Detection improvement for anti-collision radar

Qu, Yao Wen

2005

Qu, Y. W. (2005). Detection improvement for anti-collision radar. Master's thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/3162>

<https://doi.org/10.32657/10356/3162>

Nanyang Technological University

Downloaded on 26 Apr 2023 19:30:52 SGT

a 556 867

Detection Improvement for Anti-collision Radar

Qu Yao Wen

School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
Master of Engineering

2005

II

TK
6575
Q1
2005

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research done by me and has not been submitted for a higher degree to any other University or Institute.

3/18/2005

Que Jiawen

Summary

This thesis illustrates the necessity and design process of performance improvement for radar detection by using novel CFAR detectors. A qualitative discussion of the need for and applications of conventional CFAR detectors is presented first. Typical applications are given as examples of where the radar system may be utilized. A closer look under the Swerling 2 assumption is presented as well.

The second portion of the thesis generally introduce the underlying electromagnetic theories that radar detection is built upon. The radar range equation, radar cross section, noise in systems, and vehicular applications are explained. The portion focuses on the radar detection. The general detection theory of Bayes and the Neyman-Pearson theorem are applied in our analysis for detection of targets with group fluctuations. The traditional approach of Swerling model I to IV and binary detection are all discussed with relation to the detect process. Among radar environment models, Swerling II is used because of its close space and low fluctuation properties. In a scenario of closely spaced targets special attention has to be paid to anti-collision radar signal processing. I present several advanced CFAR processing techniques. This processing results in a significant improvement. Algorithms are developed for Swerling II models of radar cross section (RCS) fluctuations and binary detection. Based on the firm ground, I have made further researches in to the conventional Cell-Average (CA-CFAR) and Order-Statistic (OS-CFAR) in a homogeneous background .

In this thesis, I proposed four new radar CFAR synthesizing the advantages of CA-CFAR and OS-CFAR. In a homogeneous background, the mathematical models of the four new CFAR detectors are derived and their performance have been evaluated and compared with that of CA-CFAR and OS-CFAR. It is proved that this CFAR approach is computationally efficient and increases the detection performance. Numerous research

and simulation test results are given to show that adopting the proposed approach one can achieve much better performance than the reported methods and results to date.

Furthermore, some new methods, such as neural network and fuzzy integration are present for signal detection and CFAR data fusion as the future work. Neural network and fuzzy integration have been considered for signal detection primarily because they may be trained to operate with acceptable performance, in an environment under which the optimum signal detector is not available. Since interference attract more and more attention, recently neural networks have been considered for overcoming the obstacles of interference which limit detection accuracy in most signal detection applications.

A new method about 'car on curve' also proposed to solve the non-detection of necessary objects and reduce the false alert rate. Numerous research and simulation test results are given to illustrate the success of the design procedure and to support choices of specific types.

TABLE OF CONTENTS

1.Introduction.....	1
1.1 Introduction to Radar.....	1
1.2 Anti-collision Radar Background.....	3
1.3 The Radar Equation.....	8
1.4 Maximum Range and Noise.....	11
1.5 Radar Applications.....	12
1.6 Pulsed Radar.....	17
1.7 Doppler Radar.....	19
1.8 Frequency-Modulated-Continuous-Wave Radar.....	23
1.9 Noise in Microwave Systems.....	28
1.10 Radar Cross Section.....	30
1.11 Vehicular Applications.....	32
1.12 Objectives.....	37
1.13 Organization of This Thesis.....	38
 2.Traditional CFAR Processors.....	 40
2.1 Introduction.....	40
2.2 Statistical Decision Theory for Anti-collision Radar.....	42
2.3 Detection Criteria.....	44
2.4 Bayes's Concepts for Radar.....	48
2.5 Binary Detection.....	52

2.6 Cell Averaging CFAR.....	54
2.7 Order Statistics CFAR.....	56
2.8 Other CFAR Techniques.....	57
2.9 Mathematical Model of CA-CFAR and OS-CFAR.....	58
2.10 Results.....	61
2.11 Conclusion.....	63
3. Novel CFAR Detectors.....	64
3.1 Introduction.....	64
3.2 Detection Principle and Model Formulation	65
3.3 Mathematical Model of Novel CFAR	69
3.4 Mathematical Model of And-Ca-Os CFAR.....	71
3.5 Mathematical Model of And-Os-Os CFAR.....	72
3.6 Mathematical Model of And-Os-Os-Os CFAR	73
3.7 Mathematical Model of And-Ca-Os-Os CFAR.....	75
3.8 Results.....	77
3.9 Performance Comparison.....	87
3.10 Conclusion.....	88
4. Improved Radar Detection on Curved Section of a Road.....	89
4.1 Introduction.....	89
4.2 Radar Antennas.....	90
4.3 Anti-Collision Radar Antenna Arrays.....	92

4.4 Classical Azimuth Measurement.....	97
4.5 Trace Target on The Curve.....	100
4.6 Improve The Azimuth Measurement.....	101
4.7 Results.....	105
4.8 Conclusion.....	107
5.CFAR Radar Sensors for Collision Avoidance.....	108
5.1 Vehicular Application.....	108
5.2 Application of Novel CFAR Detectors.....	109
5.3 Conclusion.....	113
6.Conclusion and Recommendation.....	114
6.1 Conclusion.....	114
6.2 Recommendation for Future Work.....	116
References.....	119
Appendix A	134
Appendix B	136
Appendix C... ..	138

LIST OF FIGURES

1.1	Automotive radar system.....	5
1.2	Typical application for the anti-collision radar systems.....	6
1.3	Radar ranging concept with a pulsed radar.....	9
1.4	A bistatic radar with two sparely located antennas are connected to the transmitter and the receiver.....	16
1.5	A monostatic radar with single antenna and a duplexer switch connecting and disconnecting the transmitter and the receiver.....	17
1.6	Typical pulse radar systems.....	19
1.7	Principle of Doppler shift.....	20
1.8	Geometric relationships in the Doppler shift.....	22
1.9	Block diagram of a typical Doppler radar system.....	23
1.10	Block diagram of a typical FMCW radar system.....	24
1.11	Frequency-time relationships in FMCW radar. (a) Triangular frequency modulation; (b) Beat note of (a).....	26
1.12	Frequency-time relationships in FMCW radar when the received signal is shifted in frequency by the Doppler effect. (a) Transmitted and echo frequencies; (b) Beat frequency.....	28
1.13	Noise in a cascaded microwave systems.....	29
1.14	Cross section fluctuation.....	32
2.1	Block diagram of CFAR.....	42
2.2	Possible hypothesis testing errors and their probabilities.....	45
2.3	Decision regions and probabilities.....	47
2.4	Block diagram of Cell-averaging CFAR.....	55

2.5 Block diagram of Order-statistics CFAR.....	57
2.6 The effect of n on P_d of Ca-CFAR when $P_{fa}=10e-8$ and n is reference cells number and designed $P_{fa}=10e-8$	62
2.7 The effect of k on P_d of Os-CFAR when $n=16$ is the reference cells number and designed $P_{fa}=10e-4$	62
3.1 Block diagram of And-Ca-Os CFAR.....	71
3.2 Block diagram of And-Os-Os CFAR.....	73
3.3 Block diagram of And-Os-Os-Os CFAR.....	75
3.4 Block diagram of And-Ca-Os-Os CFAR.....	77
3.5 The effect of n on P_d of And-Ca-Os CFAR where n is the reference cells number and designed $P_{fa}=10e-8$	83
3.6 The effect of P_{fa} on P_d of And-Ca-Os CFAR when $n=16$, $k=12$	83
3.7 The effect of n on P_d of And-Ca-Os CFAR where $n=16$ is the reference cells number and designed $P_{fa}=10e-8$	84
3.8 The effect of P_{fa} on P_d of And Os-Os CFAR when $n=16$, $k=12$	84
3.9 The effect of k and c on P_d of And-Ca-Os-Os CFAR when the reference cells number $E=16$, $M=N=8$ and designed $P_{fa}=10e-8$	85
3.10 The effect of P_{fa} on P_d of And-Ca-Os-Os CFAR when the reference cells number $E=16$, $M=N=8$, $k=c=4$	85
3.11 The effect of l on P_d of And-Os-Os-Os CFAR when the reference cells number $E=16$, $M=N=8$, $k=c=4$, and designed $P_{fa}=10e-8$	86
3.12 The effect of P_{fa} on P_d of And-Os-Os-Os CFAR when the reference cells number $E=16$, $l=10$, $M=N=8$, $k=c=4$	86
3.13 Comparison of P_d among the Six CFAR detectors with the number of reference cells $n=16$ and $P_{fa}=10e-8$	87
4.1 Geometry configuration of a linear array antenna.....	96

4.2 Line representation of radiators of a linear array antenna..... 97

4.3 Monopulse phase comparison..... 99

4.4 Car on the road..... 101

4.5 Beam steering logic..... 103

4.6 Measuring azimuth using three antennas..... 104

4.7 Azimuth measuring error $d\theta$ versus target azimuth θ at different d/λ 106

5.1 Anti-collision FMCW radar block diagram..... 112

5.2 The structure of the applied CFAR detector..... 112

6.1 The basic diagram of a proposal fuzzy-neural network detector
for anti-collision radar systems..... 118

LIST OF TABLES

1.1. Typical RCS values at microwave frequencies..... 33

1.2 Technology and performance features..... 34

1.3 Types and characteristics of obstacle detection sensor..... 36

2.1 Summary of a statistical terminology and our radar engineering equivalents..... 49

3.1 Scaling constant T of And Os-Os CFAR for different E and k, l values..... 79

3.2 Scaling constant T of And Os-Os-Os CFAR for different E and M,N, k, l values 80

3.3 Scaling constant T of And Ca-Os-Os CFAR for different E and M,N, k, l values 81

3.4 Scaling constant T of And Ca-Os CFAR for different E and k, l values..... 82

Abbreviations

Radar:	Radio Detection and Ranging
FLAR:	Forward Looking Automotive Collision Warning Radar
AICC:	Autonomous Intelligent Cruise Control Systems
CFAR:	Constant False Alarm Rate
CA-CFAR:	Cell –Average Constant False Alarm Rate
OS-CFAR:	Order-Statistic Constant False Rate
FMCW:	Frequency Modulated Continuous Wave
CW:	Continuous Wave
NP:	Neyman-Pearson
PD:	Probability of Detection
PDF:	Probability density function
PFA:	Probability of False Alarm Rate
SNR:	Signal to Noise Ratio
RCS:	Radar Cross Section
And Os-Os CFAR:	And Order Statistic - Order Statistic Constant False Rate
And OS-Os-Os CFAR:	And Order Statistic - Order Statistic - Order Statistic Constant False Rate
And Ca-Os-Os CFAR:	And Cell average - Order Statistic – Order Statistic Constant False Rate
And Ca-Os CFAR:	And Cell average - Order Statistic Constant False Rate
IID:	Independent and Identically Distributed

Acknowledgements

With my deepest appreciation, I acknowledge my supervisors, Professor Nema Karmakar and Co-supervisor Professor Jeffrey S. Fu, for their support, guidance, understanding, inspiration, enthusiastic help and invaluable advice, for allowing me considerable freedom in conducting this research.

I wish to thank the staff of the Radar lab, especially Lim Joseph, Lim Hannah, who provided an efficient tool and opened their resource to users. And without these, it would not have been possible for me to complete this work.

Chapter 1

Introduction

1.1 Introduction to Radar

Because of the strong economic growth in the world, the size of the vehicle fleet has increased considerably during the last 10 years. Statistics of accidents show that more than half of all collisions are rear end collisions. More than half a million people die annually by road accident [1], so it is believed by people that a radar system capable of alerting a driver in a timely fashion to the existing of impending collision would have a potential for drastically reducing accident seriousness as well as frequency [2]. With these systems the car driver's stress will be reduced and car driving will be more relaxing and comfortable.

In history safety systems in car applications have been developed, which are commonly referred to as "Forward Looking Automotive Collision Warning Radar" (FLAR). Modern developments are focused on so called "Autonomous Intelligent Cruise Control Systems" (AICC), which means in addition to the Collision Warning Systems a car's brake and accelerations are controlled automatically by the radar system including a

traffic analyzing computer [3]. The collisions can be avoided totally by the use of AICC-computer.

In fact, other technologies are under investigation for vehicular applications including ultrasonic, infrared, laser and video imaging. However, radar is considered the preferred technology when all factors are considered. The weather and darkness penetration capabilities of radar are especially well suited to vehicle applications [4].

