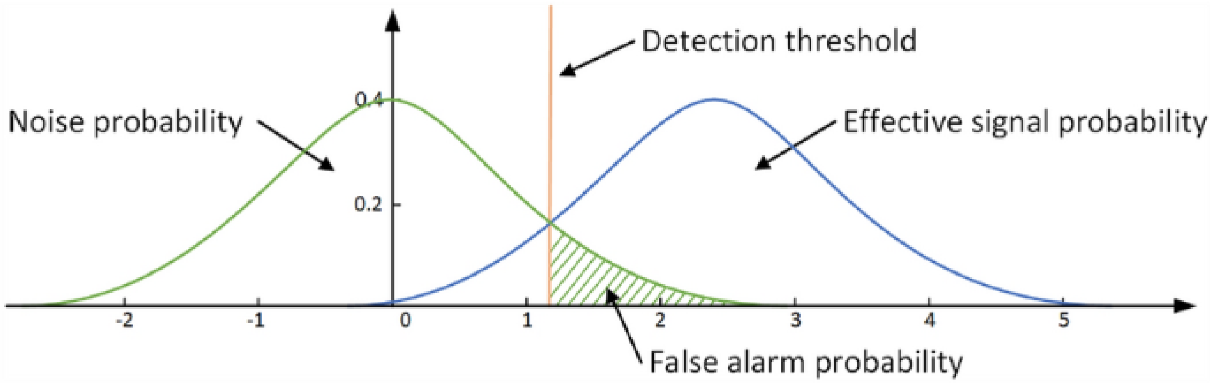

Figure 2-2 Detection Principle

2.3.1 Optimal Detection

The optimal detector operates as follows; Initially, the received signal undergoes processing through a single-pulse matched filter to enhance the signal-to-noise ratio. This filter sequentially processes each pulse individually. Subsequently, the filtered signal passes through a quadratic detector, which serves a dual purpose: it extracts the signal's envelope (demodulates it) and computes the square of this envelope's amplitude. The resulting envelope is then sampled at the pulse recurrence period, Tr.

As the radar completes scanning the current cell, it accumulates a total of N samples, all originating from the same target, with each pulse generating a single sample. These N samples are aggregated, producing an estimation of the target's echo strength. This aggregate sum is then compared against a predetermined threshold. If the sum exceeds this threshold, the presence of a target within the cell (H_1) is declared; otherwise, the cell is deemed devoid of targets (H_0).**Source spécifiée non valide.**

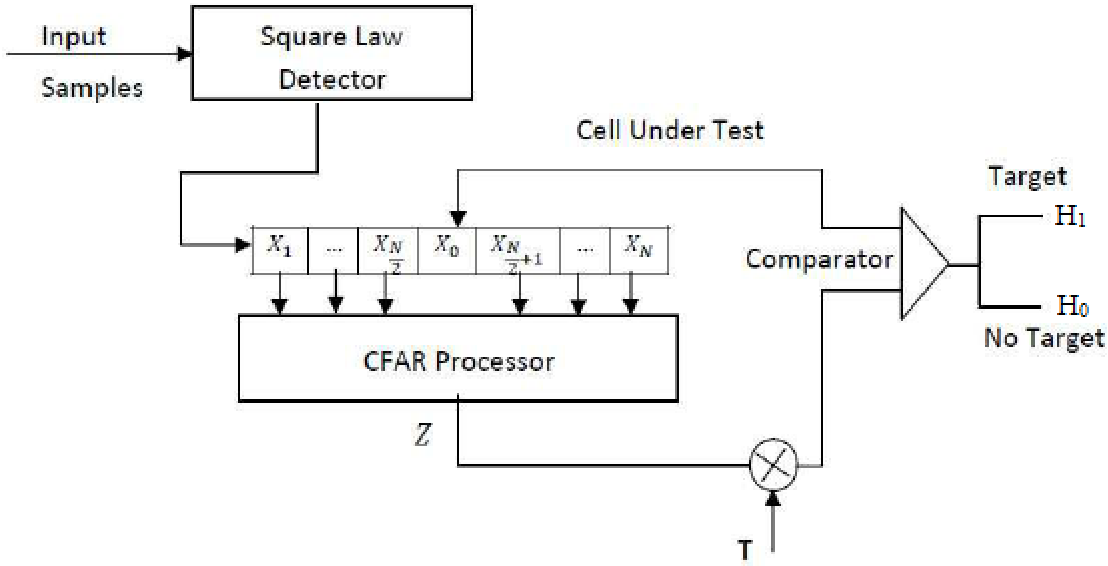

Figure 2-3 Conventional Detector

The detection problem in radar can be mathematically expressed with the following hypotheses:

$$H0: \quad X = b \quad \longrightarrow \quad Xi = bi \quad with\ i = 1, \ldots., N \quad (2.34a)$$

$$H1: \quad X = b + s \quad \longrightarrow \quad Xi = bi + si \quad with\ i = 1, \ldots, N \quad (2.34b)$$

Where X_i is the secondary data, which represent the observation vectors assumed to be independent, in the probabilistic sense of the terms of X and which are assumed to contain only the additive clutter noise, allowing the estimation of the unknown clutter parameters. From the assumption H_0, the received signal X is considered to contain only the undesirable and bad echoes for a good detection. These echoes come from the different reflectors in the environment. Their probability density function is denoted by,

$$PX\ (X|H0) \ = \ Pc\ (X|H0 \quad (2.35)$$

From hypothesis H_1, the received signal X is considered to contain the signal s with the target echoes but embedded in the same false echoes from hypothesis H_0. Its probability density is denoted by,

$$\boldsymbol{PX\ (X|H0)}$$

The task of optimal detection is to have the more likely of the two assumptions, minimising the following two errors,

- Deciding H0 when H1 is true: this is non-detection, which has the following probability

$$Pnd = P(H0|H1) = 1 - P(H1|H1) = 1 - PD \tag{2.36}$$

- Decide H_1 then that H_0 is true: this is the false alarm, which has the following probability,

$$Pfa = P(H1|H0) \tag{2.37}$$

For these predictions, it is very difficult to fully approximate these errors, unless the statistics of the Radar environment and the nature of the target to be detected are well known.

2.3.2 FIXED THRESHOLD DETECTION

In radar signal processing, making a decision about the presence or absence of a target is a critical task. The radar's output is treated as a random process, characterized by a probability density function (PDF). This introduces a statistical decision problem due to the presence of spurious noise, which poses a risk of error in recognizing the useful signal. To address this, radar detection relies on statistical methods to distinguish between the presence and absence of a target. [2]

H_0: The target is absent (noise alone).

H_1: The target is present with noise.

The detection problem is summarised in the following table

Table 2-1 Detection hypothesis

Decision	**Hypothesis H_0 (absence)**	**Hypothesis H_1 (presence)**
H_1	False Alarm **(Pfa)**	Correct decision **(Pd)**
H_0	Correct decision prob**(1-Pfa)**	Incorrect decision prob**(1-Pd)**

The detection threshold is calculated by setting the probability of false alarm. In other words, once the false alarm probability is set, the detection threshold remains constant. Thus, if the noise power increases for any reason, the threshold does not change and the detector is likely to give a series of false alarms. The false alarm rate (number of false alarms per unit of time) can then reach intolerable levels. Adaptive detection was developed to address this problem.

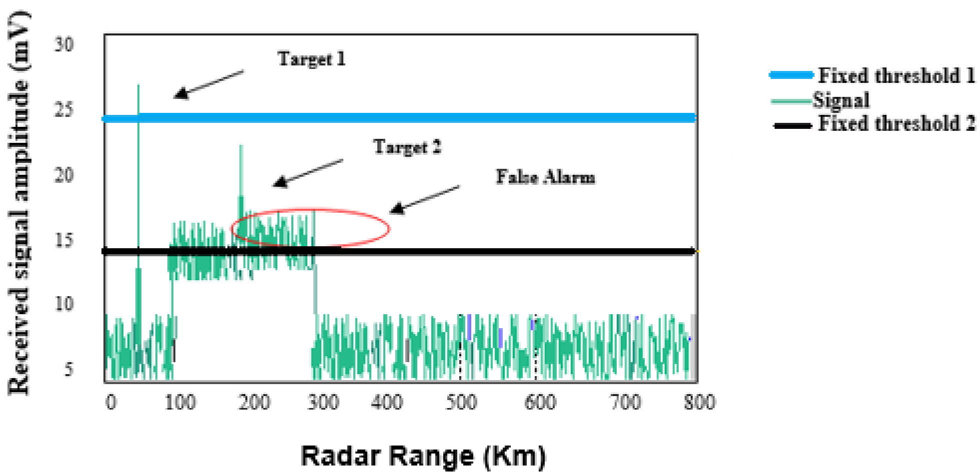

Figure 2-4 Principle of fixed threshold detection

2.4 PRINCIPLE OF ADAPTIVE DETECTION

Automatic detection consists of deciding whether or not a target is present by comparing the echo received with a detection threshold. In statistical decision theory, this involves choosing between two statistical hypotheses: H_0 for the null hypothesis (absence of the useful signal) or H_1 for the alternative hypothesis (presence of a target). In the most general case, each echo received results from the superposition of thermal noise, clutter reflections and a possible target echo. Thus, the choice of a fixed (pre-calculated) detection threshold leads to an intolerable increase in the number of false alarms when the noise level in the vicinity of the cell under test (C.T.) undergoes a significant change in the clutter.

To get around this problem, we use adaptive thresholding methods in which the detection threshold is directly linked to the noise level in the range cells surrounding the cell under test. As illustrated in **figure 2-5**, these adjacent cells, whose number is fairly small for reasons of computing time, form what is known as the 'Reference Window'. They provide a local estimate of the noise level and clutter. **Figure 2-6** shows the block diagram of a CFAR (Constant False Alarm Rate) detector, which compares the cell under test with an adaptive threshold T.Z. for each range cell. The multiplication factor T is calculated so as to maintain a constant false alarm probability equal to a set value (Design pfa).

The mathematical form of the estimator Z= X2, ... XN) represents the main difference between the various CFAR detectors proposed in the radar literature. The class of 'Mean level' detectors is by far the most widely discussed and the most suitable for homogeneous environments. The CA-CFAR (Cell Averaging) detector, whose adaptive threshold is obtained by averaging reference cells, represents the precursor of this category of detectors. [12]

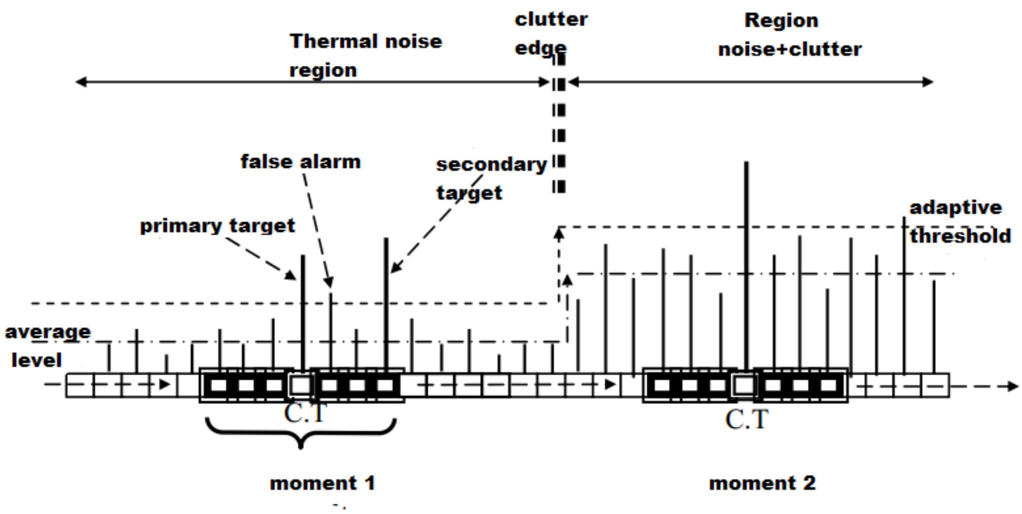

Figure 2-5 Reference cell scanning an inhomogeneous environment.