Though many radar prototypes have been produced, and results or papers have been published, to date, however, no truly effective system has been widely developed and marketed. Except the consideration to cost, the principal reason is the unacceptably low detection probability and high false alarm rates. The high detection probability and low false alarm rate requirements puts tough demands on radar sensor. For whether FLAR or AICC systems, the predominant task is to design an anti-collision radar system with small false-to-real hazard detection ratios [5]. Radar system must measure the three discriminations of a target simultaneously, those are range, velocity and azimuth angle.

Due to the strong requirements for extremely high detection probability and low false alarm rates, the target detection procedure in a radar sensor for car application is a very important point. With the use of an FMCW concept, under the restriction of limited computation power and in conjunction with typical traffic scenarios, the target detection procedure for a practical automotive cruise control system merits particular attention. In dense traffic situation, a certain number of vehicles must be reliably detected [6].

Besides this, fixed objects like traffic signs, crash barriers or trees appear in the received

echo signal. And in addition to that, ground clutter, depending on the road conditions as well as weather effects, like rain or snow clutter may become apparent, too [7].

Hence, the novel CFAR procedure as a part of the detection algorithm to be developed must cope with the high dynamics. It must work robustly in everyday traffic and in any weather conditions. Regarding this and the fact that the detector has to meet the above mentioned requirements concerning detection probability, false alarm rate and low computation complexity.

Furthermore, the statistics show that high false detections of unnecessary objects and non-detections of necessary objects in the traffic often take places when the radar vehicle is running on the curve (Fig. 1.1) [8]. A new antenna technique is proposed in this thesis to strive for accuracy of radar measurement, simulation results illustrate that the method make a good improvement over the classical antenna tracking technologies.

1.2 Anti-collision Radar Background

Radar is a radio detection and ranging system which is based upon the knowledge of the electromagnetic scattering and propagation properties of various targets and media [9].

Radar can determine the existence of a target by sensing the presence of a reflected wave.

The radar is the name of an electronic system used for detection and location of objects. The fundamental objectives of a radar system are to detect the presence of a target and estimate the position and/or motion of the target [10]. The beauty of radar is that it allows

1.2. Anti-collision Radar Background

- 4 -

an extension of senses. Vision only works when the environment is lit and clear of smoke, clouds, snow etc. Radar allows one to see or detect objects in the dark or behind clouds or objects that are tens and even hundreds of miles away.

A radar's function is intimately related to properties and characteristics of electromagnetic waves as they interface with physical objects (the targets). Thus the earliest roots of radar can be associated with the theoretical work of Maxwell (in 1865) that predicted electromagnetic wave propagation and the experimental work of Hertz (in 1886) that confirmed Maxwell's theory. The experimental work demonstrated that the radio waves could be reflected by physical objects. This fundamental fact forms the basis by which radar performs on its main functions; by sensing the presence of a reflected wave, the radar can determine the existence of a target (the process of detection). Various early forms of radar devices were developed between about 1903 and 1925 that were also able to measure distance to a target (called the target's range) besides detecting the target's presence. Radar development was accelerated during World War II. Since that time development has continued such that present-day systems are very sophisticated and advanced. In essence, radar is a maturing field, but many exciting advances are yet to be discovered due to the advent of new technologies.

Due to the versatility of radar, and its many attractive features, it has become an attractive solution to detection schemes for applications other than aircraft. Recently academic and industrial research engineers have paid a lot of attention to the use of radar for automotive applications. Such applications including collision avoidance and warning systems, automatic cruise control systems, and futuristic automated highways

1.2. Anti-collision Radar Background

- 5 -

are illustrated in Fig.1.1 and Fig 1.2. Fig 1.1 shows the close up view of an automotive radar systems. As can be seen in Fig 1.2, a car is equipped with so many warning and detection radars. These radars are capable of looking to the side, front and rare of a vehicle and warn if any detection occurs in the lines of sight of the radars.

Figure 1.1 Automotive radar systems

Figure 1.2 Typical application for the anti-collision radar systems

Several types of radar which are commonly used are Doppler, frequency-modulated, and pulsed Doppler radars. Each type of radar has its set of benefits which suit it to an application. In the study of radar for automotive applications one finds that the dominant radar technology is that of frequency-modulated radar.

As the name suggests, frequency modulated continuous wave (FMCW) radar is a technique for obtaining range information from a radar by frequency modulating a continuous signal. The technique has a very long history [12], but in the past its use has limited to certain specialized applications, such as traffic anti-collisions. However, there is now renewed interest in the technique for three main reasons. First, the most general advantage possessed by FMCW is that the modulation is readily compatible with a wide variety of solid-state transmitters. Secondly, the frequency measurement which must be performed to obtain range measurement from such a system can now be performed digitally, using a processor based on the fast Fourier transform (FFT) [13]. A third reason for the interest in FMCW radars is that their signals are very difficult to detect with conventional intercept receivers [14].

The frequency modulation used by the radar can take many forms. Linear and sinusoidal modulations have both been used in the past. Linear frequency modulation is the most versatile, however, and is most suitable, when used with an FFT processor, for obtaining range information from targets over a wide range. For this reason the renewed interest is in FMCW, in particular on linear FMCW radar.

The radar system presented in this thesis fills a niche in the vehicular radar sector. The FMCW radar transceiver presented herein provides an elegant solution to the traffic

safety. Several radar systems have already been developed to aid in head-on collision avoidance systems [15]. The goals of the research presented in this thesis is to improve detection performance for Anti-collision radar by (i) using novel CFAR detectors and (ii) antenna's precision on measurement technique. Novel CFAR detectors are presented in chapter 3 and antenna's precision measurement technique is presented in chapter 4. The anti-collision radar is made compact by using millimeter-wave frequencies.

1.3 The Radar Equation

The ability of radar to detect the presence of a target is expressed in terms of the radar equation, which is worth deriving, rather than just quoting, because of the insight it gives into the way radars work [16]. Fig 1.3 shows a pulsed radar. A transmitted carrier pulse is echoed by a target and a delayed pulse is received by a receiver of the radar.

We begin with the transmitter, which has a peak power output P_t [W]. If this power is radiated isotropically by the antenna, then the power flux (the power density per unit area) at a range R is given by

$$S = \frac{P_t}{4\pi R^2} \quad [Wm^{-2}] \quad (1.1)$$

1.3. The Radar Equation

- 9 -

Figure 1.3 Radar ranging concept with a pulsed radar

Where $4\pi R^2$ is the area of a sphere of radius R through which all the power passes.

If the transmitting antenna is not isotropic and concentrates the power towards the target, then we modify Eq. (1.1) by introducing the gain factor G_t (transmitting of the antenna).

The power flux in the direction of the beam is now

$$\text{Power flux at the target} = \frac{P_t G_t}{4\pi R^2} \quad [Wm^{-2}] \quad (1.2)$$

1.3. The Radar Equation

- 10 -

The target intercepts a portion of this incident power and re-radiates it. The measure of the incident power intercepted by the target and power radiated back towards the radar is called the radar cross-section, which is often abbreviated to RCS and is given the symbol σ . The RCS of a target has unit of area (m^2) and indicates how large the target appears to be as viewed by the radar. RCS is defined as the power re-radiated towards the radar per unit solid angle divided by the incident power flux per 4π steradians. In reality, the target may be physically much larger in area than the RCS but trying to keep a low radar profile (such as a Stealth aircraft), there is no fixed RCS for a target, no number that can be painted on the side to say how big it appears to a radar set [17]. The RCS of a target depends on the angle of incidence at which it is viewed, the radar frequency and the polarization used. The RCS also fluctuates with time, as we shall see later.

The amount of this returning power that is intercepted by the antenna of the radar is determined by its effective area A_e . The mean power received by the radar P_r is thus

$$P_r = \frac{P_t G_t \sigma A_e}{(4\pi R^2)^2} \quad [\text{W}] \quad (1.3)$$

The next move is to substitute for A_e [18] :

$$G_r = 4\pi A_e / \lambda^2 \quad (1.4)$$

where G_r = gain of the receiving antenna. Finally, the inevitable inefficiencies in a radar system must somehow be introduced and, for now, this is best done by lumping them all together as a system loss factor L_s . Loss factors may be arranged to appear on

either the top or bottom of an equation, but we will adopt the convention that L_s is always less than 1, and therefore appears on the top. Using this definition, the power received by the radar, from the target, is given by

$$P_r = \frac{P_t G_t G_r \sigma \lambda^2 L_s}{(4\pi)^3 R^4} \quad [\text{W}] \quad (1.5)$$

1.4 Maximum Range and Noise

Although Eq.(1.5) is a complete description of the power received, it is still not useful because it does not indicate whether this power is larger or smaller than the background noise level [19]. Unfortunately, noise is always present, either as internal noise from the electronics, or as external noise from such sources as the galaxy, the atmosphere, man-made interference or even deliberate jamming signals. All these noise sources are wideband compared to the radar signal, and one of the functions of a radar receiver is to tailor the bandwidth to accept the signal, without permitting any unnecessary further noise to enter.

Here we can compare the power received from the target with the noise power, in what is variously known as the signal-to-noise ratio, SNR or S/N:

$$SNR = \frac{P_r}{N} = \frac{P_t G_t G_r \sigma \lambda^2 L_s}{(4\pi)^3 R^4 N} \quad (1.6)$$

where N is the noise power in watts.

This is the all important radar equation, which is much used in one form or another. Often, the radar equation is used to solve for one unknown. For example, supposing a particular SNR is required for reliable target detection. The maximum detection range $R_{\max}$ of a given radar can be calculated from (1.6).

$$R_{\max} = \left(\frac{P_t G_t G_r \sigma \lambda^2 L_s}{(4\pi)^3 N (SNR)_{\min}} \right)^{1/4} \quad [\text{m}] \quad (1.7)$$

1.5 Radar Applications

Since its inception in the 1930's of the 20th century, radar has undergone many developmental changes. As a result of these changes it has found application in many areas which concern detecting targets on the ground, on the sea, in the air, in space, and even below ground. Interestingly many of the techniques developed in radar research are being successfully used in areas of wireless communications and signal processings. The major areas of radar application are described briefly as follows.

- **Military**

Radar is an important part of air-defense system as well as the operation of offensive missiles and other weapons. In air defense it performs the functions of surveillance (for example using high resolution synthetic aperture radar) and weapon control.

- **Synthetic Aperture Radar**

This radar achieves increased resolution in angle, or cross-range, by storing the sequentially received signals in memory over a period of time and then adding them as if they were from a large array antenna. Its output is a high-resolution image of scene.

- **Remote Sensing Application**

This term is used to imply sensing of the environment, including:

- (1) Weather
- (2) Planetary observation, such as mapping of Venus
- (3) Short-range below-ground probing
- (4) Mapping of sea ice to route shipping in an efficient manner

- **Doppler radar as weather radar**

The image comes from a Doppler weather radar, which is capable of retrieving velocity as well as reflectivity information of particles the EM waves interact with.

- **Air Traffic Control**

Radars are employed to safely control air traffic in the vicinity of airports (Air Surveillance Radar, or ASR), and en route from one airport to another (Air Route Surveillance Radar, or ARSR), as well as ground vehicular traffic and taxiing of aircraft on the ground (Airport Surface Detection Equipment, or ASDE). The radar sends out a

1.5. Radar Applications

- 14 -

short, high-power pulse of radio waves which are reflected from a plane and received by the same antenna.

- Law Enforcement and Highway Safety

The radar speed meter, familiar to many, is used by police for enforcing speed limits. Police are now using a laser technique to measure the speed of cars. This technique is called lidar, as it uses light instead of radio waves. In recent years, radar is considered for making vehicles safer by warning of pending collision, actuating the air bag, or warning of obstructions or people a vehicle in the side of blind zone. Also it is employed for the detection of intruders.

- Aircraft Safety and Navigation

The airborne weather-avoidance radar outlines regions of precipitation and dangerous wind shear to allow pilot to avoid hazardous conditions. Low-flying military aircraft rely on terrain avoidance to avoid colliding with obstructions or high terrain. Military aircraft employ ground-mapping radars to image a scene. The radio altimeter is also a radar to indicate the height of an aircraft above the terrain.

- Ship Safety

Radars are found on ships and boats for collision avoidance and to observe navigation buoys, especially when the visibility is poor. Similar shore-based radars are used for surveillance of harbors and river traffic.

- Space

Space vehicles use radar for rendezvous and docking. Large ground-based radars are used for detection and tracking of satellites. The field of radar astronomy using Earth-based systems helps in understanding the nature of meteors. Radars have been used to measure distances in the solar system.

- Industrial Applications

Radar has found applications in industry for the non-contact measurement of speed and distance. It has been used for oil and gas exploration. Entomologists and ornithologists have applied radar to study the movements of insects and birds.

Radar can be typed according to their waveform. A continuous-wave (CW) type is one that transmits continuously (usually with a constant amplitude); it can have constant frequency modulation (FM), the usual case, or can be constant-frequency. When the transmitted waveform is pulsed (with or without FM), we have a pulsed radar type. Examples of a continuous wave radar system are Doppler radar and frequency-modulated-continuous-wave (FMCW) radar. On the contrary, a pulsed radar scheme is one which has very short pulses of microwave radiation transmitted towards a potential target with a known interval between pulses.

Bistatic radar (shown as Fig 1.4) is a radar system in which the transmitter and receiver use different antennas at different locations. Monostatic radar (shown as Fig 1.5) is a

radar system in which a single antenna is used for transmitting and receiving purposes. Monostatic radar is more popular than bistatic radar.

Figure 1.4. A bistatic radar with two sparely located antennas are connected to the transmitter and the receiver.

Figure 1.5. A monostatic radar with single antenna and a duplexer switch connecting and disconnecting the transmitter and the receiver.

1.6 Pulsed Radar

The operation of a typical pulse radar may be described with the aid of the block diagram shown in Fig.1.6.

Pulsed radar is the most common form of radar used today. Pulsed radar transmits a train of narrow rectangular-shaped pulses modulating a microwave carrier signal. The distance of the target is determined by measuring the round trip time required for the pulse to reach the target and return. Due to the fact that electromagnetic waves travel at the speed of light c , the range may be determined by

$$R = \frac{cT_R}{2} \quad (1.8)$$

Where the factor of two is due to the fact that the wave must take a round trip, covering twice the distance between the radar and target [20]. Once a pulse is transmitted the system must wait for the return of that pulse before transmitting the next pulse otherwise ambiguities may occur [21]. A difficulty encountered with pulsed radar systems is the generation of high power short duration pulses. High power microwave generation puts large demands on equipment. Further it complicates the situation. The high power signal must be completely isolated from the low noise receiver front end. If the system isolation is not high enough, two system-level negatives are encountered. First, the reflected signal from a target is usually 60 dB to 100 dB lower in power than the transmitted signal. If the front end isolation is not enough the low noise amplifier in the receiver will become saturated with the transmitted signal which will drown out the returned signal. Secondly, and a more costly downside, is the possibility that the high power of the transmitter will destroy the receiver's sensitive circuitry. These problems are overcome with a high isolation duplexer switch as shown in Fig 1.6.

Fig 1.6 Typical pulsed radar systems

1.7 Doppler Radar

Doppler radar is the simplest form of a continuous wave radar system. Doppler radar has many applications such as weather forecasting and uses in vehicular sensors. However, Doppler radar has a very distinct disadvantage in that it cannot determine the range of target. Doppler radar is only useful when the relative velocity between the radar system and target is the desired information. In addition, Doppler radar cannot distinguish between zero relative velocity and the lack of a target. The mechanism by which Doppler works is that of the Doppler effect. The apparent compression of waves when the source and observation are approaching each other and the rarefaction of waves when the relative velocity is in the negative direction, or the two objects are diverging, is the Doppler effect. Target radial velocity is extracted from the Doppler frequency shift

between the transmitted signal and the received echo. Doppler shift is the frequency shift of the echo signal caused by the target's motion with respect to the radar. This is electromagnetic equivalent of the acoustic effect heard when a vehicle sounding its horns is driven past an observer. The Doppler shift is used both to measure the velocity of targets and to resolve targets occurring at the same time but moving at different velocities. The latter use is the primary method of discriminating moving targets from clutters.

Figure 1.7 Principle of Doppler shift.

By definition the Doppler shift is the difference between the frequencies of the received and transmitted waves. A positive Doppler shift is from an inbound target and a negative shift from a target outbound from the radar.

$$f_d = f_R - f_T \quad (1.9)$$

where, f_T = transmit frequency

1.7. Doppler Radar

- 21 -

f_R = receive frequency

A target velocity vector (both magnitude and direction) can be measured from the Doppler shift. The exact expression of Doppler shift is: [22]

$$f_d = f_r \left[\frac{1 + v_R / c}{1 - v_R / c} - 1 \right] \quad (1.10)$$

or,
$$f_d = f_R - f_T \quad (1.11)$$

where,
$$f_R = \left[\frac{1 + v_R / c}{1 - v_R / c} \right] f_T \quad (1.12)$$

For,
$$v_R \ll c, f_R \cong f_T \left[1 + 2 \frac{v_R}{c} \right] \quad (1.13)$$

yields the Doppler shift:

$$f_d \cong 2 f_T \frac{v_R}{c} . \quad (1.14)$$

Only the radial component of velocity contributes to the Doppler shift. Figure 1.7 depicts the role of radial velocity in the direction of targets in clutter [23], a fixed radar. No target Doppler shift occurs when the velocity is tangential to the radar's antenna axis.

The radial velocity is:

$$v_R = v \cdot \cos(\gamma_H) \cos(\gamma_V) \quad (1.15)$$

where, γ_H = the horizontal angle between the radar's axis and the target's velocity vector

γ_V = the vertical angle between the radar's axis and the target's velocity vector

Figure 1.8: Geometric relationships in the Doppler shift.

A block diagram of a typical Doppler radar system may be seen in Fig.1.9 It is interesting to note the less complicated system architecture as compared to a pulsed radar system. Doppler radar may be used in addition to other schemes such as pulsed radar. If a pulsed radar system is pointed towards a target with a non-zero relative velocity then a Doppler frequency shift will be superimposed upon the returned pulse. Thus velocity and range information may be obtained simultaneously from a pulsed Doppler radar system.

Figure 1.9: Block diagram of a typical Doppler radar system

1.8 Frequency-Modulated-Continuous-Wave Radar

Frequency-modulated-continuous-wave (FMCW) radar is one form of continuous wave radar. The significant advantage of FMCW radar system is that it can detect target range and velocity simultaneously by computing the time delay and the Doppler shift in the received signal. FMCW use a form of frequency modulation. The frequency modulation provides a signature relationship between the frequency of the transmitted signal and the duration of the round trip of the signal from the radar to the target. Another significant advantage of FMCW radar system may be seen in Fig. 1.10. Although the dramatic increase in information available from a FMCW radar system, we easily observe the substantially less complicated design compared to a pulsed system.

Figure 1.10 Block diagram of a typical FMCW radar system

Figure 1.11 shows a sketch of a triangular LFM (linear frequency modulated) waveform. The dashed line in Fig 1.11 represents the return waveform from a stationary target at range R . The beat frequency f_b is also sketched in Fig 1.11 (b). It is defined as the difference between the transmitted and received signals. The time delay Δt is a measure of target range, as defined in Eq.(1.16):

$$\Delta t = \frac{2R}{c} \quad (1.16)$$

Fig 1.11 (a) shows a triangular frequency-modulation waveform. The resulting beat frequency as a function of time is shown in Fig 1.11 (b) for triangular modulation. The beat note is of constant frequency except at the turn-around region. If the frequency is modulated at a rate f_m over a range Δf , the beat frequency is

$$f_b = \frac{4f_m \Delta f R}{c} \quad (1.17)$$

Where c is the speed of light, and R is the range of the target. [24] Thus the beat frequency in Eq.(1.17) is a direct indicator of the range of the target.

In the above, the target was assumed to be stationary. If this assumption is not applicable, a Doppler frequency shift will be superimposed on the FM range beat note and an erroneous range measurement results. The Doppler frequency shift causes the frequency-time plot of the echo signal to be shifted up or down (Fig.1.12 a). On one portion of the frequency-modulation cycle, the beat frequency (Fig.1.12 b) is increased by the Doppler shift, while on the other portion, it is decreased. If, for example, the target is approaching the radar, the beat frequency f_{bu} produced during the increasing, or up, portion of the FM cycle will be the difference between the beat frequency due to the range f_b and the Doppler frequency shift f_d [Eq (1.18)]. Similarly, on the decreasing portion, the beat frequency f_{bd} is the sum of the two [Eq.(1.19)].

$$f_{bu} = f_b - f_d \quad (1.18)$$

$$f_{bd} = f_b + f_d \quad (1.19)$$

Fig 1.11 Frequency-time relationships in FMCW radar.

The range frequency f_b may be extracted by measuring the average beat frequency; That

is $f_b = \frac{1}{2}[f_{bu} + f_{bd}]$ and $f_d = \frac{1}{2}[f_{bd} - f_{bu}]$. So the range to the target R, and its relative

velocity: V, are found with (1.20) and (1.21), respectively. [25]

$$R = \frac{(f_{bu} + f_{bd})c}{8f_m\Delta f} \quad (1.20)$$

$$V = \frac{(f_{bd} - f_{bu})}{4f_0} \quad (1.21)$$

where c is the velocity of light, f_0 is the center frequency of the transmitted signal.

f_m is the modulation frequency and Δf is the maximum frequency deviation.

When two or more targets and objects exist, the beat signals obtained from them have multiple frequency components. Consequently, in order to detect the distance to a target and its relative velocity accurately, it is essential to select the pair of the beat signals from the same object without error. In order to use a millimeter-wave radar as the sensor for an adaptive cruise control (ACC) system or an automated driving system, it is necessary to reduce the target misrecognition rate as much as possible.

Figure 1.12 Frequency-time relationships in FMCW radar when the received signal is shifted in frequency by the Doppler effect

1.9 Noise in Microwave Systems

Noise power is a result of random processes such as the flow of charges or holes in a solid state device and the thermal vibrations in any component at a temperature above absolute zero. In either case the noise level of a system sets the lower limit on the strength of a signal that can be detected in the presence of the noise. Thus in a radar

system the noise characteristics of the receiver are one of the most important system parameters.

All sources of noise may be equated to a noisy resistor at a certain temperature. [26]

The noise produced by a resistor in a specified bandwidth, B, will produce the noise power

$$P_n = kTB \tag{1.22}$$

Where k is Boltzmann’s constant, T is the temperature of the resistor in degrees Kelvin, and B is the system bandwidth in Hz. It is clear that the only way to get a completely noiseless system is to keep the system temperature at absolute zero since a system with zero bandwidth is useless.

Figure 1.13 Noise in a cascaded microwave systems

It is also interesting to note that the noise figure of a microwave system is dominated by the noise figure of the first stage. The noise figure of a cascaded microwave system

$$F_N = F_1 + \frac{F_2 - 1}{G_1} + \frac{F_3 - 1}{G_1 G_2} + \dots + \frac{F_N - 1}{G_1 G_2 \dots G_{N-1}} \quad (1.23)$$

Where F_N and G_N are the noise figure and gain of each stage. [26] A cascaded microwave system and its noise-related parameters is illustrated in Fig 1.13. It is very clear that the noise figure of the first stage is the dominant term in the summation in Eqn (1.23).

To support the hypothesis, we can take Fig 5.1 (page 111) as an example. We can see that the first stage of the system is a low noise amplifier (LNA), assume its noise figure is 1dB with a gain of 10dB then the noise figure of the second stage (mixer) will only contribute 1/10 th of its noise to the overall system noise figure. This implies that the most crucial part in a radar system is the low noise front end of the receiver because the second stage is generally a mixer, whose noise performance tends to be poor or even terrible. For different radars there will be different percentage of noise contribution. It can be varied from 10% to more than 50%.

1.10 Radar Cross Section

The radar cross section (RCS) of a target (shown as Fig 1.14) is an (fictional) area intercepting that amount of power, which, when scattered equally in all directions,

produces an echo at the radar equal to that from the target. Mathematically the RCS is expressed as [27]

$$\sigma = \frac{\text{power reflected toward source/unit solid angle}}{\text{incident power density}/4\pi} = \lim_{R \rightarrow \infty} 4\pi R^2 \left| \frac{E_r}{E_i} \right|^2 \quad (1.24)$$

where, R = distance between radar and target

E_r = reflected field strength at radar

E_i = strength of incident field at large

Although many forms of the RCS formula exist, the version presented in Eq (1.24) is the most commonly used. The lower case character sigma (σ) is the most commonly used symbol to represent RCS in radar literature. In theory, the RCS can be determined by solving Maxwell's equations with the proper boundary conditions applied.

Usually, an object which is not symmetric will have a RCS with angular variations which require a study at each angle of interest. A widely available table with typical RCS values of several targets may be seen in Table 1.1. [28] It is informative to notice that objects with large flat surfaces such as cars and pickup trucks have RCS values much larger than those of objects considerably larger, such as jumbo jets.

Figure 1.14 : Cross section fluctuation

1.11 Vehicular Applications

The use of radar technology in commercial vehicular applications can provide great benefits in safety and driver's convenience. Radar can be used for forward and side obstacle detection and collision warning as well as extended applications including adaptive cruise control and automatic braking for collision avoidance. Other technologies are under investigation for these applications including ultrasonic, infrared, laser and video imaging. However, as can be seen in Table 1.2 and 1.3, radar is considered the preferred technology when all factors are considered. The weather and darkness penetration capabilities of radar are especially well suited to vehicular applications.