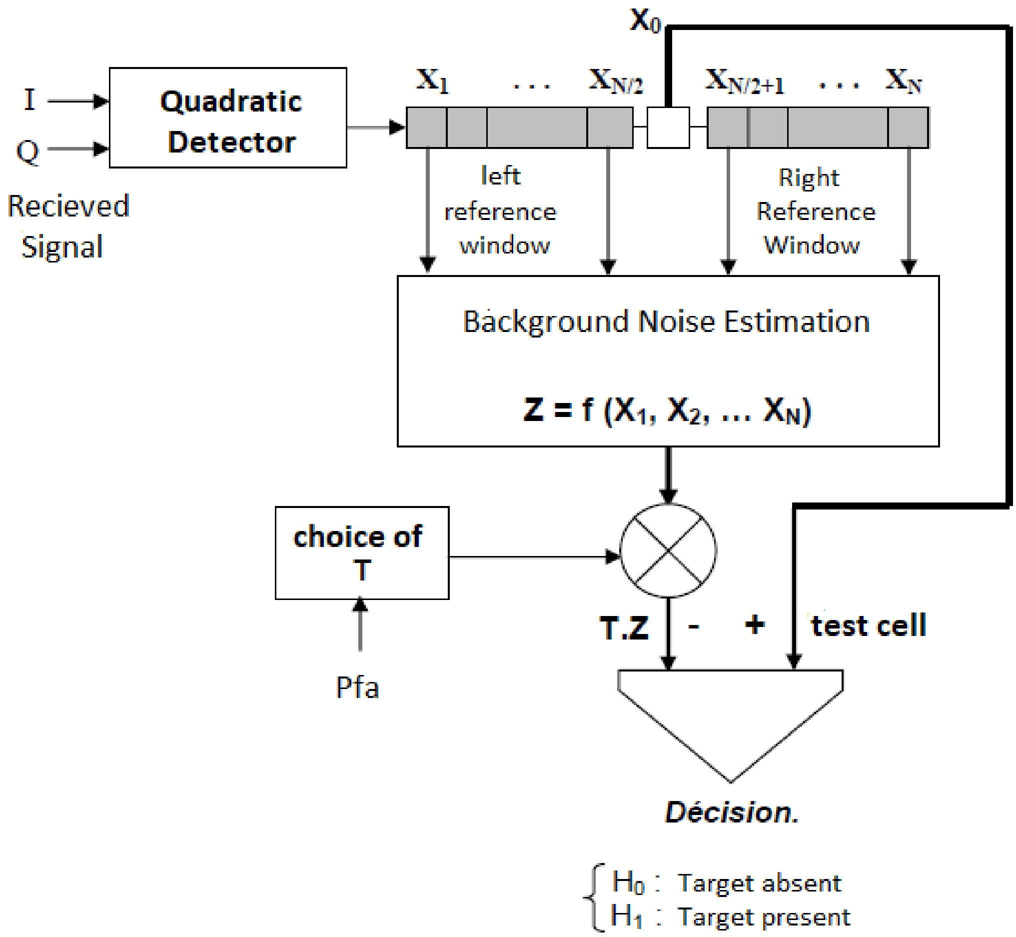

Figure 2-6 Block diagram of a constant false alarm rate detector.

2.5 Conclusion

In this chapter, we have discussed fundamental decision criteria and detection techniques, emphasizing the limitations of fixed threshold detection in non-homogeneous environments. To address these limitations, adaptive threshold detection, ensuring a Constant False Alarm Rate (CFAR), is employed. This lays the foundation for understanding more sophisticated detection methods.

Radar detection techniques have evolved significantly, catering to various applications. Traditional methods like pulse radar and continuous wave radar have been complemented by advanced techniques such as Synthetic Aperture Radar (SAR), phased array radar, and cognitive radar. Each of these techniques offers distinct advantages and capabilities. The integration of radar systems with other sensor modalities and the application of artificial intelligence has further enhanced radar performance and versatility, making them more accurate, efficient, and intelligent.

CHAPTER 3

DATA FUSION BASED PSO

CHAPTER 3

3.1 Introduction

Particle Swarm Optimization (PSO) and radar detection systems share a fundamental similarity—they both harness the power of collective intelligence to solve complex optimization and decision-making problems, respectively. PSO, inspired by the coordinated movement of bird flocks or fish schools, uses a population of particles to explore and converge towards optimal solutions in a search space. Similarly, radar detection systems employ distributed sensors and adaptive algorithms to collaboratively detect targets amidst noise and uncertainty.

PSO operates with each particle adjusting its position based on its own best-known solution and the global best solution found by the entire swarm. This iterative process allows PSO to efficiently navigate complex landscapes and find optimal solutions. Likewise, in radar detection, multiple sensors make local decisions based on adaptive Constant False Alarm Rate (CFAR) techniques like Censored Limited-Memory Median Detector (CLMD k) or Ordered Statistic (OS) algorithms. These local decisions are then integrated using data fusion techniques to derive a global decision, optimizing detection accuracy while controlling false alarms.

Recent advancements in radar technology, influenced by principles akin to PSO, emphasize decentralized detection systems that leverage distributed sensor networks. Researchers like Barkat and Varshney have pioneered decentralized CFAR detection theories, optimizing local detector thresholds and fusion rules to maximize global detection probabilities while maintaining low false alarm rates. Elias-Fusté et al. further extended this research by integrating multiple CFAR algorithms at the local level, enhancing the robustness of detection systems across diverse operational environments.

Both PSO and radar detection systems exemplify the synergy between distributed intelligence and adaptive optimization techniques. By harnessing collective decision-making processes, they enhance reliability, coverage, and efficiency in their respective domains. As research continues to evolve, the integration of PSO-inspired principles into radar technology promises to further advance the capabilities of detection systems, ensuring their effectiveness in increasingly complex scenarios.

3.2 CFAR DETECTOR STUDY

3.2.1 CFAR definition

CFAR s the abbreviation of "constant false alarm rate ". CFAR is one of the substantial parts of radar signal processing, derivated from the proposition of Finn and Johnson [13] In 1968, which aim to control the detection threshold according to the noise power, based on cells surrounding the cell under investigation. the aim of this control is to get a constant false alarm detector which adapt contininiously the threshold with the noise potential which is estimated from the cells that surround the cell under test.

3.2.2 Principles of operation

The operating principle of CFAR is the detection based on setting an adaptive threshold by the process of a ranged group of samples within the reference window surrounding the cell under test .The threshold is determined with the estimated value of the total noise potential and clutter which are unknown , plus they are varied in time which means variables.The operation of estimating noise plus clutter value is processed in reference window extracted from cells surrounding the CUT , in order to realise this operation the probability of false alarm Pfa has to be maintained [14].

The framed part in (Figure 3.1) is the CFAR processor which receive samples from the integrator to exploit them in estimating the value of Z.

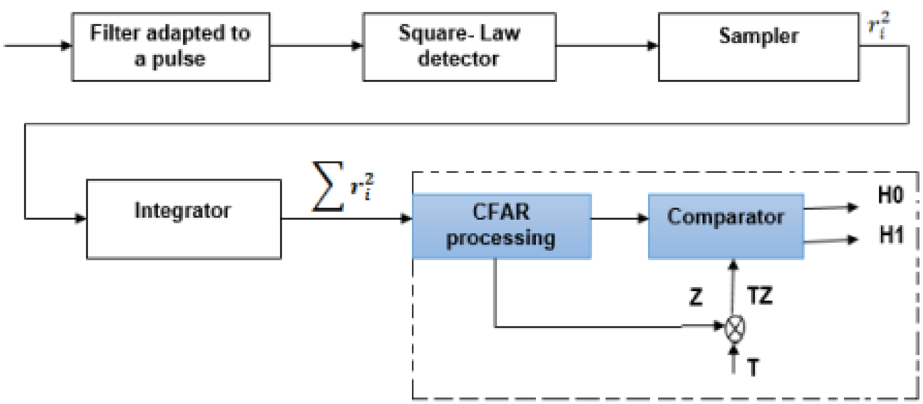

Figure 3-1 adaptive *detector diagram*

For estimating the clutter's level the CFAR detector utilise the samples within the reference cells(Figure 3.2) where N is the number of reference cells.The two cells surrounding the cell under test are called the guard cells which are considered as non reference cells in order to eliminate the overflow of energy from the CUT to the near cells .

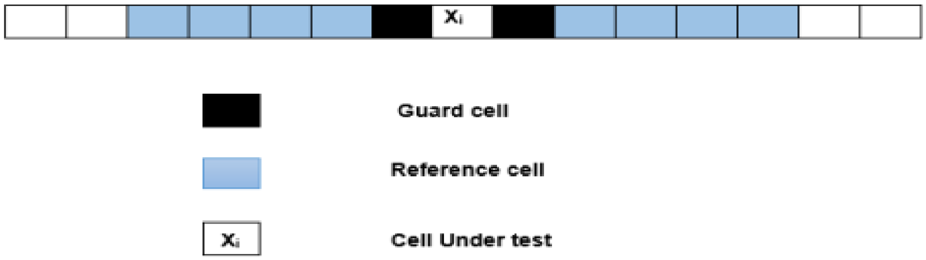

Figure 3-2 reference window

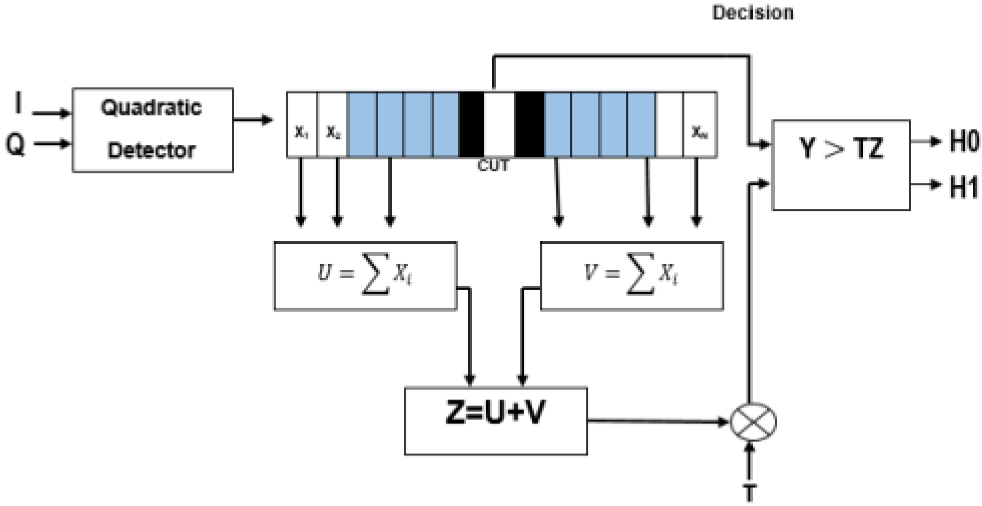

Figure 3-3 CFAR processor

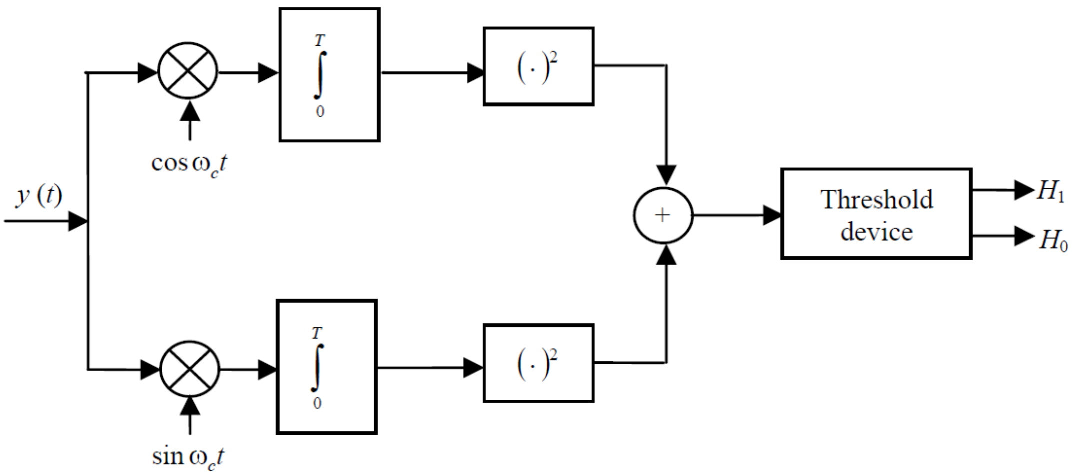

Figure 3-4 Non-Coherent Detector

After the estimation of Z with a specific algorithm, Z has to be multiplied with a scale factor T in order to get an adaptive threshold which is going to be compared with Y (the amplitude within the cell under test). After the comparison, decisions are taken based on these hypothesis:

- If $Y>TZ$ H1 presence of a targe
- If $Y<TZ$ H0 Absence of a target

All CFAR detectors differ in the method used for Z estimation and are designed to work under the conditions of a given clutter model. Clutter methods differ in the distribution of amplitudes in the reference cells. The clutter is said to be homogeneous if the amplitudes of the samples in the distance cells are statistically independent and identically distributed [3]. Otherwise, other distributions, including the Ryleigh distribution, are used as clutter models. one of the most difficult problems in radar systems is the detection of targets under varying environments.