Table 1.1. Typical RCS values at microwave frequencies

Radar Target	RCS, m^2
Conventional unmanned winged missile	0.5
Small, single engine aircraft	1.0
Small fighter or jet airliner	2.0
Large fighter	6.0
Medium bomber or jet airliner	20
Jumbo jet	40
Small open boat	100
Small pleasure boat	2.0
Cabin cruiser	10
Pickup truck	200
Automobile	100
Bicycle	2
Human being	1
Bird	0.01
Insect	10^{-5}

Table 1.2 Technology and performance features

<div>Technologies</div> <div>Performance Feature</div>	Ultra-sonic	Infrared	Laser	Video	Radar
Darkness Penetration	Good	Good	Good	Poor	Good
Adverse Weather Penetration	Poor	Poor	Poor	Poor	Good
Low Cost Hardware Possibility	Good	Good	Fair	Poor	Good
Low Cost Signal Processing	Good	Good	Good	Poor	Good
Sensor Dirt/moisture Performance	Fair	Poor	Poor	Poor	Good
Long Range Capability	Poor	Fair	Good	Good	Good
Target Discrimination Capability	Poor	Poor	Fair	Good	Good
Minimizing False Alarms	Poor	Poor	Fair	Fair	Good
Temperature Stability	Poor	Fair	Good	Good	Good

A demand for assisted driving in poor conditions has spurred manufacturers to search for a solution. Infrared solutions have a serious drawback which has kept research into these systems to a minimum. An infrared sensor cannot “see” through air with a lot of moisture in it. Thus a system based upon infrared would not function in dense fog and heavy rain or snow. One of the research goals for automobile sensors is the ability to improve safety and comfort in adverse weather conditions. Due to the serious shortcomings of infrared sensors most research has now become focused upon the use of electromagnetic radiation in the form of radar to solve vehicular sensing requirements.

In collision avoidance systems, a radar system warns the operator of the vehicle when it is too close to an adjacent vehicle or when the closing speed to the next vehicle exceeds a prescribed rate. Such systems are currently available in up-scale cars such as Cadillac, Lexus, and Mercedes. These installations consist of simple radar systems that look out of the front of the car. An automated cruise control system may be an extension of a collision avoidance system. The current state of cruise control in vehicles is limited to speed control. The operator sets a computer to a desired speed once the speed is achieved. The computer then adjusts the accelerator to keep the vehicle at a constant speed regardless of the car, which is on a hill or on a flat road. Future automated cruise control systems will integrate radar systems with current cruise control technology to make driving safer and more comfortable. A radar system may be implemented in an automated cruise control system in order to feed closing rate vehicle proximity

Table 1.3 Types and characteristics of obstacle detection sensor

Sensor	Advantages	Disadvantages
Ultrasonic Sensor	<ul style="list-style-type: none">•Simple structure and low cost•Relative velocity detectable (directly)	<ul style="list-style-type: none">•Difficulty of medium to long distance detection•Highly affected by wind
Laser radar	<ul style="list-style-type: none">•Comparatively inexpensive•Minor technical difficulties	<ul style="list-style-type: none">•Weak to rain and dirt
Microwave Radar	<ul style="list-style-type: none">•Strong against rain and dirt•Relative velocity detectable(directly)	<ul style="list-style-type: none">•Presently expensive•compliance with Radio Law prerequisite
Image sensor	<ul style="list-style-type: none">•Compact size•Number of objects detectable	<ul style="list-style-type: none">•Weak to rain, dirt and night time application•Complex recognition logic

information to a decision making computer. The computer would then make speed adjustments accordingly. A step beyond automated cruise control is the concept of an

automated highway. In an automated highway application all the vehicles on a roadway would have radar coverage on all sides of the vehicle. In addition, all vehicles would be equipped with computers that are networked to a “highway” computer that controls the speed of traffic, what lane a vehicle is in, and how many vehicles may get on the highway. While such systems are still some way in the future, research is currently being performed on related topics.

1.12 Objectives

The anti-collision radar detection properties depend basically on the performance of CFAR detector design (work in FMCW radar systems). The research activities presented here is focused into a new type of CFAR detector to meet the requirements of reliability (extremely low false alarm rate) and short response time (extreme short delay) for traffic applications. The main aspects are summarized as follows:

- 1.) Improved anti-collision system detection performance;
- 2.) Improved anti-collision system detection probability on the curve;
- 3.) Improved anti-collision system reliability;
- 4.) Extremely low system false alarm rate;
- 5.) Shorter reaction time;
- 6.) Low cost.

1.13 Organization of This Thesis

The following chapters of this report will describe in detail the theory and design of Anti-collision radar detection systems.

Chapter 1 discusses fundamentals and theories of radar detection in general. The FMCW concepts for anti-collision radar, RCS, Detection criteria, and Vehicular applications are described in detail in this chapter.

Chapter 2 gives a brief introduction to the traditional CFAR processors, including CA-CFAR, OS-CFAR and other CFAR techniques. All conventional CFAR detectors' advantages and limitations are discussed in detail.

In Chapter 3, four novel CFAR detectors synthesizing the advantages of CA-CFAR and OS-CFAR are proposed. Each CFAR detector's features are presented in details. The simulation results and performance analysis show that the new approaches can improve the radar systems performance and are very useful in practices.

Chapter 4 proposes a novel detection antenna design technique to improve the detection performance of anti-collision radar systems, especially when the car is on a road curve.

Chapter 5 introduces an application of the novel CFAR algorithm on the vehicular technology of collision avoidance.

Finally, in chapter 6, some concluding remarks of the work of this dissertation are given. This chapter also gives recommendations for our future work of the CFAR data fusion including fuzzy-neural network fusion implementation and proposal of some other novel ideas.

Chapter 2

Traditional CFAR Processors

2.1 Introduction

Anti-collision radar performance is often degraded by the presence of false targets, or clutter. To combat this problem, radar detection processing can use an algorithm to estimate the clutter energy in the target test cell, and then adjust the detection threshold to reflect changes in this energy at different test cell positions. The threshold algorithms use detection cells near target test cell to estimate the background clutter level, and then set the threshold to guarantee the desired false alarm probability. This technique approaches a constant false alarm rate (CFAR) in most clutter backgrounds.

A basic method of approaching CFAR operation uses cell averaging (Finn and Johnson, 1968). Here several resolution cells on each side of the cell being tested for a target are sampled to develop an estimate of the noise level. N represents the number of reference cells. The square-law detected range samples (here we set $N=2n$, n is the numbers of the sliding windows) are sent serially into a shift register $N+1=2n+1$.

A relatively simple algorithm uses the average received energy in $2N$ nearby range cells to obtain a threshold. This algorithm yields a CFAR when the clutter in the estimation cell is identically, independently, and Rayleigh envelope distributed [29]. As N increases, the signal-to-noise ratio (SNR) required by this algorithm to guarantee a particular probability of detection, decreases. When N approaches infinity the variance of the clutter power estimate vanishes, and the threshold is set optimally in terms of minimizing required SNR.

Constant false alarm rate (CFAR) processors are the commonly used detectors in radar systems to maintain control of the false alarm rate in the face of local variations in the background noise level. In the CFAR detection scheme, the square-law detected range samples are sent serially into a shift register $N+1=2n+1$. The target decision is commonly performed using the sliding window technique.

In Fig 2.1, Y is the cell under test, X_1 to X_{2n} are the reference cells. If the value of Y is larger than the product of Z and T , i.e. $Y > ZT$, then the target is detected. Otherwise, if Y is less than the product of Z and T , i.e. $Y < ZT$, we will get the report from radar of no target.

In this chapter, we will discuss some traditional CFAR processors and their distinguishing characteristic.

Fig.2.1: Block diagram of CFAR

2.2 Statistical Decision Theory for Anti-collision Radar

Reverend Thomas Bayes’s (1702-1761) introduced the fundamental concepts of classical statistical decision theory [30]. The theory assumes probabilistic descriptions of the measurement values and prior knowledge to compute a probability value for each hypothesis. Bayes’s methods provided a means to update one’s degree of belief expressed as a probability about a hypothesis on the basis of prior knowledge and recent

observations (Appendix A). For the first time, this provided a tool for quantitative inferences or learning. Bayesian and related statistical decision approaches are directly applied to the processing of multisensor data to perform binary decisions (the detection problem: signal present or absent). Although originally applied to single sensors, extensions to multiple sensors have developed optimal decision criteria for distributed decision making when the decisions are distributed between sensors and the central node where decisions are fused [31,32]. In our application, bases detection and classification on decision theory, in which measurements are compared with alternative hypotheses to decide which hypothesis "best" describes the measurement.

A generalization of minimum P_e criterion assigns costs to each type of error. Suppose that we wish to design a system to automatically inspect a machine part. The result of the inspection is either to use the part in a product if it is deemed satisfactory or else to discard it. We could set up the hypothesis test

H_0 : part is defective

H_1 : part is satisfactory

and assign costs to the errors. Let C_{ij} be the cost if we decide H_i , but H_j is true. For example, we would probably want $C_{10} > C_{01}$. If we decide the part is satisfactory but it proves to be defective, the entire product may be defective and we incur a large cost (C_{10}). If, however, we decide that the part is defective when it is not, we incur the smaller cost of the part only (C_{01}). Once costs have been assigned, the decision rule is based on minimizing the expected cost or Bayes risk R defined as [33]:

$$R = E(C) = \sum_{i=0}^1 \sum_{j=0}^1 C_{ij} P(H_i | H_j) P(H_j) \quad (2.1)$$

Usually, if no error is made, we do not assign a cost so that $C_{00} = C_{11} = 0$. However, for convenience we will retain the more general form. Also, note that if $C_{00} = C_{11} = 0$, $C_{10} = C_{01} = 1$, then $R = P_e$.

Under the reasonable assumption that $C_{10} > C_{00}$, $C_{01} > C_{11}$, the detector that minimizes the Bayes risk is to decide H_1 if [34]

$$\frac{P(x / H_1)}{P(x / H_0)} > \frac{(C_{10} - C_{00})P(H_0)}{(C_{01} - C_{11})P(H_1)} = \gamma \quad (2.2)$$

See Appendix A for the proof. Once again, the conditional likelihood ratio is compared to a threshold.

2.3 Detection Criteria

The detector that maximizes the probability of detection for a given probability of false alarm is the likelihood ratio test as specified by the Neyman-Pearson (NP) Theorem (Appendix B). The threshold is found from the false alarm constraint.

As shown in Fig 2.2, we can make two types of errors. If we decide H_1 but H_0 is true, we make a Type I error. On the other hand, if we decide H_0 but H_1 is true, we make a Type II error. Note that with this scheme these two errors are unavoidable to some extent

but may be traded off against each other [35]. Clearly, the Type I error probability ($P(H_1;H_0)$) is decreased at the expense of increasing the Type I error probability ($P(H_0;H_1)$). It is not possible to reduce both error probabilities simultaneously. A typical approach then in designing an optimal detector is to hold one error probability fixed while minimizing the other.

Fig 2.2 Possible hypothesis testing errors and their probabilities

As shown in Fig 2.3, let R_1 be the set of values in that R^N that map into the decision H_1 or

$$R_1 = \{x: \text{decide } H_1 \text{ or reject } H_0\} \tag{2.3}$$

2.4. Bayes's Concepts for Radar

- 46 -

This region is termed as the critical region in statistics. The set of points in R^N that map into the decision H_0 is the complement set of R_1 or $R_0 = \{x: \text{decide } H_0 \text{ or reject } H_1\}$. Clearly, $R_0 \cup R_1 = R^N$ since R_0 and R_1 partition the data space. The P_{fa} constraint then becomes

$$P_{fa} = \int_{R_1} P(x; H_0) dx = a \quad (2.4)$$

In statistics, a is termed as the significance level or size of the test. Now there are many sets R_1 that satisfy (2.3). Our goal is to choose the one that maximizes

$$P_D = \int_{R_1} P(x; H_1) dx \quad (2.5)$$

In statistics, P_D is called the power of the test and the critical region that attains the maximum power is the best critical region. Table 2.1 is a summary of a statistical terminology and our radar engineering equivalents.

The NP theorem tells us how to choose R_1 if we are given $P(x; H_0)$, $P(x; H_1)$,
To maximize P_D for a given $P_{FA} = a$ decide H_1 if

$$L(x) = \frac{P(x; H_1)}{P(x; H_0)} > \gamma \tag{2.6}$$

where the threshold γ is found from

$$P_{FA} = \int_{(x:L(x)>\gamma)} P(x; H_0) dx = a \tag{2.7}$$

The function $L(x)$ is termed the likelihood ratio since it indicates for each value of x the likelihood of H_1 versus the likelihood of H_0 .