3.2.3 Environment (background)

the environment is the medium which surrounds a system, in our case the environment is the medium crossed by the electromagnetic waves intervening of a radar and are reflected, about the reflected signals the environments of the radar differ, the behavior of the signal emitted in a space differs according to the crossed medium for example: if a radar emits signals in a space the signals reflected from the sea or of a region that it rains or a forest it is not the same .

3.2.3.1 Homogenous background

this is the ideal environment for radar detection, it is the case of absence of clutter and interfering targets, the homogeneity is that the reflected signal samples are described by identically distributed independent exponential random variables

3.2.3.2 Non homogenous background

When the reference window scans the environment in a given direction, different nonhomogeneous situations can affect the configuration of the reference cells. These situations are caused by the presence of interfering targets (secondary targets) and/or clutter edges at the reference channel **(figure 3.2).**

The objective of the CFAR is to be able to stipulate the detection threshold, in the face of the variations undergone in the environment around , indeed several situations can decrease the CFAR performances , for that several CFAR algorithms are proposed to preserve and improve the performances of the CFAR detector , the CFAR detectors differ according to the difference of the algorithms, knowing that the difference of these algorithms provides the mathematical method of the form of the estimator Z=f(X1,X2,….,XN) conceived to estimate the value of the noise power and the clutter [7].

3.3 TYPES OF CFAR PROCESSORS

3.3.1 CA- CFAR processor

3.3.1.1Definition

CA-CFAR is the most optimal processor in the homogeneous environment: while it keeps the false alarm rate constant it maximises the probability of Pd detection, so it is the most desirable processor if there are no clutter edges and no interfering targets in the reference window, however this is not a practical assumption: the performance of this processor degrades significantly in an non-homogeneous environment [15].

The CA-CFAR detector assumes that the signal at the output of the Law-square detector is described by independent exponential identically distributed random variables (homogenous environment).

This detector arithmetically averages the reference cells to estimate the clutter level. if N is the number of reference cells, this detector calculates the Sum U of N=2 samples preceding and the Sum V of the N=2 samples following the cell under test, taking into account the guard cells :

$$\boldsymbol{U} = \sum_{\mathrm{i}=1}^{\frac{\mathrm{N}}{2}} \mathbf{X}_{\mathrm{i}} \qquad (3.1)$$

$$V = \sum_{i=N/2+1}^{N} X_i \tag{3.2}$$

The two windows U and V are then summed in order to obtain an estimate Z of the interfering target.

$$Z = U + V \tag{3.3}$$

The threshold is calculated by multiplying Z by the scale factor T and the detector makes a decision by comparing TZ to the sample amplitude Y in the reference cell,

$$Y \underset{H_0}{\overset{H_1}{\gtrless}} T_Z \tag{3.4}$$

The notation (3.4) means that if Y excides the threshold TZ, then the decision in favour of H_1, otherwise it is in favour of H_0.

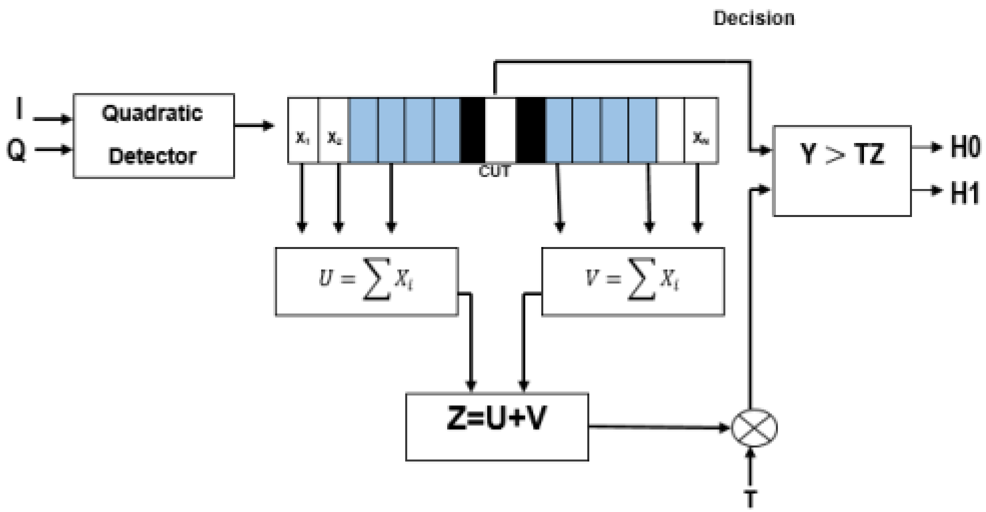

Figure 3-5 CA-CFAR processor

3.3.1.2 Probabilistic study

The conditional probability density of the output of the cell under test is written,

$$fy_{/H_i}(y'/H_i) = \begin{cases} \frac{1}{2\sigma^2(1+s)} \exp\left[-\frac{y}{2\sigma^2(1+s)}\right], \text{for } i = 1 \\ \frac{1}{2\sigma^2} \exp\left[-\frac{y}{2\sigma^2}\right], \text{for } i = 0 \end{cases} \tag{3.5}$$

Where σ2 represents the power of the noise and S the signal to noise ratio. the hypothesis H_0 corresponds to the case where the noise is alone while the hypothesis H_1 corresponds to the case where the noise is accompanied by a target signal.

The probability of detection Pd is given by:

$$Pd = [P(Y > TZ / H1)] \tag{3.6}$$

Where Z is the estimated noise level.from equations (3.5) and (3.6), we have ,

$$P_d = \left[\int_{\mathrm{TZ}}^{\infty} \frac{1}{2\sigma^2(1+s)} \exp\left[-\frac{y}{2\sigma^2(1+s)}\right] dy\right] \tag{3.7}$$

$$P_d = \left[\exp\left(-\frac{TZ}{2\sigma^2(1+s)}\right)\right] \tag{3.8}$$

Where Mz is the moment generating function (MGF) of the random variable Z which is written for the CA-CFAR detector:

$$\boldsymbol{z} = \sum_{i=1}^{N} \boldsymbol{x_i} \tag{3.9}$$

Where Xi is the random variable that describes the amplitude of the sample in the nth reference cell.

On the other hand, the probability density given by (3.5) is a special case of the probability density of the Gamma distribution G(α,β)

$$f_x(x) = \frac{1}{(\alpha)\beta^{\alpha}} x^{\alpha-1} \exp\left(-\frac{x}{\beta}\right) \tag{3.10}$$

Which has for FGM [9],

$$M_x(t) = \frac{1}{(1-\beta t)^{\alpha}} \tag{3.11}$$

For α = 1, we get an exponential probability density,

$$f_x(x) = \frac{1}{\beta} \exp\left(-\frac{x}{\beta}\right) \tag{3.12}$$

Of the same form as given by (3.5) with β = 2σ 2 (1+S) for hypothesis H1 and β = 2σ2 for the hypothesis H_0.thus , substituting in equation (3.11) α and β we obtain , The FMG of random variable Xi ,

$$M_x(t) = \frac{1}{(1-2\sigma^2 t)} \tag{3.13}$$

Which,combined with relation (3.9) and assuming that Xi are idependent and identically distributed , gives the FMG of Z ,

$$Mz\ (t)\ =\ Mx\ N(t) \tag{3.14}$$

$$= \frac{1}{(1-2\sigma^2 t)^n N} \tag{3.15}$$

Finally, from equations (3.8) and (3.15) ,we find that the probability of detection is :

$$P_d = \left(\frac{1+s}{1+s+T}\right)^N \tag{3.16}$$

The false alarm probability Pfa is obtained simply by setting S=0 in (3.16) because Pfa corresponds to the H0 hypothesis where the signal-to-noise ratio S is zero (no signal).

$$Pfa = (1 + T) - N \tag{3.17}$$

The formula (3.17) is used to calculate the scaling factor for a fixed false alarm probability.

Table 3-1 the scaling factor for different false alarm probabilities Pfa and different values of N

Pfa / N	10^{-4}	10^{-5}	10^{-6}
8	2.16	3.21	4.62
16	0.77	1.05	1.37
24	0.46	0.61	0.77
32	0.33	0.43	0.53

The use of the CA-CFAR detector in situations similar to those shown in (figure 1.10) leads to a significant loss of detection or an increase in the false alarm rate. In the case where the cell under test is immersed in the clutter, (figure1.8), the cells drowned in thermal noise contribute to an underestimation of the detection threshold, resulting in a higher probability of false alarm.

In (figure1.9), the cell under test being in thermal noise, the cells belonging to the clutter tend to increase the detection threshold and consequently to degrade the detection probability. This particular situation is known as "masking effect".

3.3.2 OS-CFAR Processor

3.3.2.1 Definition

To overcome the problems encountered by the SO and GO-CFAR detectors (derived from CA-CFAR) in the case of a non-homogenous environment ,Rohling [16] introduced a new detector based on order statistics ,i.e on the statistical properties of an ordered set of samples .the samples are ordered according to their increasing amplitude to obtain the following sequence of ordered samples ,

$$X(1) \leq X(2) \leq \cdots \leq X(k) \leq \cdots \leq X(N \quad (3.18)$$

The samples X(k), of order k , is then selected to represent the Z-statistical test ,

$$Z = X(k) \quad (3.19)$$

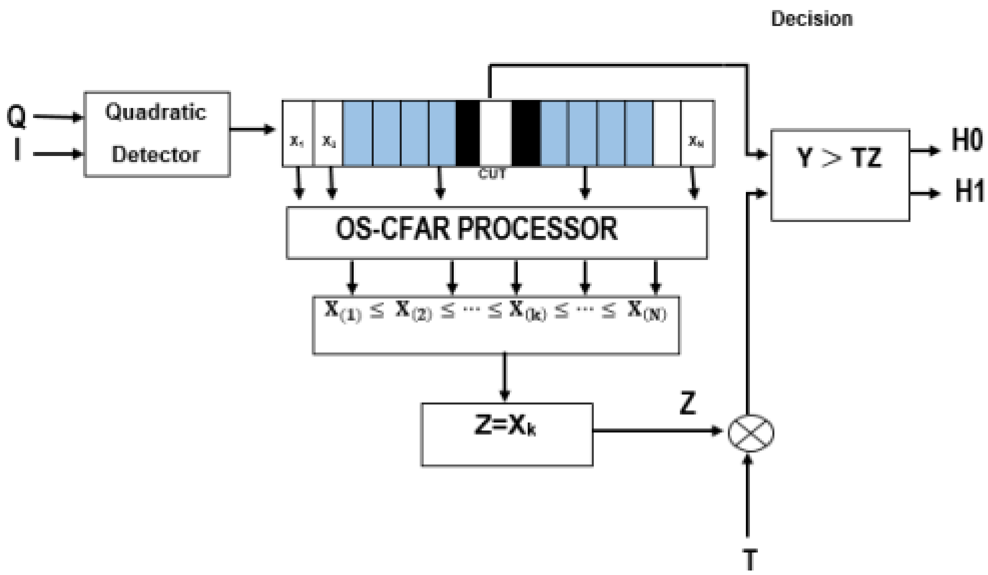

Figure 3-6 OS-CFAR processor

This detector offers some immunity to interfering targets .indeed , the echoes from the latter occupy the highest positions in the ordered sequence (3.20) and will therefore be eliminated .it is obvious that if m is the number of interfering targets ,which appear in the reference window, the parameter k should be chosen such that k ≤ N-m if this condition is not verified , the chosen sample will correspond to an echo of an interfering target and thus the detection of the primary target is compromised .in [9,10], the analysis of the effect of the parameter k on the detection performance in a Gaussian clutter or interference has been studied and the recommended value for k is:

$$k = \frac{3N}{4} \tag{3.20}$$

This value offers a compromise between immunity to interfering targets and low detection losses in the case of a homogeneous clutter.

3.3.2.2Probabilistic study

The probability density function $\boldsymbol{fx(k)(x)}$ of the kth sample of the ordered sequence (3.18) is given by:

$$f_{x(k)}(x) = k\binom{N}{k}[F_X(x)]^{k-1}[1 - F_X(x)]^{N-k} f_X(x) \tag{3.21}$$

Where N is the number ordered samples and $\boldsymbol{fx(k)(x)}$ and $\boldsymbol{FX(x)}$respectively the probability density and distribution function of an unordered sample.

In the case of a Rayleigh distribution, equation (3.21) becomes:

$$f_{X(k)}(x) = \frac{k}{\mu}\binom{N}{k}\left[e^{-x/\mu}\right]^{N-K+1}\left[1 - e^{-x/\mu}\right]^{k-1} \tag{3.22}$$

The expressions for the false alarm and detection probabilities are given by:

$$P_{fa} = k\binom{N}{k}\frac{\Gamma(N - k + T + 1)\Gamma(k)}{\Gamma(N + T + 1)} \tag{3.23}$$

$$P_d = k\binom{N}{k}\frac{\Gamma\left(N - k + \frac{T}{(1+s)} + 1\right)\Gamma(k)}{\Gamma\left(N + \frac{T}{(1+s)} + 1\right)} \tag{3.24}$$

Where T denotes the scale factor of the OS-CFAR, S the signal-to-noise radio,Γ the gamma function defined by ,

$$\Gamma(x) = \int_0^{\infty} t^{x-1} e^{-t} dt, x > 0 \tag{3.25}$$

And that comes down to:

$$\Gamma(x + 1) = x! \tag{3.26}$$

In the case where x is positive integer and:

$$\binom{N}{k} = \frac{N!}{k!\,(N-k)!} \tag{3.27}$$

Table 3-2 *the scaling factor for different false alarms probabilities and the number of the reference cells.*

Pfa / N	10^{-4}	10^{-5}	10^{-6}
8	18.78	30.08	46.70
16	11.08	15.54	20.95
24	9.34	12.59	16.30
32	8.585	11.34	14.40

3.3.3 CMLDk CFAR Processor

3.3.3.1Definition

The CMLDk is an optimal processor in the non-homogeneous background, it works like a CA-CFAR processor in the homogeneous background, the output of the detected quadratic receiver is sampled in the range by the range resolution cells, as shown in **(Figure 2.18)** In the window of the reference test cell, we can have noise and/or echoes from a fixed number of targets and interfering targets. The first target return echo is observed in the cell under test. The outputs of the reference cells j=1,2,...,N, are then fed into a calibration device which in turn transmits the samples in ascending order of importance to give the N ordered samples. The number of interfering cells is assumed to be known a priori, and not to exceed the k-point. Thus, to form the background estimator, the k cells with the highest power must be censored and the remaining cells summed**.** [17]

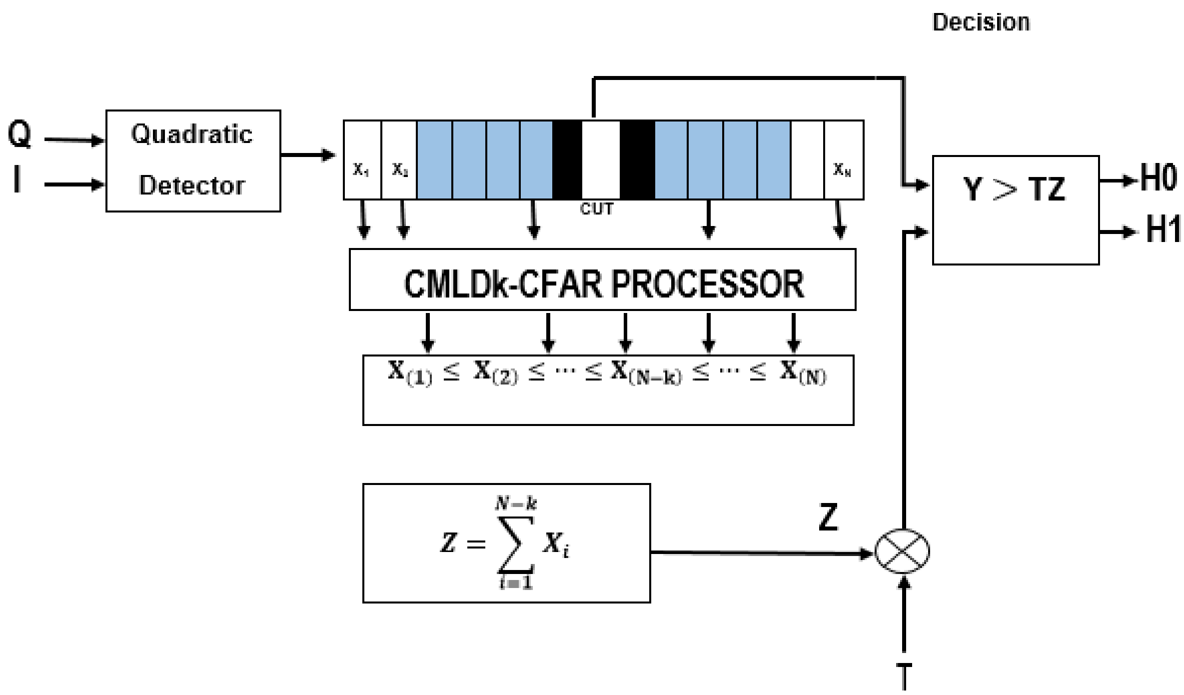

Figure 3-7 CMLDk- CFAR processor

the CMLDk CFAR sorts all reference cells currently in descending order and then removes k reference cell samples from the maximum value of the sample, and takes the linear combination of the remaining reference cells as the Z power detection cell clutter estimate.

3.3.3.2Probabilistic study

the moment generating function is given as:

$$\begin{cases} \Phi_z(\omega) = \int_0^{\infty} f_z(z)\exp(-z\omega)dz & \text{(a)} \\ \Phi_{X_0/H1}(\omega) = \int_0^{\infty} P_{X_0/H1}(x)\exp(-x\omega)dx & \text{(b)} \\ \Phi_{X_0/H0}(\omega) = \int_0^{\infty} P_{X_0/H0}(x)\exp(-x\omega)dx & \text{(c)} \end{cases} \quad (3.28)$$

Using equation (3.28a) and (3.28b), we obtain,

$$P_d = -\sum_i \text{Res}\left[\omega^{-1}\Phi_{X_0/H1}(\omega)\Phi_z(-T\omega), \omega_i\right] \quad (3.29)$$

With:

P_d probability of detection

ω_i are the real negative poles of $\Phi_{X_0/H1}$

T scaling factor

In monopulse processing $\Phi_{X_0/H1}$, is given by:

$$\Phi_{X_0/H_1}(\omega) = \frac{(1+\omega)^{\eta-1}}{(1+b\omega)^{\eta}} \quad (3.30)$$

With : b=1+SNR/η and η > 0 (degrees of freedom) η=1 corresponds to the models SW1 and SW2 ,η=2 corresponds to the targets SW3 and SW4 .In order to determine $P_d(k)$ in a homogeneous medium as a function of Tk , one has to find the expression of Φ_z under the assumption that the reference cells X1,X2.....,XN are IID variables, exponentially from a reference sample of size N , are non-independent and non-identically distributed processes (even though the N reference cells are IID) .

If the Xi follow an exponential distribution (μ=1), then the probability density (pdf) of the statistic X(k) of order k is given by:

$$fk(x) = k\binom{N}{K}[1-exp(-x)]kexp-(N-k+1)x \quad (3.31)$$

The relation **(4.1)** shows that Z is expressed as a function of non-independent processes, which does not allow to have directly its MGF, to circumvent this problem, one uses the normalized deviation variables [9] defined by:

$$Yj = (N - j + 1)(X(j) - X(j - 1)) \qquad (3.32)$$

with j=1,...,N-k and X(0)=0

In [9], it is shown that the variables Yj are positive, independent and follow the samedistributionas the reference sample (exponential pdf). Inverting the transformation **(4.7)** we obtain:

$$X(j) = \sum_{i=1}^{i=1} \frac{Y_j}{N + 1 - i} \qquad (3.33)$$

to express Z in terms of Y_j , we substitute **(4.8)** into **(4.1)** ,

$$Z = \sum_{j=1}^{N-K} a_j Y_j \qquad (3.34)$$

$$a_j = \frac{N - K + 1 - j}{N + 1 - j} \qquad (3.35)$$

According to [9] and using **(4.9)** , the FGM of Z can be expressed as :

$$\Phi Z(\omega) = \Phi_{Y_{1,Y2\ldots,N-K}}(a_1\omega, a_2\omega, \ldots, a_{N-K\omega}) \qquad (3.36)$$

As long as the Yj are statistically independent, the joint FGM of the variables Y1,...,YN-k is simply the product of the individual FGMs of each Yj , so ,

$$\Phi_z(\omega) = \prod_{j=1}^{N-k} \int_0^{\infty} e^{-Y_j(a_j\omega+1)} dY_j \qquad (3.37)$$

By integrating this expression, we obtain :

$$\Phi_z(\omega) = \prod_{j=1}^{N-k} \left\{1 + \frac{N-k+1-j}{N+1-j}\omega\right\}^{-1} \tag{3.38}$$

for k fixed and knowing that $\Phi X0H1$ ⁄possesses a single pole at point ω0=−(1+SNR)-1 for targets SW1 and SW2 in monopulse), pd(k) is obtained by substituting **(4.13)** and **(4.5)** (with ɳ=1) in **(4.4)**, thus*:*

$$P_d = \binom{N}{N-k} \prod_{j=1}^{N-k} \left(\frac{T_k}{1+SNR} + \frac{N-j+1}{N-k-j+1}\right)^{-1} \tag{3.39}$$

the probability of false alarm is obtained from the previous equation by cancelling the SNR.

3.3.4 DISTRIBUTED CFAR DETECTION WITH DATA FUSION

We consider n distributed CA-CFAR detectors with a data fusion center as shown in ***Figure 3-8***. [18]

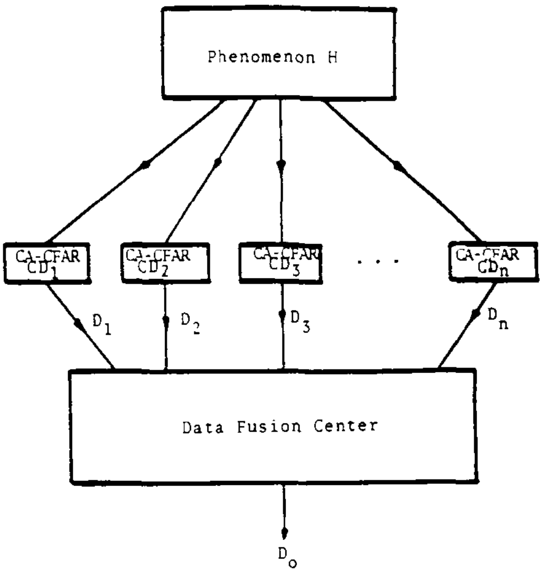

Figure 3-8 Distributed CFAR Detection With Data Fusion.