Figure 2.3 Decision regions and probabilities

2.4 Bayes's Concepts for Radar

Bayes's decision theory is a systematic method of assigning cost factors to the correct and incorrect decisions that can be made process (Appendix A). We make use of a particular form of the general theory as usually applied to radar [36]. Two important specializations are used. First, we will average $P(\hat{X}/\hat{S}_r(\theta))$ over all random parameters and use the result to ultimately solve the optimum detection problem. Second, we will choose special cost factors for radar (below). Let us define

$$\overline{P(X/S_r(\theta))_\theta} = \int P(X/S_r(\theta))P(\theta)d\theta \quad (2.8)$$

Hence, here we define $X(t)$ as the received waveform, $\hat{X}$ is a vector random variable having all the observation random variable X_{ik} as its components [37]. When no target is present the joint probability density functions of the observation random variables will be different than when target is present. In the former case $X(t)$ consists of noise only, while in the latter case $X(t)$ is the sum of the received signal plus noise. The joint probability density functions of the observation random variables, conditional on no signal and signal present cases, respectively, are denoted by $P(\hat{X}/0)$ and $P(\hat{X}/\hat{S}_r(\theta))$. The notation $\hat{S}_r(\theta)$ is used to imply that the received signal, $S_r(t)$, may depend on some random parameters $\theta_1, \theta_2, \dots, \theta_M$, defined by the vector

Table 2.1 Summary of a statistical terminology and our radar engineering equivalents.

Statisticians	Radar Engineers
Test statistic($T(x)$) and threshold(γ)	Detector
Null hypothesis(H_0)	Noise only hypothesis
Alternative hypothesis(H_1)	Signal + noise hypothesis
Critical region	Signal present decision region
Type I error(decide H_1 when H_0 true)	False alarm(FA)
Type II error(decide H_0 when H_1 true)	Miss (M)
Level of significance or size of test(α)	Probability of false alarm(PFA)
Probability of Type II error(β)	Probability of miss (PM)
Probability of test ($1 - \beta$)	Probability of detection(PD)

$$\hat{\theta} = (\theta_1, \theta_2, \dots, \theta_M) \tag{2.9}$$

and that sample values of $S_r(t)$ are present in samples of $x(t)$ when signal is present. The corresponding signal sample vector is

$$\hat{S}_r(\theta) = (\hat{S}_{r1}(\theta), \hat{S}_{r2}(\theta), \dots, \hat{S}_{rN}(\theta)) \tag{2.10}$$

where the component vectors are over intervals:

$$\hat{S}_{ri}(\theta) = (\hat{S}_{ri1}(\theta), \hat{S}_{ri2}(\theta), \dots, \hat{S}_{rik}(\theta)) \tag{2.11}$$

for $i = 1, 2, \dots, N$. The elements of (2.11) are just the sample values of $S_r(t)$ at times t_{ik} :

$$\hat{S}_{rik}(\theta) = S_r(t_{ik}) \quad (2.12)$$

The left side of (2.8) is a notational definition; the over bar represents the statistical average of the quantity with respect to all the random parameters of the vector $\hat{\theta}$. The right side of (2.8) defines the actual averaging operation; here $P(\hat{\theta})$ is the joint probability density function of random variables $(\theta_1, \theta_2, \dots, \theta_M) = \hat{\theta}$. $P(\hat{\theta})$ uses the actual density for those random variables that are known and uses the least favorable (uniform) density for those variables with unknown statistics.

Ultimately the signal processor must process the various observations to produce a single variable from which a decision is made of target plus noise present (referred to as decision S+N) or noise only present (referred to decision N). If we think of any one set of observations, which is one value of $\hat{X}$ as a point in NK-dimensional hyperspace, then some points will correspond to the decision S+N call the space of such points Γ_1 . All other hyperspace points, denoted by Γ_0 , must correspond to the decision N. All of hyperspace denoted by Γ , is the sum of the two spaces, or $\Gamma = \Gamma_1 + \Gamma_0$. Based on these spaces we define average detection probability $\bar{P}_d$; average miss probability $\bar{P}_{miss}$; false alarm probability P_{fa} ; and noise probability P_{noise} by [37-39]

$$\bar{P}_d = \int_{\Gamma_1} \overline{P(\hat{X} / \hat{S}_r(\theta))}_{\theta} d\hat{X} = \text{average detection probability} \quad (2.13)$$

$$\overline{P_{miss}} = \int_{\Gamma_0} \overline{P(\hat{X}/\hat{S},(\theta))_{\theta}} d\hat{X} = 1 - \overline{P_d} = \text{average miss probability} \quad (2.14)$$

$$P_{fa} = \int_{\Gamma_1} \overline{P(\hat{X}/0)} d\hat{X} = \text{false alarm probability} \quad (2.15)$$

$$P_{noise} = \int_{\Gamma_0} \overline{P(\hat{X}/0)} d\hat{X} = 1 - P_{fa} = \text{noise probability} \quad (2.16)$$

Clearly the final decision process can lead to only four outcomes, two are correct and two are wrong. Bayes's theory assigns costs to these decisions as follows:

$$1. \text{ Decide N when N is true: Cost} = C_{11} \quad (2.17 \text{ a})$$

$$2. \text{ Decide N when S+N is true: Cost} = C_{12} \quad (2.17 \text{ b})$$

$$3. \text{ Decide S+N when N is true: Cost} = C_{21} \quad (2.17 \text{ c})$$

$$4. \text{ Decide S+N when S+N is true: Cost} = C_{22} \quad (2.17 \text{ d})$$

Now let D be a random variable representing the radar's "decision"; it can only have outcomes N and S+N. Similarly let T be a random variable representing the "true case;" it has outcomes N and S+N with probabilities of occurrence defined as $P(T=N) = q$ and $P(T=S+N) = p = 1-q$, respectively. The joint probabilities of the four outcomes of (2.17), with T independent of D, are

$$P(N, N) = P(D = N, T = N) = P_{noise}q \quad (2.18 \text{ a})$$

$$\bar{P}(N, S+N) = \bar{P}(D=N, T=S+N) = \bar{P}_{miss}p \quad (2.18 \text{ b})$$

$$P(S+N, N) = P(D=S+N, T=N) = P_{fa}q \quad (2.18 \text{ c})$$

$$P(S+N, S+N) = \bar{P}(D=S+N, T=S+N) = \bar{P}_d p \quad (2.18 \text{ d})$$

The Bayes procedure defines an average cost, denoted by $\bar{L}$, for the four decisions of (2.17) [38, 39]

$$\begin{aligned} \bar{L} &= C_{11}P(N, N) + C_{12}\bar{P}(N, S+N) + C_{21}P(S+N, N) + C_{22}\bar{P}(S+N, S+N) \\ &= C_{11}q + C_{12}p + \int_{\Gamma_1} \int_{\Gamma_2} \{ (C_{21} - C_{11})qp(\hat{X}/0) - (C_{12} - C_{22})p\overline{P(\hat{X}/\hat{S}_r(\theta))_\theta} \} d\hat{X} \end{aligned} \quad (2.19)$$

The last form of (2.19) has used (2.18) and (2.13) through (2.16).

2.5 Binary Detection

In binary detection the radar observes a particular range cell in each of N pulse intervals and counts the number of threshold crossings (single-pulse detections) that takes place. This number can be as small as zero, or as large as N if the range cell gives a detection in every one of the N pulse intervals. At the end of N pulse intervals the radar declares a target is present if M or more threshold crossings occur, and no target is present if less than M crossings occur. M is called as a second threshold. Clearly the important parameters in making a final detection are P_{fa1} , P_{d1} , M , and N . In this section we relate these parameters to the overall desired false alarm and detection probabilities, which we

denote by P_{fa} and P_d , respectively. The discussions to follow center mainly on the nonfluctuating target. Binary detection is known by various names, such as M of N detection, and coincidence detection. It appears to have been originated by Swerling (1952) and Schwartz (1956). Some early theoretical work was due to Harrington (1955) and Capon (1960). More recently Miller (1985), Brunner (1990), Weiner (1991), and Han et al (1993) have extended the theory to include fluctuating targets and distributed detection systems.

False alarm probability P_{fa} corresponds to when noise only is being received. Assume that the N pulse intervals result in sequence of exactly k threshold crossing followed by exactly $N-k$ noncrossings (for the range cell under examination). The probability of this sequence is $P_{fa1}^k (1 - P_{fa1})^{N-k}$. The order in which threshold crossings occurs is not important, and any sequence of exactly k crossings in N intervals has the same probability. Form combinatorial analysis the number of such sequences equals the binominal coefficient [39, 40, 41]

$$\binom{N}{K} = \frac{N!}{K!(N-k)!} \quad (2.20)$$

Thus the probability if sequence of exactly k threshold crossings (of an order) in N intervals is

$$P(k \text{ of } N) = \binom{N}{K} P_{fa1}^k (1 - P_{fa1})^{N-k} \quad (2.21)$$

2.6. Cell Averaging CFAR

- 54 -

A false alarm will occur if, at the end of N intervals, M or more crossings occur. Its probability becomes

$$P_{fa} = \sum_{k=M}^N P(k \text{ of } N) = \sum_{k=M}^N \binom{N}{K} P_{fa1}^k (1 - P_{fa1})^{N-k} \quad (2.22)$$

when a target with constant cross section is present, the preceding steps can be repeated to obtain the probability of detection. The steps again lead to (2.22) except with P_{fa1} replaced by P_{d1} :

$$P_d = \sum_{k=M}^N \binom{N}{K} P_{d1}^k (1 - P_{d1})^{N-k} \quad (2.23)$$

This expression and (2.23) are the two fundamental quantities that define binary detection.

2.6 Cell Averaging CFAR

An popular CFAR processor is the cell averaging (CA) CFAR processor which adaptively sets the threshold by estimating the mean level in a window of N range cells. The CA-CFAR processor is the optimum CFAR processor (maximizes detection probability) in a homogeneous background when the reference cells contain independent and identically distributed (IID) observations governed by an exponential distribution. As

2.6. Cell Averaging CFAR

- 55 -

the size of the reference window increases, the detection probability approaches that of the optimum detector which is based on a fixed threshold.

Fig.2.4: Block diagram of Cell-averaging CFAR

Two major problems that require careful investigation in such a CFAR detection scheme are those presented by 1) regions of clutter power transition and by 2) multiple target environments. The first situation occurs when the total noise power received within a single reference window changes abruptly. The presence of such a clutter edge may result in severe performance degradation in an adaptive threshold scheme leading to excessive false alarms or serious target masking depending upon whether the cell under test is a sample from clutter background or from relatively clear background with target return, respectively. The second situation is encountered when there are two or more closely spaced targets in range. The interfering targets that appear in the reference window along with the target under investigation (known as primary target) may raise the

threshold unnecessarily. Often a CFAR detector only reports the stronger of the two targets.

2.7 Order Statistics CFAR

The order statistics (OS) CFAR processor estimates the noise power simply by selecting the k -th largest cell in the reference window of $2n$, the threshold is obtained from one of the ordered samples of the reference window. The range samples are first ordered according to their magnitudes, and the statistic Z is taken to be the k -th largest sample. Rohing has noted that the false alarm probability of the OS processor is dependent of the total noise power in the exponential noise model. The order statistics (OS) CFAR scheme is suitable to alleviate these problems above [discussed in 2.6] to some degree. Its performance in a multiple target environment is clearly superior.

Fig.2.5 Block diagram of Order-statistics CFAR

The OS –CFAR processor exhibits some loss of detection power in homogeneous noise background compared to the CA processors.

2.8 Other CFAR Techniques

There are other CFAR detectors which are now shown as follows to deal with different clutter or target situations.

- a) Trimmed-mean CFAR: The trimmed-meanTM [42] scheme is a more generalized OS-CFAR processor in which the ordered range cells of a particular

reference window are trimmed or censored from both the upper and the lower ends.

- b) **Excisor-CFAR:** In excisor CFAR, a hard (upper) limit is applied to the cells' amplitude for threshold calculation [43]. This prevents large outliers from biasing the threshold. Values above the limit are removed from the threshold calculation.
- c) **CM/L-CFAR:** A new CFAR procedure is presented, which relies on a hybrid clutter-map/L-CFAR [44, 45] strategy, aimed at improving the system robustness against possible nonhomogeneities, while reserving target detect ability in a homogeneous environment. In CM/L-CFAR procedure, the returns from the range cells in each map cell are preliminarily processed through an L-filter, prior to being used for estimation purposes: this preserves the proper system immunity of CM-CFAR, to spatial discontinuities in the radar cross-section of clutter, while introducing robustness against range spread or spurious targets.