It is assumed that the number of range cells at the ı th detector is N_j, i = 1,2,..., n. The target to be detected is a slowly fluctuating target model of Swerling type I. The target is embedded in a white Gaussian noise of unknown level. Let the probability of false alarm and the probability of detection at the individual detectors be denoted by P_{Fi}, and P_{Di}, i = 1,2,..., n, respectively. If the average noise power is σ^2, then the conditional probability density function of the test statistic q^i_0 from the test cell of detector i, i = 1, 2...., n, is given by:

$$P_{Q_0^L/H_j}\left(q_0^i/H_j\right) = \begin{cases} \dfrac{1}{2\sigma^2\left(1+S_j\right)} e^{-q_0^1/2\sigma^2(1,S_1)}, \text{ pour l'hyypothése } H_1 & \text{(a)} \\ \dfrac{1}{2\sigma^2} e^{-q_0^i/2\sigma^2}, \text{ pour l'hypothése } H_0 & \text{(b)} \end{cases} \quad (3.40)$$

where Si, i = 1, 2...., n, is the target signal-to-noise radio (SNR) at each CA-CFAR detector. The hypothesis H_o represents the case of noise alone, while hypothesis H_1 represents the noise plus target signal case. To simplify the mathematical derivations, we assume S1 = S, = . . . = S_n = S, where S is the target SNR. Results for the case of unequal target SNRs can be obtained in a straightforward manner. The probability of detection P_{Di} for detector i,

i = 1, 2,..., n, is given by:

$$P_D^i = \int_0^\infty \Pr\left(Q_0^i > T_i q^i \mid Q^i, \mathrm{H}_1\right) P_Q^i\left(q^i\right) dq^i \quad (3.41)$$

where is the scaling factor at the CA-CFAR detector i, i = 1, 2,. .. ,n, and $P_Q^i\left(q^i\right)$ denotes the probability density function of the adaptive threshold at the ith CA-CFAR detector. Also,

$$P_D^i = \int_0^\infty \Pr\left(Q^i > \frac{T_i q^i}{Q^i}, H_1\right) P_Q^i\left(q^i\right) \cdot dq^i = \exp\left[-\frac{T_i q^i}{(1+S)}\right] \quad (3.42)$$

Since the noise samples, for each CA-CFAR detector, are identically distributed, the probability of detection of the individual detectors can be written as:

$$P_{D_i} = \frac{(1+S)^{N_i}}{(1+S+T_i)^N}, i = 1,2, \ldots, n. \quad (3.43)$$

Each CA-CFAR detector transmits its decision to the data fusion center. These local decisions of individual detectors are denoted by Di, i = 1,2, . . ., n, where

$$D_i = \begin{cases} 0, & \text{if detector } i \text{ decides } \mathrm{H}_0 \\ 1, & \text{if detector } i \text{ decides } \mathrm{H}_1 \end{cases}$$

In order to be able to express the overall probability of detection P_D the overall probability of false alarm P_F and the overall probability of a miss P_M at the data fusion center, in terms of the probabilities of false alarm and miss at the local detectors, i.e., P_{Fi}s and $P_{M;}$s, we define the following quantities:

$$D = (D1, D2, \ldots, DN) \quad (3.44)$$

$$M_{\mathrm{D}} = \prod_{S^0} P_{M_j} \prod_{S^1} \left(1 - P_{M_k}\right) = P(\mathbf{D} \mid \mathrm{H}_1) \quad (3.45)$$

$$F_{\mathrm{D}} = \prod_{S^0} \left(1 - P_{F_j}\right) \prod_{S^1} P_{F_k} = P(\mathrm{D} \mid \mathrm{H}_0) \quad (3.46)$$

$$PkD = Pr(Do = k\,I\,D) \qquad k = 0,1 \quad (3.47)$$

D_0 = global decision at data fusion center.

S_0 = Set of all j, (j # 0), such that D_j is an (Gc) element of D and D_j = 0

S' = Set of all k, (k # 0), such that D_k is an element of D and D_k = 1.

Then, we may express P_0, P_M, and P_F as follows.

$$P_M = \sum_{\mathrm{D}} P_{0\mathrm{D}} M_{\mathrm{D}} \quad (3.48)$$

$$P_F = \sum_{\mathrm{D}} P_{1\mathrm{D}} F_{\mathrm{D}} \tag{3.49}$$

$$P_D = 1 - P_M \tag{3.50}$$

where $\boldsymbol{\Sigma}_{\mathrm{D}}$ = summation over all possible values of D. The transition probabilities POD and PID are determined by the given fusion rule. Since D can take 2^n possible values, there are 2^n possibilities for P_{0D} and P_{1D}. The goal is to maximize the overall probability of detection while keeping the overall probability of false alarm constant. To do this, we use the calculus of extrema and form the objective function.

$$\text{Fitness } (N_i, K_i, T_i) = \mathrm{abs}(1 - \mathrm{Pd}) + \mathrm{v.abs}\ (\mathrm{Pf} - \mathrm{Pfa}) \tag{3.51}$$

where N_i is the number of reference cells at the i^{th} sensor, K_i is the rank order at the i^{th} sensor, T_i is the threshold at the i^{th} sensor and α0 is the overall desired probability of false alarm. P_d is the overall probability of detection and Pfa is the overall probability of false alarm. We assume that all the receivers are identical for a fixed number of cells in each detector N_i = 32. The number of receivers considered in each system is D = 2, 3, and 5 for the OS-CFAR and CMLD local detector are considered. Also, the two fusion rules, “AND” and “OR” are tested to evaluate the performance of the methods used. [19]

Once the threshold multipliers T_j, i = 1,2, . . ., n, are obtained, all the PF, S are fixed and the optimum PD results. Now, we give specific results for the AND and the OR fusion rules. We also find the optimum threshold multipliers to maximize PO while PF is maintained at the desired value.

3.3.4.1Data Fusion Center with AND Fusion Rule

In Table I, we present the AND fusion rule. [18] *From this table, we see that the global decision at the data fusion centre is one only if all of the detectors decide a one. The transition probabilities are:*

$$P_{0\mathrm{D}} = \begin{cases} 0, & \text{if } \mathrm{D} = [1,1 \dots, 1]^{\mathrm{T}} \\ 1, & \text{otherwise} \end{cases} \tag{3.52}$$

And

$$P_{1\mathrm{D}} = \begin{cases} 1, & \text{if } \mathrm{D} = [1,1 \dots, 1]^{\mathrm{T}} \\ 0, & \text{otherwise.} \end{cases} \tag{3.53}$$

Substituting (3.52), (3.53), and (3.50) into (3.48) and (3.49) and rearranging terms, P_D and P_F can be written as:

$$P_D = \prod_{i=1}^{n} P_{D_i} \tag{3.54}$$

$$P_f = \prod_{i=1}^{n} P_{f_i} \tag{3.55}$$

That is:

$$P_D = \prod_{i=1}^{n} \frac{(1+S)^{N_i}}{(1+S+T_i)^{N_i}} \tag{3.56}$$

$$P_F = \prod_{i=1}^{n} \frac{1}{(1+T_i)^{N_i}} \tag{3.57}$$

Table 3-3 *AND Fusion Rule.*

D_1	D_2	D_3	…	D_{n-1}	D_n	D_0
0	0	0		0	0	0
0	0	0		0	1	0
0	0	0		1	0	0
0	0	0		1	1	0
1	1	1		0	0	0
1	1	1		0	1	0
1	1	1		1	0	0
1	1	1		1	1	1

3.3.4.2 Data Fusion Center with OR Fusion Rule:

When the fusion rule is OR at the data fusion center, the global decision at the output of the system is zero, i.e., hypothesis H_0 is true, only if the local decisions are all zero [18]. S_o, the transition probabilities are:

$$P_{1u} = \begin{cases} 0, & \text{if } \mathbf{u} = [0,0,\dots,0]^T \\ 1, & \text{otherwise} \end{cases} \tag{3.58}$$

$$P_{0u} = \begin{cases} 1, & \text{if } \mathbf{u} = [0,0,\dots,0]^T \\ 0, & \text{otherwise} \end{cases} \tag{3.59}$$

Following similar steps as in the previous section we get:

$$P_D = 1 - P_M = 1 - \prod_{i=1}^{n} P_{M_i} \tag{3.60}$$

And;

$$P_F = 1 - \prod_{i=1}^{n} \left(1 - P_{F_i}\right). \tag{3.61}$$

Table 3-4 OR Fusion Rule.

D_1	D_2	D_3	…	D_{n-1}	D_n	D_0
0	0	0		0	0	0
0	0	0		0	1	1
0	0	0		1	0	1
0	0	0		1	1	1
1	1	1		0	0	1
1	1	1		0	1	1
1	1	1		1	0	1
1	1	1		1	1	1

For the OS-CFAR processor the Pd_i and Pfa_i are given by:

$$\mathrm{Pd}_i = \prod_{j=0}^{K-1} \frac{(N-j)}{\left(N-j+\frac{T}{(1+S)}\right)} \tag{3.62a}$$

$$\mathrm{Pfa}_i = \prod_{j=0}^{K-1} \frac{(N-j)}{(N-j+T)} \tag{3.62b}$$

For the CMLDk-CFAR processor the Pd_i and Pfa_i are given by:

$$\mathrm{Pd}_i = \binom{N}{K} \prod_{j=1}^{K} \left[\frac{T}{1+S} + \frac{N-j+1}{K-j+1}\right]^{-1} \tag{3.63a}$$

$$\mathrm{Pfa}_i = \binom{N}{K} \prod_{j=1}^{K} \left[T + \frac{N-j+1}{K-j+1}\right]^{-1} \tag{3.63b}$$

3.4 PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization (PSO) algorithm is a computational technique inspired by the collective behaviour of natural organisms, such as birds or fish, that move together to achieve a common goal. In PSO, a group of particles (representing potential solutions) navigates through a problem's solution space to find the best possible solution. Each particle adjusts its position based on its own best-known solution (personal best) and the best solution discovered by the entire group (global best). This collaborative movement enables particles to converge toward optimal solutions over iterations. PSO is widely used for optimization problems in various fields, leveraging the power of collective intelligence to explore complex solution spaces and find optimal outcomes efficiently. [20]

PSO is a famous metaheuristic technique to solved optimization issue.

However, PSO belongs to the stochastic optimization method, which is mainly driven by two random streams utilized in the search mechanism. In such simulation iterations, the random streams are used as the uncertainty of the acceleration coefficients for the cognition and social factors.

3.4.1 Optimization with PSO Algorithm

The PSO algorithm is an optimisation tool for engineers that can solve more complex problems than traditional methods [21]. Inspired by animal behaviour, the PSO algorithm starts with a random population matrix where the rows are called particles and contain the values of the variable. Evolution is interested in finding the best solution with fast convergence. The individuals are referred to as particles, and are grouped together in a swarm. Each particle in the swarm represents a candidate solution to the optimisation problem. Each individual in a particle swarm is composed of three-dimensional vectors. The current position $s_{m,n}^{\text{old}}$, the previous best position $s_{m,n}^{\text{localbest}}$ and the velocity $v_{m,n}^{\text{old}}$ of the mth particle, define the dimensionality D of the search space for n=[1, D]. The particles update their velocities and positions based on the best local and global solutions as follows [21] [22]:

$$v_{m,n}^{\text{new}} = w.\,v_{m,n}^{\text{old}} + \Gamma_1 r_1\left(s_{m,n}^{\text{localbest}} - s_{m,n}^{\text{old}}\right) + \Gamma_2 r_2\left(s_{m,n}^{\text{globalbest}} - s_{m,n}^{\text{old}}\right), \qquad (3.62)$$

$$s_{m,n}^{\text{new}} = s_{m,n}^{\text{old}} + v_{m,n}^{\text{new}}. \tag{3.63}$$

where $s_{m,n}^{\text{globalbest}}$ is the best global solution and r_1, r_2 are independent random numbers uniformly distributed over [0,1]. The cognitive parameter Γ_1 and the social parameter Γ_2 act through diversification by seeking new solutions. The second term of (3.62) is the influence component or (personal influence) which allows the particles to return to the best position obtained. The third term in (3.63) is the social influence component, which causes the particle to follow the direction of its best neighbour. The last two terms act as intensification, exploring previous solutions and finding a better solution for a given region [22] [23]

If w =1, the particle's motion is entirely influenced by the previous motion, so the particle may keep going in the same direction. On the other hand, if 0≤ w <1, such influence is reduced, which means that a particle instead goes to other regions in the search domain.

$s_{m,n}^{\text{localbest}}$ And its current position $s_{m,n}^{\text{old}}$. It has been noticed that the idea behind this term is that as the particle gets more distant from the $s_{m,n}^{\text{localbest}}$ (Personal Best) position, the difference $\left(s_{m,n}^{\text{localbest}} - s_{m,n}^{\text{old}}\right)$ Must increase; hence, this term increases, attracting the particle to its best own position. The parameter r_1 existing as a product is a positive constant, and it is an individual-cognition parameter. It weighs the importance of the particle's own previous experiences.

The difference $\left(s_{m,n}^{\text{globalbest}} - s_{m,n}^{\text{old}}\right)$ Works as an attraction for the particles towards the best point until it's found at t iteration. Likewise, r_2 is also a social learning parameter, and it weighs the importance of the global learning of the swarm. And Γ_2 plays precisely the same role as Γ_1.

- r_1 =r_2 =0, all particles continue flying at their current speed until they hit the search space's boundary.
- r_1 >0 and r_2 =0, all particles are independent.
- r_1 >0 and r_2 =0, all particles are attracted to a single point in the entire swarm.

- $r_1 = r_2 \neq 0$, all particles are attracted towards the average of localbest and globalbest.