2.9 Mathematical Model of CA-CFAR and OS-CFAR

The formulas were derived under the assumptions that the receiver noise is Gaussian distributed, the detection envelope is Rayleigh distributed, and with Swerling case II target, Y represents the cell under test. T is the scaling factor and the cells are independent, identically distributed (IID).

2.8. Mathematical Model of CA-CFAR and OS-CFAR-59-

The detection probability and false probability [46, 47, 48] are defined and calculated as follows:

Under H_0 , we have

$$f_0(y) = \frac{1}{\mu} \exp\left(-\frac{y}{\mu}\right) \quad (2.24)$$

Under H_1 , we have

$$f_1(y) = \frac{1}{(1+\lambda)\mu} \exp\left(-\frac{y}{(1+\lambda)\mu}\right) \quad (2.25)$$

where λ is the signal-to-noise-ratio (SNR)

For the CA-CFAR processor,

$$P = \frac{1}{N} \sum_{i=1}^N y_i \quad (2.26)$$

The PDF of P is [49]:

$$f_P(p) = \frac{N^N}{\mu} \left(\frac{p}{\mu}\right)^{(N-1)} \frac{\exp(-Np/\mu)}{\Gamma(N)} \quad (2.27)$$

The CDF of P is:

2.9. Mathematical Model of CA-CFAR and OS-CFAR

- 60 -

$$F_P(p) = 1 - \exp(-Np / \mu) \sum_{i=0}^{N-1} \frac{(Np / \mu)^i}{i!} \quad (2.28)$$

For the OS-CFAR processor, $Q=q(k)$, The PDF of Q is [50] :

$$f_Q(q) = \frac{1}{\mu} k \binom{N}{k} [1 - \exp(-q / \mu)]^{k-1} \exp[-(N - k + 1)q / \mu] \quad (2.29)$$

The CDF of Q is:

$$F_Q(q) = \sum_{i=k}^N \binom{N}{i} [1 - \exp(-q / \mu)]^i \exp[-(N - i)q / \mu] \quad (2.30)$$

For CA-CFAR,

$$P_{fa} = \frac{1}{(1 + T / N)^N} \quad (2.31)$$

$$P_D = \frac{1}{\{1 + T / [(1 + \lambda)N]\}^N} \quad (2.32)$$

For OS-CFAR,

$$P_{fa} = k \binom{N}{k} \frac{\Gamma(N - k + T + 1) \Gamma(k)}{\Gamma(N + T + 1)} \quad (2.33)$$

$$P_D = k \binom{N}{k} \frac{\Gamma[N - k + T / (1 + \lambda) + 1] \Gamma(k)}{\Gamma[N + T / (1 + \lambda) + 1]} \quad (2.34)$$

2.10 Results

The actual probability of detection achieved by the CA-CFAR and OS-CFAR detectors has been evaluated by means of computer simulation. The results are shown as Fig 2.6 and Fig 2.7, respectively.

As false alarm probability is fixed, the scaling constant T can be calculated, so that the performance can be evaluated.

For CA-CFAR detector's simulation, the reference cells number n are 8, 16, 32, 64, respectively, and the false alarm probability is 10^{-8} . It can be seen that as the n increases, the detection probability will increase.

For OS-CFAR detector's simulation, we can draw the conclusion: if the reference cells number n is fixed, as k increases, the detection probability will increase.

Fig 2.6 The effect of n on P_d of CA-CFAR when $P_{fa}=10e-8$ and n is reference cells number and designed $P_{fa}=10e-8$

F2.7 The effect of k on P_d of OS-CFAR when $n=16$ is the reference cells number and designed $P_{fa}=10e-4$

2.11 Conclusion

In this Chapter, the effective and flexible traditional CFAR processors, including CA-CFAR, OS-CFAR and other CFAR techniques, are introduced and applied to solve the anti-collision radar detection problems. We have analyzed the performance of CA-CFAR and OS-CFAR processors. Those conventional CFAR detectors' advantages and limitations are discusses in detail. Meanwhile, we derive the formulations for these CFAR detectors and show the simulation results in that situation.

Chapter 3

Novel CFAR Detectors

3.1 Introduction

In all radars' detection is the process of deciding whether or not a target is present. It is accomplished by comparing the signal-plus-interference which radar received, after all processing has occurred, to a threshold. If the signal-plus-interference, or interference alone, crosses the threshold, a detection is declared. If not, no detection occurs.

Because noise and clutter are always random phenomena, a decision concerning the presence or absence of a target echo is to be made by setting up a decision threshold. In these systems, thresholds are set automatically by sensing the average interference level and setting the threshold based on it, so that a small constant rate of false alarms occurs.

The CA-CFAR method was first introduced by Finn and Johnson [51]. This adaptive method can play an effective part in much noise and clutter environments, and provide nearly the best ability of signal detection while preserving the enough constant false

alarm rate. Rohling [52] proposed the OS-CFAR processor. This processor possesses the good ability to counter the multiple targets.

Although the CA-CFAR method can provide a good ability of signal detection while preserving the enough constant false alarm rate, such a CFAR detection performance is usually degraded for two major problems: 1) regions of clutter power transition and by 2) multiple target environments.

Compared to the CA processors, The OS –CFAR processor exhibits some loss of detection power in homogeneous noise background.

To make full use of the collected data, four new radar CFAR detectors synthesizing the advantages of CA-CFAR and OS-CFAR are proposed. It is defined as And-Ca-Os CFAR, And-Os-Os CFAR, And–Os-Os-Os , and And-Ca-Os-Os CFAR algorithm as shown in Fig 3.1, Fig 3.2, Fig 3.3, Fig 3.4 respectively, where N represents the number of reference cells, T is the scaling constant.

These CFAR structure are computationally efficient. In the following sections, the exact mathematical formulas for the four CFAR algorithms are derived and their performance are shown.

3.2 Detection Principle and Model Formulation

3.2 Detection Principle and Model Formulation

- 66 -

A block diagram of the modified CFAR detectors is shown in Fig 3.1. The system collects a number $E=M+N$ of reference samples and implements the adaptive threshold test [53, 54]

$$V \underset{H_0}{\overset{H_1}{\geq}} TZ \quad (3.0)$$

where Z is the final background noise estimation, T is a threshold parameter to control the desired probability of false alarm, P_{fa} and V is the cell-under-test variate. The different themes of all CFAR detectors is to estimate Z according to different methods. If the decision about the presence (hypothesis H_1) of a target in the test cell has been made according to Eqn (3.0), the right reference window stops shifting. The test cell variate V will be censored. Thus, generally speaking interfering target numbers in the right sub-window are always less than those in the left sub-window. This is a new kind of automatic censoring technique in CFAR detection schemes. By using the techniques we can achieve better detection performance both in the presence and absence of interference.

A binary hypothesis testing paradigm under the Swerling case 2 assumption is

under H_0 , we have

$$f_0(v) = \frac{1}{\mu} \exp\left(-\frac{v}{\mu}\right) \quad (3.1)$$

3.2 Detection Principle and Model Formulation

- 67 -

under H_1 , we have

$$f_1(v) = \frac{1}{(1+\lambda)\mu} \exp\left(-\frac{v}{(1+\lambda)\mu}\right) \quad (3.2)$$

where λ is the per pulse average SNR. Without loss of generality, and because we analyse only the cases of homogeneous reference and multiple target environment, the noise level is set to unit, i.e, $\mu=1$. Thus, the reference cell variates x_i , $i \in M$ and y_j , $j \in N$ are taken to be statistically independent and identically distributed (IID) with common PDF:

$$f_x(x) = f_y(y) = e^{-x} \quad x > 0 \quad (3.3)$$

The local estimators operate on reference samples taken in a range surrounding the cell-under-test variate V . We refer to X as the leading and Y as lagging window estimator. Functions of $(x_1, \dots, x_m)$ and $(y_1, \dots, y_n)$ are the local pools of reference samples. The modified CFAR use the local estimators below

$$X = x_{(k)} \quad Y = y_{(i)} \quad (3.4)$$

It has been shown that the j th ranked sample (out of a total N_1 samples) has a probability density function

$$f_j(x) = j \binom{N_1}{j} [F_*(x)]^{j-1} [1 - F_*(x)]^{N_1-j} f_*(x) \quad (3.5)$$

3.2 Detection Principle and Model Formulation

- 68 -

where j is equal to k or l , N_1 is M or N and $F_*(x), f_*(x)$ correspond with $F_x(x), F_y(x)$, and $f_x(x), f_y(x)$ respectively.

Using Eqns (3.2) and (3.3) in Eqn (3.5) we get the PDF of the k -th ranked sample of the leading window and the l -th ranked sample of the lagging window, respectively

$$f_k(x) = f_x(x) = k \binom{M}{k} [\exp(-x)]^{M-k+1} [1 - \exp(-x)]^{k-1} \quad (3.6)$$

and

$$f_l(x) = f_y(x) = l \binom{N}{l} [\exp(-x)]^{N-l+1} [1 - \exp(-x)]^{l-1} \quad (3.7)$$

And we can write their CDF, respectively, as

$$F_k(x) = F_x(x) = \sum_{i=k}^M \binom{M}{i} [1 - \exp(-x)]^i [\exp(-x)]^{M-i} \quad (3.8)$$

and

$$F_l(y) = F_y(y) = \sum_{j=l}^N \binom{N}{j} [1 - \exp(-y)]^j [\exp(-y)]^{N-j} \quad (3.9)$$

For any CFAR employing Eqn (3.0), where V and Z are independent random variables we can show, following Ritcey and Hines [54] that

$$P_d = \Pr(V \geq TZ) = - \int_{\mathcal{C}^-} \frac{du}{i2\pi} \mu^{-1} h(\mu) d(-T\mu) \quad (3.10)$$

where $h(\mu) = E(e^{-\mu v})$ and $d(\mu) = E(e^{-\mu z})$ are moment generating functions(MGF). For a Swerling case 2 primary target, $h(\mu) = (1 + b\mu)^{-1}$, $b = 1 + \lambda$. Here $d(-T\mu)$ is analytic in the LHP and Eqn (3.11) can immediately be evaluated in terms of the residue at the simple pole, $\mu = -b^{-1}$. Thus, the detection probability is simply related to the MGF of the z by

$$P_d = d\left(\frac{T}{b}\right) \quad (3.11)$$

and the false-alarm probability is given by

$$P_{fa} = d(T) \quad (3.12)$$

Obviously, the MGF $d(u)$ of the reference cell estimator Z is a key quantity in our analysis.

3.3 Mathematical Model of Novel CFAR

3.3. Mathematical Model of Novel CFAR

- 70 -

In the And-OS-OS-OS CFAR detector, the estimation of the noise level in the cell under test in the sum of the outputs of leading window the k th order statistics and the lagging window the l th order statistics, i.e.

$$Z=X+Y \quad (3.13)$$

The PDF of Z defined by eqn.3.14 is given by (Eqn.3.13)

$$f_z(z) = \int_0^z f_x(x) f_y(z-x) dx \quad z>0 \quad (3.14)$$

Using Eqn.(3.13), the MGF of the noise –level estimation in Eqn.(3.14) is given for a homogeneous environment by

$$d_1(\mu) = \int_0^\infty e^{-\mu z} f_x * f_y(z) dz = d_x(\mu) d_y(\mu) \quad (3.15)$$

where

$$d_x(\mu) = k \binom{M}{k} \int_0^\infty e^{-\mu z} [\exp(-z)]^{M-k+1} [1 - \exp(-z)]^{k-1} dz = k \binom{M}{k} \frac{\Gamma(M-k+\mu+1) \Gamma(k)}{\Gamma(M+\mu+1)} \quad (3.16)$$

$$d_y(\mu) = l \binom{N}{l} \int_0^\infty e^{-\mu z} [\exp(-z)]^{N-l+1} [1 - \exp(-z)]^{l-1} dz = l \binom{N}{l} \frac{\Gamma(N-l+\mu+1) \Gamma(l)}{\Gamma(N+\mu+1)} \quad (3.17)$$

By substituting Eqn.(3.15) into Eqn.(3.11) and Eqn (3.12), respectively, we obtain the detection probability of the CFAR.

So based on derivation above, we got mathematical models of the new CFAR detectors as follows (section 3.4 - 3.7):

3.4 Mathematical Model of And-Ca-Os CFAR

This CFAR structure is computationally efficient. As shown in Fig 3.1, where N,M represents the number of reference cells, T is the scaling constant and Z_1 , Z_2 represent the numbers calculated from CA processing and OS processing respectively.

Fig.3.1 Block diagram of And-Ca-Os CFAR

3.4. Mathematical Model of And-Ca-Os CFAR

- 72 -

In homogeneous back ground, with all the cells are IID, The false alarm probability P_{fa} and the detection probability P_D are defined as

$$P_{fa} = k \binom{E}{k} \frac{\Gamma(E - k + T + 1) \Gamma(k)}{\Gamma(E + T + 1)} \frac{1}{(1 + T/E)^E} \quad (3.18)$$

$$M + N = E$$

$$P_D = \frac{k}{\{1 + T / [(1 + \lambda)E]\}^E} * \binom{E}{k} \frac{\Gamma[E - k + T / (1 + \lambda) + 1] \Gamma(k)}{\Gamma[E + T / (1 + \lambda) + 1]} \quad (3.19)$$

where E is the number of reference cells, T is the scaling constant as stated before. λ is the signal-to-noise ratio and k is the reference cell [55, 56].

3.5 Mathematical Model of And-Os-Os CFAR

This CFAR structure is shown in Fig 3.2, where N, M represents the number of reference cells, T is the scaling constant and Z_L, Z_K represent the numbers calculated from different OS processing windows respectively.

In homogeneous back ground, with all the cells are IID, The false alarm probability P_{FA} and the detection probability P_D are defined as

$$P_D = k \binom{E}{k} \frac{\Gamma[E - k + T/(1 + \lambda) + 1] \Gamma(k)}{\Gamma[E + T/(1 + \lambda) + 1]} * L \binom{E}{L} \frac{\Gamma[E - L + T/(1 + \lambda) + 1] \Gamma(L)}{\Gamma[E + T/(1 + \lambda) + 1]} \quad (3.20)$$

$$P_{FA} = k \binom{E}{k} \frac{\Gamma(E - k + T + 1) \Gamma(k)}{\Gamma(E + T + 1)} * L \binom{E}{L} \frac{\Gamma(E - L + T + 1) \Gamma(L)}{\Gamma(E + T + 1)} \quad (3.21)$$

$$M + N = E$$

where E is the number of reference cells, T is the scaling constant as stated before. λ is the signal-to-noise ratio and k is the reference cell.

Fig.3.2 Block diagram of And-Os-Os CFAR

3.6 Mathematical Model of And-Os-Os-Os CFAR

3.5. Mathematical Model of And Os-Os CFAR

- 74 -

This CFAR structure is shown in Fig 3.3, where N, M represents the number of reference cells, T is the scaling constant.

In homogeneous back ground, with all the cells are IID, the false alarm probability P_{fa} and the detection probability P_D are defined as

$$P_{fa} = k \binom{M}{k} \frac{\Gamma(M-k+T+1)\Gamma(k)}{\Gamma(M+T+1)} * l \binom{E}{l} \frac{\Gamma(E-l+T+1)\Gamma(l)}{\Gamma(E+T+1)} * c \binom{N}{c} \frac{\Gamma(N-c+T+1)\Gamma(c)}{\Gamma(N+T+1)} \quad (3.22)$$

$$P_D = k \binom{M}{k} \frac{\Gamma[M-k+T/(1+\lambda)+1]\Gamma(k)}{\Gamma[M+T/(1+\lambda)+1]} * l \binom{E}{l} \frac{\Gamma[E-l+T/(1+\lambda)+1]\Gamma(l)}{\Gamma[E+T/(1+\lambda)+1]} * c \binom{N}{c} \frac{\Gamma[N-c+T/(1+\lambda)+1]\Gamma(c)}{\Gamma[N+T/(1+\lambda)+1]} \quad (3.23)$$

$$M+N=E$$

where E is the number of reference cells, T is the scaling constant as stated before. λ is the signal-to-noise ratio and k is the reference cell.

Fig.3.3 Block diagram of And-Os-Os-Os CFAR

3.7 Mathematical Model of And-Ca-Os-Os CFAR

This CFAR structure is shown in Fig 3.4, where N, M represents the number of reference cells, T is the scaling constant.

3.7. Mathematical Model of And-Ca-Os-Os CFAR

- 76 -

In homogeneous back ground, with all the cells are IID, the false alarm probability P_{fa} and the detection probability P_D are defined as

$$P_D = k \binom{M}{k} \frac{\Gamma[M - k + T/(1 + \lambda) + 1] \Gamma(k)}{\Gamma[M + T/(1 + \lambda) + 1]} * \frac{1}{\{1 + T/[(1 + \lambda)E]\}^E} * c \binom{N}{c} \frac{\Gamma[N - c + T/(1 + \lambda) + 1] \Gamma(c)}{\Gamma[N + T/(1 + \lambda) + 1]} \quad (3.24)$$

$$P_{fa} = k \binom{M}{k} \frac{\Gamma(M - k + T + 1) \Gamma(k)}{\Gamma(M + T + 1)} * \frac{1}{(1 + T/E)^E} * c \binom{N}{c} \frac{\Gamma(N - c + T + 1) \Gamma(c)}{\Gamma(N + T + 1)} \quad (3.25)$$

$$M + N = E$$

where E is the number of reference cells, T is the scaling constant as stated before. λ is the signal-to-noise ratio and k is the reference cell.

Fig.3.4 Block diagram of And-Ca-Os-Os CFAR

3.8 Results

The actual probability of detection achieved by the novel CFAR detectors in a homogeneous environment has been evaluated by means of computer simulation. The detection performance of the detectors is also compared with that of the traditional CA-CFAR detector and OS-CFAR detector.

As false alarm probability is fixed, the scaling constant T can be calculated to evaluate performances. The program (see Appendix C) which based on Secant Line iteration is used to calculate the threshold. It combats the heavy work caused by Divide line method and complicated work (need to calculate complex differential coefficient) result from the Newton iteration method.

For different reference numbers E , and k , l , c , M , N value settings and false alarm probabilities, the scaling constant T s of new CFAR detectors are listed below respectively.

It can be seen from the calculated T values that as number of reference cells E increases, T decreases. This is rationale since the more information can be obtained, the more decisive the threshold and so the lower T value. It also could be seen when the false alarm probability decreases, the threshold scaling factor T increases.. As T increases, the detection probability will decrease, this is due to the higher the scaling constant, the higher the threshold, it is more difficult for the cell under test to go beyond the threshold, so the P_D will decrease. This is the same trend as the CA-CFAR and OS- CFAR. To illustrate this further, the detection probabilities versus P_{fa} and different reference cells E have been plotted (Fig 3.5 to Fig 3.13).

Table 3.1 Scaling constant T of And-Os-Os CFAR for different E and k, l values

	E=16	E=16	E=16	E=16	E=32	E=32	E=32	E=32
	k=8	k=10	k=12	k=14	k=16	k=20	k=24	k=28
	L=8	L=10	L=12	L=14	L=16	L=20	L=24	L=28
$P_{fa} = 10^{-4}$	9.4671	6.3679	4.4251	3.0249	7.9113	5.4640	3.8383	2.6026
$P_{fa} = 10^{-5}$	12.8324	8.4938	5.8479	3.9816	10.2815	7.0501	4.9329	3.3420
$P_{fa} = 10^{-6}$	16.7233	10.8850	7.4214	5.0300	12.8318	8.7342	6.0863	4.1189
$P_{fa} = 10^{-7}$	21.2205	13.5733	9.1602	6.1771	15.5756	10.5219	7.3012	4.9347
$P_{fa} = 10^{-8}$	26.4173	16.5944	11.0802	7.4307	18.5269	12.4192	8.5801	5.7906
$P_{fa} = 10^{-9}$	32.4214	19.9883	13.1991	8.7990	21.7012	14.4322	9.9262	6.6880

Table 3.2 Scaling constant T of And-Os-Os-Os CFAR for different E and M,N, k, l values

	M=8 E=16	M=8 E=16	M=8 E=16	M=8 E=16	M=8 E=16	M=8 E=16	M=16 E=32	M=16 E=32
	N=8 l=14	N=8 l=12	N=8 l=10	N=8 l=8	N=8 l=14	N=8 l=14	N=16 l=16	N=16 l=28
	k=4	k=4	k=4	k=4	k=2	k=6	k=8	k=8
	c=4	c=4	c=4	c=4	c=2	c=6	c=8	c=8
$P_{fa} = 10^{-4}$	3.7530	4.6611	5.5990	6.6384	5.2094	2.6529	5.4246	3.1690
$P_{fa} = 10^{-5}$	4.9938	6.2289	7.5396	9.0323	7.0367	3.5008	7.0694	4.0883
$P_{fa} = 10^{-6}$	6.3807	7.9964	9.7549	11.8099	9.1276	4.4352	8.8460	5.0632
$P_{fa} = 10^{-7}$	7.9291	9.9872	12.2813	15.0290	11.5163	5.4634	10.7636	6.0961
$P_{fa} = 10^{-8}$	9.6559	12.2279	15.1604	18.7565	14.2419	6.5938	12.8322	7.1901
$P_{fa} = 10^{-9}$	11.5802	14.7483	18.4395	23.0698	17.3491	7.8351	15.0626	8.3481

3.8. Results

Table 3.3 Scaling constant T of And-Ca-Os-Os CFAR for different E and M,N, k, l values

	M=8 E=16	M=8 E=16	M=8 E=16	M=8 E=16	M=16 E=32	M=16 E=32	M=16 E=32
	N=8	N=8	N=8	N=8	N=16	N=16	N=16
	k=2	k=4	k=6	k=6	k=8	k=12	k=14
	c=2	c=4	c=6	c=2	c=8	c=12	c=14
$P_{fa} = 10^{-4}$	7.7981	5.1454	3.3758	4.8153	4.4732	2.8945	2.2128
$P_{fa} = 10^{-5}$	10.4164	6.8196	4.4599	6.4054	5.7619	3.7265	2.8511
$P_{fa} = 10^{-6}$	13.3645	8.6767	5.6534	8.1746	7.1242	4.6044	3.5344
$P_{fa} = 10^{-7}$	16.6812	10.7335	6.9640	10.1386	8.5631	5.5295	4.2516
$P_{fa} = 10^{-8}$	20.4100	13.0087	8.4005	12.3149	10.0817	6.5034	5.0075
$P_{fa} = 10^{-9}$	24.6003	15.5229	9.9726	14.7232	11.6835	7.5276	5.8033

Table 3.4 Scaling constant T of And-Ca-Os CFAR for different E and k, l values

	E=16 k=8	E=16 k=10	E=16 k=12	E=16 k=14	E=32 k=16	E=32 k=20	E=32 k=24	E=32 k=28
$P_{fa} = 10^{-4}$	6.7885	5.7910	4.8580	3.9295	6.0727	5.1910	4.3401	3.4558
$P_{fa} = 10^{-5}$	8.9421	7.6046	6.3696	5.1583	7.7876	6.6490	5.5582	4.4346
$P_{fa} = 10^{-6}$	11.3150	9.5906	8.0182	6.4971	9.5887	8.1765	6.8330	5.4610
$P_{fa} = 10^{-7}$	13.9291	11.7645	9.8147	7.9532	11.4800	9.7763	8.1666	6.5361
$P_{fa} = 10^{-8}$	16.8084	14.1432	11.7710	9.5346	13.4659	11.4514	9.5610	7.6613
$P_{fa} = 10^{-9}$	19.9793	16.7454	13.9001	11.2504	15.5510	13.2052	11.0185	8.8378

Fig 3.5 The effect of n on P_d of And-Ca-Os CFAR where n is the reference cells number and designed $P_{fa}=10e-8$

Fig 3.6 The effect of P_{fa} on P_d of And-Ca-Os CFAR when $n=16, k=12$

Fig 3.7 The effect of n on P_d of And-Ca-Os CFAR where $n=16$ is the reference cells number and designed $P_{fa}=10e-8$

Fig 3.8 The effect of P_{fa} on P_d of And-Os-Os CFAR when $n=16, k=12$

Fig 3.9 The effect of k and c on P_d of And-Ca-Os-Os CFAR when the reference cells number $E=16$, $M=N=8$ and designed $P_{fa}=10e-8$

Fig 3.10 The effect of P_{fa} on P_d of And-Ca-Os-Os CFAR when the reference cells number $E=16$, $M=N=8$, $k=c=4$

Fig 3.11 The effect of l on P_d of And-Os-Os-Os CFAR when the reference cells number $E=16$, $M=N=8$, $k=c=4$, and designed $P_{fa}=10e-8$

Fig 3.12 The effect of P_{fa} on P_d of And-Os-Os-Os CFAR when the reference cells number $E=16$, $l=10$, $M=N=8$, $k=c=4$

3.9 Performance Comparison

Fig 3.13 Comparison of P_d among the six CFAR detectors with the number of reference cells $n=16$ and $P_{fa}=10e-8$

To compare the performance among the And-Os-Os CFAR, And-Ca-Os CFAR, And-Os-Os-Os CFAR, And-Ca-Os-Os CFAR, Ca-CFAR and Os-CFAR detectors, the formulations of Os-CFAR and Ca-CFAR are derived from the same approach as And-Os-Os CFAR, And-Ca-Os CFAR, And-Os-Os-Os CFAR, and And-Ca-Os-Os CFAR. The detection probability and false alarm probability of each CFAR detector is shown above. The detection probability under different signal-to-noise is actually compared among the six detectors. In Fig 3.13, the number of reference cells is $n=16$, a designed probability of false alarm $P_{fa}=10e-8$. It can be seen that the And-Ca-Os CFAR is achieving the best detection probability in the six detectors. And-Ca-Os CFAR is better than And-Os-Os-Os CFAR and And-Os-Os CFAR. The And-Os-Os CFAR has a very close performance with

the CA-CFAR. The Os-CFAR probability detection performance is the worst among the six CFAR detectors. From the simulation results, for the new CFAR detectors there will be different improved percentage of probability of detection contribution. It can be varied from 0.60% to more than 49% at different signal-to-noise ratios.