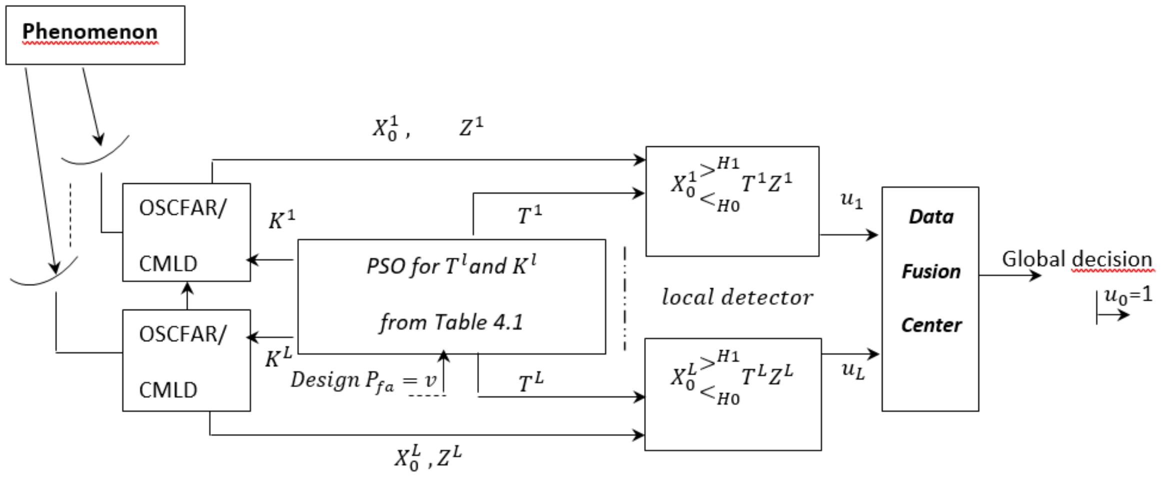

Figure 3-9 Block diagram of the Distributed processor OSCFAR/CMLDk based PSO algorithm *[1]*

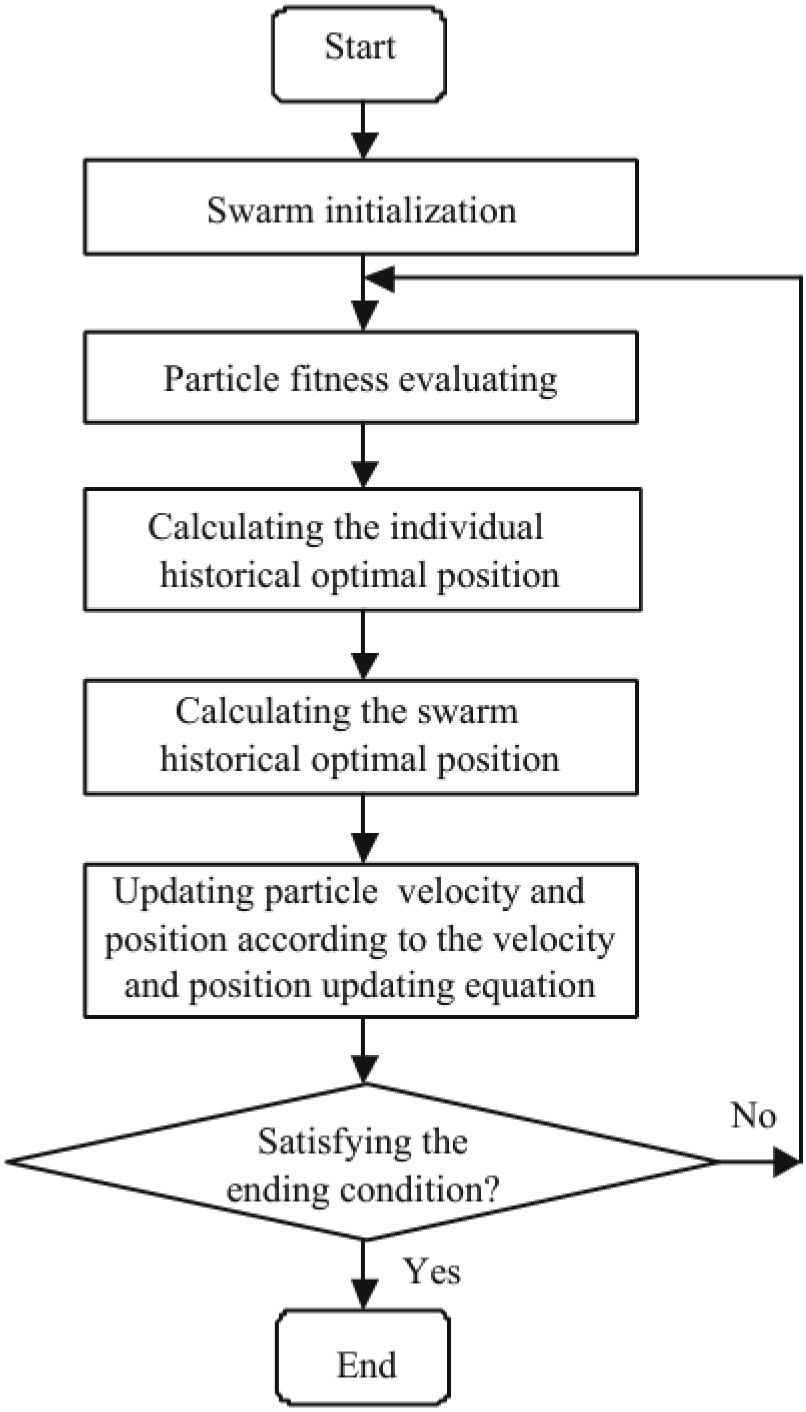

Figure 3-10 Flowchart of the particle swarm optimization algorithm

Thus, the movement of a particle is influenced by three components: the inertia component, the cognitive component and the social component.

The process begins with the initialisation of each particle, the corresponding fitness is then evaluated, a comparison is made between the best fitness value using the value of the old and the new $s_{m,n}^{\text{localbest}}$, the particle with the best fitness value is chosen as the $s_{m,n}^{\text{globalbest}}$, the velocity of the particle is then calculated according to (4. 54), followed by an update of the particle's position according to (4.55). At this stage, as long as the maximum number of iterations or the minimum error criterion is not reached, the test is repeated.

The velocity makes the particle moving in the same direction as the previous flight. A weighting inertia coefficient w is used to control the search field and reduce the influence of w_{max}. Thus, $v_{m,n}^{\text{old}}$ is multiplied by the inertia factor w. The best performance can be achieved by initialising w at 0.9, then gradually reducing it to 0.4. The particles start with a low velocity and perform extensive exploration. For this, the operation of the system improves during its convergence to the solution [21] [24]

3.5 CONCLUSION

Classical CFAR detection appears to be limited in its adaptability to complex environments. However, the utilization of distributed fusion rules and optimization tools such as Particle Swarm Optimization (PSO) significantly enhances its effectiveness. By employing AND and OR logic in distributed fusion rules for OS-CFAR and CMLDk-CFAR detectors, integration of data from multiple sensors is optimized, thereby improving overall detection performance. PSO further refines parameters like threshold T and K, enhancing data fusion algorithms and ensuring robust and reliable detection outcomes across diverse operational environments. This approach underscores the adaptive capability of CFAR detectors, making them more suitable for real-world applications where environmental conditions vary.

CHAPTER 4

SIMULATION

CHAPTER 4

4.1 INTRODUCTION

In this thesis, multiple scenarios are analyzed using the concept of applying particle swarm optimization (PSO) to adaptive threshold-based detectors, namely CMLDk-CFAR and OS-CFAR detectors. We consider a distributed system in which the local sensors do not produce a binary decision but rather optimized values of the parameters K and T. We analyze the PSO-optimized CMLDk-CFAR and OS-CFAR. We examine sensor networks with 2, 3, and 5 sensors using the optimized AND and 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 present the variation of the probability of detection for the CMLDk-CFAR and OS-CFAR detectors as a function of the SNR. These representations are made for the two CFAR types studied in the previous chapter, CMLDk and OS–CFAR. The simulation results are presented for non-homogeneous background.

4.2 CFAR ALGORITHMS DESCRIPTION

We have simulated different CFAR Algorithms using MATLAB platform in order to extract the most reliable from the studied detectors through comparison between their figures. These Algorithms are supposed in Additive White Gaussian Noise.

4.2.1 OS-CFAR ALGORITHM

This Algorithm is based on order statistics, we declare the reference window the SNR and k=3*N/4. all the samples are going to be sorted in order to select the k^{th} position in the range cells then the estimator Z = X(k). in PSO program we fix the Pfa to get the scaling factor T_{OS}. the product TZ, then corresponds to the threshold which is going to be compared to the signal within the cell under investigation, if the signal exceeds TZ then H_1 is true, otherwise, H_0 is true.

4.2.2 CMLDk-CFAR Algorithm

This Algorithm is based on censoring with a fixed point. we declare the interferences, the reference window, SNR. the samples are then sorted according to their magnitude, the greatest ones representing the interferences are censored and the rest are summed to perform the estimated noise level Z. in PSO program we fix the Pfa to get the scaling factor T_{CMLD}. The product TZ, then corresponds to the threshold which is going to be compared to the sample within the cell under investigation, if the signal exceeds TZ then H_1 is true, otherwise, H_0 is true.

4.2.3 PARTICLE SWARM OPTIMIZATION ALGORITHM

The Particle Swarm Optimization (PSO) algorithm, inspired by the social behaviour of birds flocking or fish schooling, is used here to optimize the parameters K and T for the CFAR detectors. The PSO algorithm initializes a swarm of particles, each representing a potential solution with random positions and velocities in the search space. Each particle's position corresponds to candidate values for K and T. The fitness of each particle is evaluated using the fitness function **(4.1)** where v is a weight parameter, Pd is the probability of detection, Pf is the false alarm probability, and Pfa is the desired false alarm probability. Each particle updates its personal best position if the current position has a better fitness value, and the global best position is updated if any particle's personal best is better than the current global best. The velocity of each particle is updated based on its inertia, cognitive, and social components, and positions are subsequently updated. The process repeats until a stopping criterion is met, such as a maximum number of iterations or a sufficiently small change in the global best fitness value. The optimized parameters K and T are then used to calculate the scaling factors and thresholds for the CFAR detection process, ensuring the detectors are optimally tuned for improved detection performance under various conditions and backgrounds, thereby enhancing adaptability and robustness in practical scenarios.

4.3 RESULTS AND DISCUSSIONS

We evaluate and validate the performance in terms of detection and mean acquisition time, of the proposed distributed adaptive acquisition schemes, using Monte Carlo simulations from 10^5 trials for a false alarm rate υ=10^{-4} and $\sigma_n^2 = 1$. To ensure that the system can converge to the global optimal using PSO, we set $0 < \Gamma_1 + \Gamma_2 < 4$ et $(\Gamma_1 + \Gamma_2)/2 - 1 < \mathrm{w} < 1$, where w is a linear function decreasing in time from 0.9 to 0.4, and Γ_1 = Γ_2 are set to 1.49618 [78, 80, 81]. The population is composed of 40 particles, each expressed as a vector$[K^1, K^2, \ldots, K^L; T^1, T^2, \ldots, T^L]$, the maximum number of generations is taken to be 200.

We set an SNR of 20 dB by applying the OR and AND fusion rules for the PSO to calculate the off-line values of T and K leading to the best performance. Table 4.1

below shows the corresponding optimum values of T and K in different situations. The boundary values of T and K are set to [0-500] and [1-N^l], respectively, where N^l is the reference window size of the lth sensor, N=32, l=2,3,5

Simulation stop criteria is when fitness achieves 10^{-6} and P_d approaches 1.

Table 4-1 Best results of Data Fusion AND/OR for OS-CFAR and CMLDk-CFAR detectors using PSO algorithm with Different Pfa Values

	AND rule			**OR rule**		
Detector / Pfa	D=2	D=3	D=5	D=2	D=3	D=5
OS-CFAR						
10^{-4}	K=20 T=12.2177 Pd=0.8948	K=20 T=7.6083 Pd=0.9012	K=20 T=4.3265 Pd=0.9061	K=20 T=33.5678 Pd=0.9801	K=20 T=35.6253 Pd=0.9967	K=20 T=38.3188 Pd=0.99999
10^{-5}	K=20 T=16.0866 Pd=0.8638	K=20 T=9.8386 Pd=0.8742	K=20 T=5.5176 Pd=0.8819	K=20 T=46.2355 Pd=0.9644	K=20 T=48.7296 Pd=0.9923	K=20 T=51.9944 Pd=0.9996
10^{-6}	K=20 T=20.3477 Pd=0.8312	K=20 T=12.2177 Pd=0.8464	K=20 T=6.7557 Pd=0.8574	K=20 T=61.5894 Pd=0.9412	K=20 T=64.6121 Pd=0.9839	K=20 T=68.5688 Pd=0.9987
CMLDk-CFAR						
10^{-4}	K=20 T=2.0845 Pd=0.8917	K=20 T=1.2857 Pd=0.8993	K=20 T=0.7252 Pd=0.9049	K=20 T=5.8926 Pd=0.9778	K=20 T=6.2657 Pd=0.9961	K=20 T=6.7551 Pd=0.9999
10^{-5}	K=20 T=2.7633 Pd=0.8591	K=20 T=1.6707 Pd=0.8712	K=20 T=0.9277 Pd=0.8801	K=20 T=8.2001 Pd=0.9599	K=20 T=8.6570 Pd=0.9907	K=24 T=9.2561 Pd=0.9995
10^{-6}	K=20 T=3.5179 Pd=0.8244	K=20 T=2.0845 Pd=0.8420	K=20 T=1.1393 Pd=0.8548	K=20 T=11.0230 Pd=0.9330	K=20 T=11.5812 Pd=0.9804	K=24 T=12.3128 Pd=0.9982

In this chapter, we present different scenarios to analyze the detection performance of the mentioned processors in both homogeneous and non-homogeneous environments. The performance is evaluated using the probability of detection (Pd) and the false alarm rate control (Pfa). We have considered a fixed number of reference windows with N=32. The desired Pfa values vary between Pfa=10^{-4} ,10^{-5} and 10^{-6}. We employ Particle Swarm Optimization (PSO) to optimize the values of K and T. We examine the performance with networks of 2, 3, and 5 detectors. The results are presented for non-homogeneous background, highlighting the robustness and adaptability of the optimized CFAR detectors under varying environmental conditions.

4.3.1 Fitness Function

In Figure 4-1, the plot illustrates the evolution of the best fitness values over generations using PSO for both CMLDk and OS CFAR detectors. The fitness function varies accordingly for each detector type, reflecting their specific optimization goals. Despite these variations, both plots demonstrate a consistent trend where the best fitness values decrease over generations. This convergence towards lower fitness values indicates PSO's effectiveness in optimizing parameters tailored to each CFAR detector type, ultimately enhancing their performance in detecting signals while minimizing false alarms.

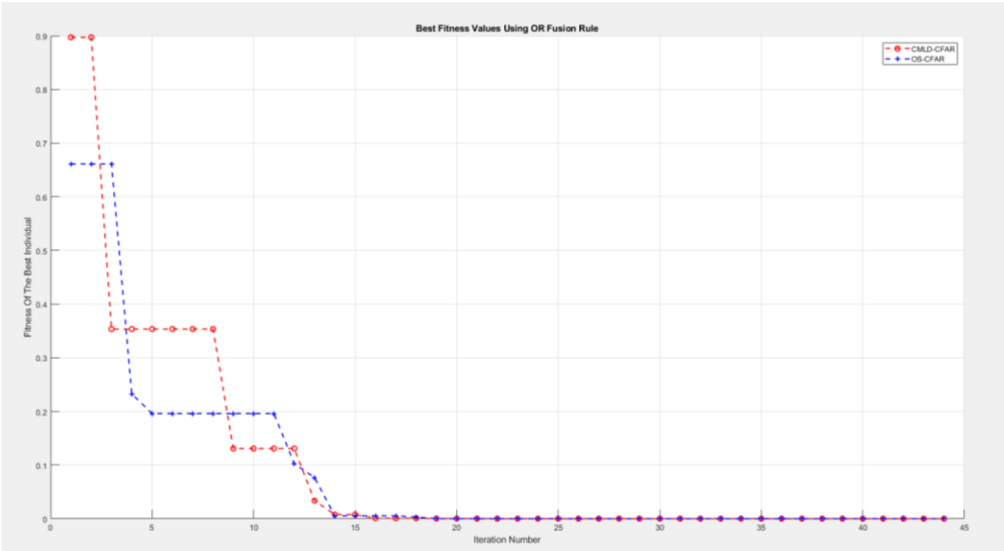

Figure 4-1 Evolution of Best Fitness Values for CMLDk and OS CFAR Detectors Using PSO

Table 4-2 PSO-Optimized Threshold Values for OS-CFAR and CMLDk-CFAR Detectors Using AND/OR Fusion Rules in The Presence of 8 Interferences and a fixed value of Pfa=10^{-4}

THRESHOLD	D=2	D=3	D=5
$T_{OS\text{-}CFAR}$ OR RULE	9.3823	9.8631	10.4812
$T_{OS\text{-}CFAR}$ AND RULE	3.8383	2.4659	1.4364
T_{CMLDk} OR RULE	0.9416	0.9898	1.0517
T_{CMLDk} AND RULE	0.3861	0.2483	0.1448

4.3.2 PERFORMANCE ANALYSIS

In a non-homogeneous background, the results of the probability of detection (Pd) as a function of SNR for the mentioned CFAR detectors are plotted in (Figure 4.2) and (Figure 4.3). (Figure 4.2) shows the performance of the OS-CFAR detectors, while (Figure 4.3) illustrates the performance of the CMLDk-CFAR detectors. With N=32 reference windows and Optimized T values using Particle Swarm Optimization (PSO) in the presence of K=8 interferences, and a fixed value of probability of false alarm Pfa=10^{-4}. When using both the OR and AND fusion rules, the detection performance increases as the number of detectors increases from 2 to 3 to 5. This indicates that increasing the number of detectors enhances detection performance. Moreover, it is observed that the OR fusion rule consistently outperforms the AND fusion rule across all configurations.

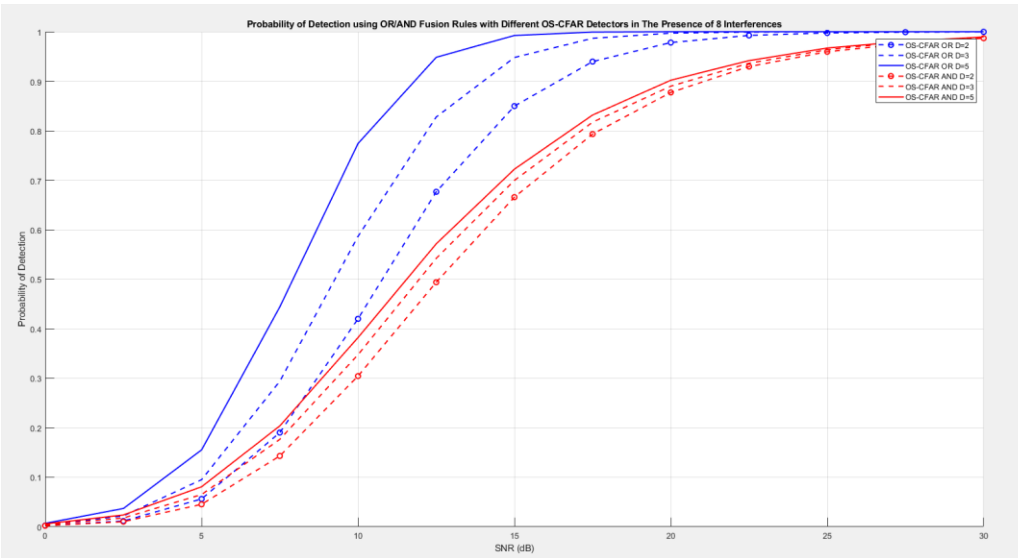

Figure 4-2 Pd Using AND/OR Fusion Rules for D=2,3,5 OS-CFAR Detectors and Pfa=10^{-4} in The Presence of 8 Interferences

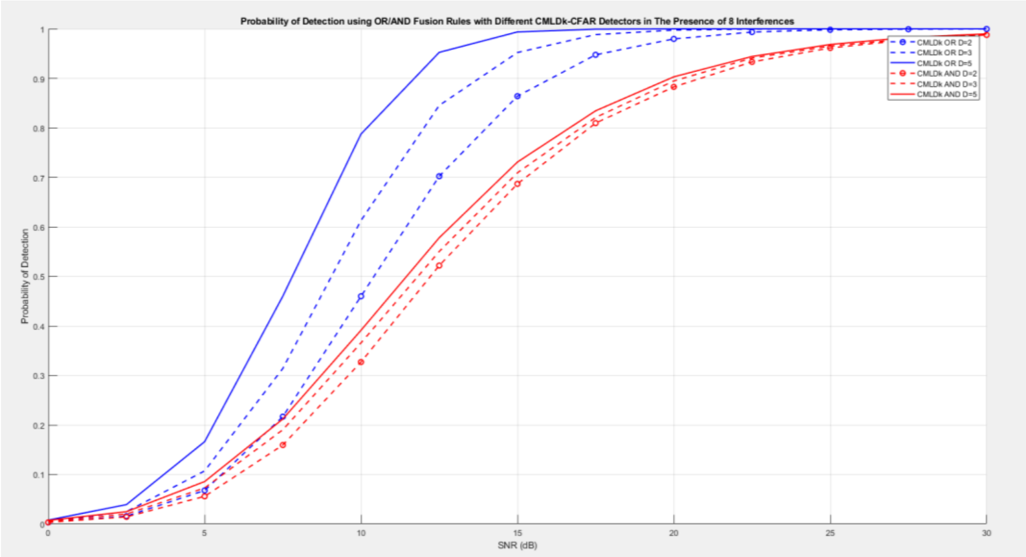

Figure 4-3 Pd Using AND/OR Fusion Rules for D=2,3,5 CMLDk-CFAR Detectors and Pfa=10^{-4} in The Presence of 8 Interferences

We also observe in Figure 4-4 that that the performance of both the CMLDk-CFAR and OS-CFAR systems is almost identical in the presence of the same number of interferences k=8. This is partially due to the low number of interferences while using multiple parallel distributed CFAR detectors with data fusion.

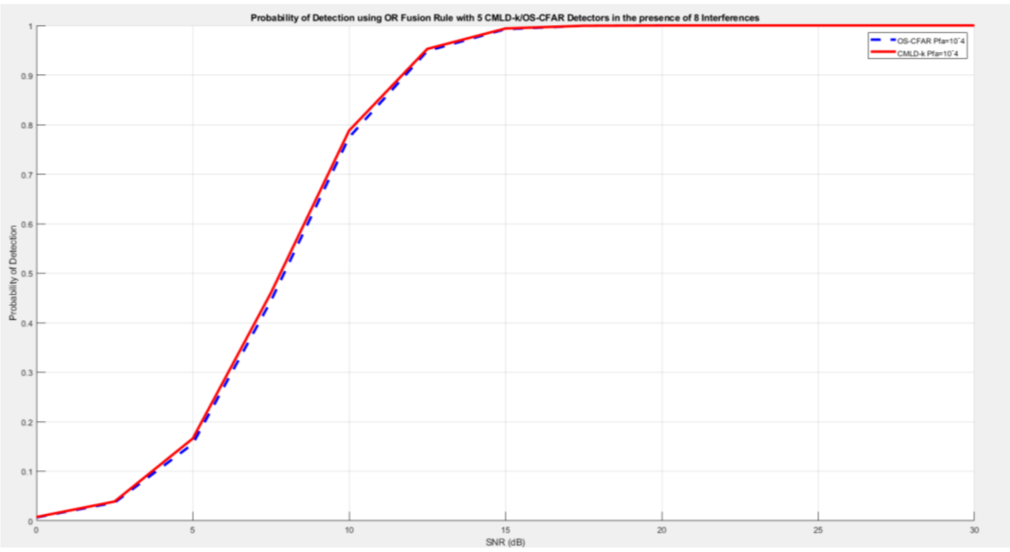

Figure 4-4 Pd Using OR Fusion Rule for D=5 CMLDk-CFAR and OS-CFAR Detectors and Pfa=10^{-4} in The Presence of 8 Interferences

Table 4-3 PSO-Optimized Threshold Values for Different OS-CFAR and CMLDk-CFAR Detectors Using OR Fusion Rules and Pfa=10^{-4} in The Presence of 10 Interferences

THRESHOLD	D=2	D=3	D=5
$T_{OS\text{-}CFAR}$ -OR RULE	11.2910	11.8776	12.6328
T_{CMLDk} -OR RULE	1.1981	1.2607	1.3414

Table 4-4 PSO-Optimized Threshold Values for 5 OS-CFAR Detectors and 5 CMLDk-CFAR Detectors Using OR Fusion Rules in The Presence of 16 Interferences

THRESHOLD	Pfa =10^{-4}	Pfa = 10^{-5}	Pfa = 10^{-6}
$T_{OS\text{-}CFAR}$ -OR RULE	23.0299	30.3217	38.7509
T_{CMLDk} -OR RULE	3.1497	4.1762	5.3721

In a non-homogeneous background with 10 and 16 interferences, the detection performance is analyzed for Pfa=10^{-4} using the OR fusion rule. (Figure 4-5) presents the performance of 5 OS-CFAR detectors and 5 CMLDk-CFAR detectors in the presence of 10 interferences, while (Figure 4-6) shows the performance of the same detectors in the presence of 16 interferences. Although the presence of said interferences challenges the robustness of the detectors, the PSO-optimized CFAR. detectors continue to demonstrate strong performance.

As shown in (Figure 4-5) while in the presence of 10 interferences, the probability of detection (Pd) remains high despite the increased interference levels; for Pfa=10^{-4} both the OS-CFAR and CMLDk detectors reach their peak (Pd=1) value at SNR=17.5 dB. Although it is important to note that the CMLDk-CFAR system still slightly outperformed the OS-CFAR system.

In the presence of 16 interferences (Figure 4-6), we observe a significant performance degradation for the OS-CFAR detectors compared to the CMLDk-CFAR detectors. For Pfa=10^{-4}, this is confirmed by comparing the SNR values at which the peak (Pd=1) is attained: for CMLDk detectors this peak is achieved for the same previous value of SNR=17.5dB, compared to the value of SNR=22.5dB for the OS-CFAR detectors. This improvement is attributed to the CMLDk-CFAR' algorithm's ability to effectively eliminate interferences while decreasing the threshold T through PSO optimization.

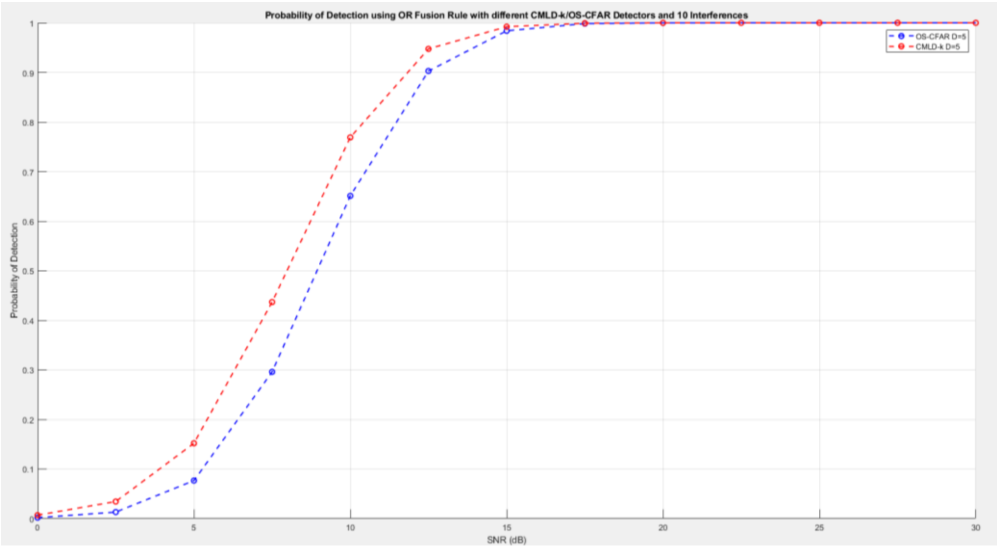

Figure 4-5 Detection Performance of 5 OS-CFAR and 5 CMLDk-CFAR Detectors in The Presence of 10 Interferences Using PSO Optimization at Pfa=10^{-4}

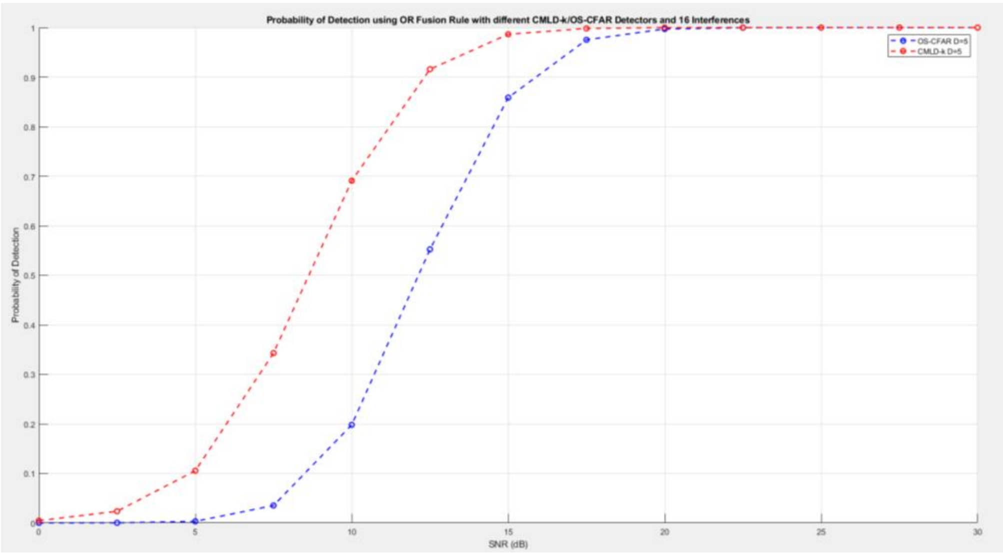

Figure 4-6 Detection Performance of 5 OS-CFAR and 5 CMLDk-CFAR Detectors in The Presence of 16 Interferences Using PSO Optimization Pfa=10^{-4}

Alas we wanted to study the effect of minimizing the probability of false alarm to the performance of both systems in the presence of high number of interferences k=16,

Figure 4-7 shows the results of using varying Pfa values at Pfa=10^{-4} ,Pfa=10^{-5} and Pfa=10^{-6} while maintaining OR fusion rule for 5 parallel distributed OS-CFAR and CMLDk-CFAR detectors. For both OS-CFAR and CMLD-k CFAR detectors, as Pfa decreases (from 10^{-4} to 10^{-6}), the probability of detection at a given SNR also decreases. This is expected because a lower Pfa means the detector is more conservative, resulting in fewer false alarms but also potentially missing more true detections. We still note that the CMLD-k CFAR detector maintains a better performance compared to the OS-CFAR detector due to its nature of operation.

Even though The OR fusion rule used in combining the 5 parallel distributed detectors helps in enhancing the detection performance. The overall trend indicates that even with fusion, individual detector performance (influenced by Pfa) plays a significant role. We also need to mention the importance of Particle Swarm Optimization (PSO) in finding optimized threshold (T) values for both OS and CMLD-k CFAR detectors. By effectively balancing detection probability and false alarm rate, PSO ensures high performance even with numerous interferences. This optimization significantly enhances the detection capabilities of both detectors, as shown in the graphs.

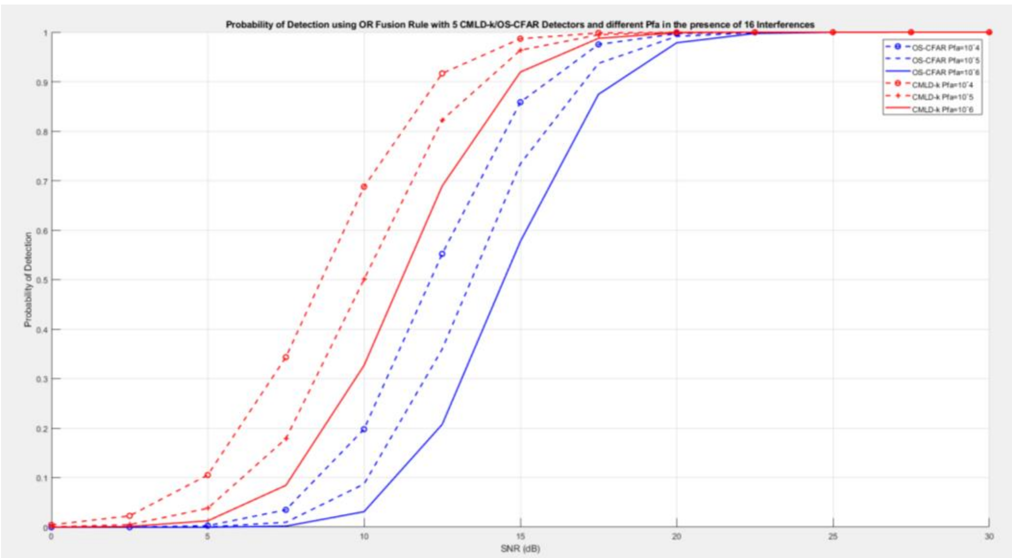

Figure 4-7 Detection Performance of 5 OS-CFAR and 5 CMLDk-CFAR Detectors in The Presence of 16 Interferences Using PSO Optimization at Varying Pfa Values

4.4 CONCLUSION

In this chapter, we examined the detection performance of PSO-optimized CFAR detectors, specifically OS-CFAR and CMLDk-CFAR, in non-homogeneous backgrounds. By varying the number of detectors used in parallel distributed data fusion with the OR/AND fusion rule and different Pfa values, we demonstrated how the probability of detection (Pd) changes with the signal-to-noise ratio (SNR) in different interference scenarios. Our simulations show that the PSO-optimized CMLDk-CFAR detectors consistently outperform the OS-CFAR detectors, especially in the presence of high levels of interference. The results indicate that using a larger number of detectors enhances detection performance, with the OR fusion rule proving to be more effective than the AND fusion rule, and the Pfa value of 10^{-4} proved to be the most productive as it has the lowest chance of missing true detections. These findings highlight the robustness and effectiveness of the PSO-optimized CMLDk-CFAR and OS-CFAR algorithms in challenging environments.

GENERAL CONCLUSION

In this thesis, we have explored the performance of various CFAR (Constant False Alarm Rate) detectors, specifically focusing on PSO-optimized OS-CFAR and CMLDk-CFAR in non-homogeneous environments. The primary motivation for this study was to optimize the threshold T using Particle Swarm Optimization (PSO) for use in distributed CFAR fusion with AND/OR fusion rules. Our study included an in-depth analysis of these distributed data fusion rules to enhance detection capabilities. Initially, we studied the fundamental principles behind different types of CFAR detectors, providing a comprehensive understanding of radar system parameters and components.

We first presented the basic parameters of a radar system, including its main components: transmitter, receiver, antenna, and detector. We discussed the radar equation, which is used to calculate the range of a radar based on its technical characteristics. The Doppler effect was introduced as a method to estimate the radial speed of a target and to distinguish between moving and stationary targets. We also covered the importance of properly limiting the range of a radar to avoid ambiguity in distance estimation and introduced Swerling models, which are used to model fluctuating targets and estimate radar detector performance. The decision-making process in radar detection was also examined, focusing on how a target's presence is determined by comparing a test sample to a threshold.

Then we delved into the basic notions of decision criteria in detection and the techniques used in radar systems. We identified the limitations of fixed threshold detection in non-homogeneous environments, which led to the need for adaptive threshold detection to ensure a constant false alarm rate.

Finaly, we explored the operational principles of various CFAR (Constant False Alarm Rate) detectors. The CA-CFAR detector estimates noise levels by maintaining a fixed Probability of False Alarm (Pfa), but its performance degrades in non-homogeneous environments. This limitation prompted the development of ordered statistics processors, such as the OS-CFAR detector, which selectively estimates noise levels to mitigate CA-CFAR issues. The OS-CFAR uses the 3*N/4 threshold value to balance immunity to interfering targets with minimal detection losses in cluttered environments. Another approach, the CMLDk-CFAR detector, relies on fixed censoring points assuming known interference levels. Moving forward, we focused on distributed fusion rules tailored for OS-CFAR and CMLDk-CFAR detectors. These rules leverage AND and OR logic to optimize detection performance by integrating data from multiple sensors effectively. Subsequently, we applied Particle Swarm Optimization (PSO) to optimize parameters like threshold T and K. By refining these parameters using PSO, we enhanced our data fusion algorithms, aiming to improve overall detection capabilities. Among the different Pfa values tested, $Pfa=10^{-4}$ consistently provided the best detection performance. Additionally, we observed that increasing the number of detectors from 2 to 3 to 5 improves detection performance, with the OR fusion rule consistently outperforming the AND fusion rule. This adaptive approach ensures that our CFAR detectors can dynamically adjust to diverse environmental conditions, enhancing their robustness and reliability in real-world detection scenarios.

These findings highlight the robustness and effectiveness of the PSO-optimized CMLDk-CFAR algorithm, making it a superior choice for challenging environments with high levels of interference. This research contributes to the advancement of CFAR detection technology, providing a solid foundation for future studies and practical implementations in radar and communication systems.

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