3.10 Conclusion

In this chapter, we propose four novel CFAR detectors synthesizing the advantages of CA-CFAR and OS-CFAR. They are the improvement from the traditional CA-CFAR and OS-CFAR. Analytical expressions for the detection probability and false alarm probability of the four detectors are obtained. The performance of the proposed CFAR detectors has been examined first and then compared with that of CA-CFAR and OS-CFAR. It is proved that the And-Ca-Os CFAR approach is computationally efficient and increases the detection performance extremely among these CFAR detectors. So we recommend And-Ca-Os CFAR to the anti-collision radar applications.

Chapter 4

Improved Radar Detection on Curved Section of a Road

4.1 Introduction

In anti-collision radar systems, the high detection probability and low false alarm rate puts tough demands on radar sensor, especially on radar antenna [57]. People have realized to get high detection probability and low false alarm rates, radar antenna must measure the three discriminations of a target simultaneously, those are range, velocity and azimuth angle.

Due to the strong requirements for extremely high accurately detection, the anti-collision radar antenna design for car application is a very important point. The statistics show that high false detections of unnecessary objects and non-detections of necessary objects in the traffic often take places when the radar vehicle is running on the curve. To

cope with the difficult situation, I proposed a new antenna techniques to improve the radar detection performance. The novel antenna could robustly work in everyday any traffic situations and in any weather conditions. The method make a good improvement over the classical antenna tracking technologies.

4.2 Radar Antennas

The purpose of the radar antenna is to act as a transducer between free-space propagation and guided-wave (transmission-line) propagation. The function of the antenna during transmission is to concentrate the radiated energy into a shaped beam which points in the desired direction in space. On reception the antenna collects the energy contained in the echo signal and delivers it to the receiver. Thus the radar antenna is called upon to fulfill reciprocal but related roles. In the radar equation derived in Chapter 1 [Eqn.1.7] these two roles were expressed by the transmitting gain and the effective receiving aperture. The two parameters are proportional to one another. An antenna with a large effective receiving aperture implies a large transmitting gain.

The large apertures required for a long-range detection result in narrow beamwidths, one of the prime characteristics of radar [60]. Narrow beamwidths are important if accurate angular measurements are to be made or if targets close to one another are to be resolved. The advantage of microwave frequencies for radar application is that with apertures of relatively small physical size, but large in terms of wavelengths, narrow beamwidths can be obtained conveniently.

Radar antennas are characterized by directive beams which are scanned, usually rapidly. In our design, the radar antenna will be considered either as a transmitting or a receiving device, depending on which is more convenient for the particular discussion.

The electric field intensity is written as [61, 62]

$$E = \frac{M_0 e^{j\omega(t-\tau)}}{4\pi r \epsilon \lambda_*^2} \left[\frac{j2\lambda_*}{r} \left(1 + \frac{\lambda_*}{r} \right) \cos \theta \hat{r} + \left\{ \frac{j\lambda_*}{r} \left(1 + \frac{2\lambda_*}{r} \right) - 1 \right\} \sin \theta \hat{\theta} \right] \quad (4.1)$$

As $\lambda_* \rightarrow \infty$ and $\omega=0$, Eqn (4.1) reverts to Eqn (4.2), the static terms.

The electric field intensity E is seen to propagate through space with a velocity c for $r \gg \lambda_*$, as does V . The situation where $r \gg \lambda_*$ is referred to as the far field for the doublet [63]. More is said of the division of a radiating field in front of an antenna into regions. In the instance where $r \gg \lambda$, where is left in Eq (4.1) is the radiation term. [64] Specifically

$$E = -\frac{M_0 e^{j\omega(t-\tau)}}{4\pi r \epsilon \lambda_*^2} \sin \theta \hat{\theta} \quad (4.2)$$

However, close to the dipole, r in Eq (4.1) would not be much larger than λ_* , E will involve five components: two varying as r^{-2} ; two varying r^{-2} but leading by $\pi/2$ (radians); and finally the r^{-1} term leading the other r^{-2} term by π (radians). Equation (4.2) demonstrates the r^{-1} dependence for an oscillating doublet ensuring conservation of energy [65].

4.3 Anti-collision Radar Antenna Arrays

The antenna array radiation pattern can be derived from basic relations by considering the propagation of electric field from a set of radiating elements. The works of Schekunoff (1943) and Stratton (1941) provide the background material applicable to the linear array discussed in this section [66, 67, 68]. Consider N radiating elements, equally spaced a distance d apart, each element radiating equal amplitude α_0 , but with a phase progression difference between adjacent elements, as shown in Figure 4.1. The phase difference in adjacent elements may be expressed by

$$\Delta\phi = 2\pi \frac{d}{\lambda} \sin \theta \quad (4.3)$$

where θ is the look angle; that is, angle taken of the incoming wave. To accommodate for the progressive beam scanning effect, a phase progression $\delta\delta$ between adjacent elements is introduced [69, 70] The total phase difference of the radiating fields from the adjacent elements may be expressed as

$$\psi = \Delta\phi + \delta\delta = 2\pi \frac{d}{\lambda} \sin \theta + \delta\delta \quad (4.4)$$

4.3 Anti-collision Radar Antenna Arrays

- 93 -

The outputs E_i of all the elements are summed via lines of equal length to give the sum output E , as in Figure 4.2. If source 1 is taken as the phase centre so that the field from source 2 is advanced by ψ , source 2 is advanced by 2ψ , and progressively onwards until the source N is advanced by $(N-1)\psi$, then the sum output E can be written as a geometric series [71]:

$$E = \alpha_0(1 + e^{j\psi} + e^{j2\psi} + \dots + e^{j(N-1)\psi}) \quad (4.5)$$

For brevity, $\alpha_0=1$. multiply Eq (4.5) by $e^{j\psi}$ and by simple geometry,

$$Ee^{j\psi} = \alpha_0(e^{j\psi} + e^{j2\psi} + e^{j3\psi} + \dots + e^{jN\psi}) \quad (4.6)$$

Subtracting Eq (4.6) from Eq (4.5) and dividing by $(1 - e^{j\psi})$,

$$E = \frac{1 - e^{jN\psi}}{1 - e^{j\psi}} = \frac{e^{\frac{jN\psi}{2}} \left[e^{-\frac{jN\psi}{2}} - e^{\frac{jN\psi}{2}} \right]}{e^{\frac{j\psi}{2}} \left[e^{-\frac{j\psi}{2}} - e^{\frac{j\psi}{2}} \right]} \quad (4.7)$$

Rearranging Eq (4.7),

$$E = \left\{ e^{\frac{j(N-1)\psi}{2}} \right\} \left[\frac{\sin\left(\frac{N\psi}{2}\right)}{\sin\left(\frac{\psi}{2}\right)} \right] \quad (4.8)$$

4.3 Anti-collision Radar Antenna Arrays

- 94 -

noting that $e^{-jx} - e^{jx} = -2j \sin x$. Two terms emerge from Eq (4.8): the term $\{ \}$ in curly brackets is the phase of the field shifted $(N-1)\psi/2$; and the second term $[]$ represents an amplitude factor or simply array factor, $f_a(\psi)$. Specifically [72, 73, 74]:

$$f_a(\psi) = \frac{\sin\left(\frac{N\psi}{2}\right)}{\sin\left(\frac{\psi}{2}\right)} \quad (4.9)$$

The array field strength is the magnitude of Eq (4.8) and Eq (4.9), and noting that ψ is directly related to the physical dimension of the antenna in the form [75]:

$$|E(\theta)| = \left| \frac{\sin\left(\frac{N\psi}{2}\right)}{\sin\left(\frac{\psi}{2}\right)} \right| = \left| \frac{\sin\left(N \left\{ \frac{\pi d}{\lambda} \sin \theta + \frac{\delta\delta}{2} \right\}\right)}{\sin\left(\frac{\pi d}{\lambda} \sin \theta + \frac{\delta\delta}{2}\right)} \right| \quad (4.10)$$

Note that this expression represents voltage distribution. It can be converted to power, as the array radiation pattern, or antenna gain $G(\theta)$, by the normalized square of the amplitude [76,77]:

$$G(\theta) = \frac{|E(\theta)|^2}{N^2} = \left[\frac{\sin \left(N \left\{ \frac{\pi d}{\lambda} \sin \theta + \frac{\delta \delta}{2} \right\} \right)}{N \sin \left(\frac{\pi d}{\lambda} \sin \theta + \frac{\delta \delta}{2} \right)} \right]^2 \quad (4.11)$$

In essence, the array pattern could be defined as the full elevation pattern of a broadside array that substitutes (imaginary) isotropic radiators in place of the elements actually used [78]. The broadside of the array is the direction in which maximum radiation is almost perpendicular to the plane (line) of the array [79]

When directive elements are used, the resultant radiation pattern is expressed as

$$G(\theta) = G_i(\theta) = \left[\frac{\sin \left(N \left\{ \frac{\pi d}{\lambda} \sin \theta + \frac{\delta \delta}{2} \right\} \right)}{N \sin \left(\frac{\pi d}{\lambda} \sin \theta + \frac{\delta \delta}{2} \right)} \right]^2 \quad (4.12)$$

where $G_i(\theta)$ is the individual element factor, or radiation pattern of an individual element.

In a two dimensional rectangular planar array, the radiation pattern may sometimes be written as the product of the two planes that contain the principal axes of the antennas [80]. Following equation (4.12) and neglecting phase progression effect for simplicity (i.e. $\delta \delta = 0$), the product radiation pattern

$$G(\theta)|_{n,m} = \left[\frac{\sin\left(n \frac{\pi d}{\lambda} \sin \theta_n\right)}{n \sin\left(\frac{\pi d}{\lambda} \sin \theta_n\right)} \right]^2 \left[\frac{\sin\left(m \frac{\pi d}{\lambda} \sin \theta_m\right)}{m \sin\left(\frac{\pi d}{\lambda} \sin \theta_m\right)} \right]^2 \quad (4.13)$$

where n, m = number of radiators in θ_n, θ_m dimensions with spacing d , a respectively.

Note that θ_n, θ_m are not necessarily the elevation, azimuth angles normally associated with antenna beam [81,82].

An advantage of two-dimensional array is that one can scan and shape the beam in two directions. However this type of array tends to have a rather complex and costly feed network.

Fig 4.1 Geometry configuration of a linear array antenna

Fig 4.2 Line representation of radiators of a linear array antenna

4.4 Classical Azimuth Measurement

Monopulse tracking is a process through which the radar receiver processes two (or sometimes four) signals for phase and amplitude information [83, 84, 85]. Amplitude comparison monopulse is used in situations where more than one antenna is used and each antenna illuminates a slightly different space [86]. This is commonly the case with reflector antennas where multiple feed antennas may be used to produce multiple beams. However, in the case of automotive radar, when design space is at a premium and costs must be minimized, multiple small antennas are often used together in an array

environment. In this situation it is far more practical to use phase comparison monopulse.

Phase comparison monopulse functions on the fact that if a target is not directly at the broadside of an antenna array then the reflected signal will cause a phase difference in each element of the array [87, 88]. Fig 4.3 is an illustration of a phase comparison radar's antenna array. The distance from antenna 1 to the target is

$$R_1 = R + \frac{d}{2} \sin(\theta) \quad (4.14)$$

where d is the distance between antenna 1 from antenna 2, R is the distance from the middle point (of antenna 1 and antenna 2) to the target. and the distance from antenna 2 to the target is

$$R_2 = R - \frac{d}{2} \sin(\theta) \quad (4.15)$$

The phase difference between the reflected signals in the two antenna elements is approximately

$$\Delta\phi = \frac{2\pi}{\lambda} d \sin(\theta) \quad (4.16)$$

When θ , as seen in Fig. 4.5, is a small angle. The phase difference between antenna channels is approximately a linear function of the angle θ .

Fig 4.3 Monopulse phase comparison

A phase comparison monopulse system requires a circuit that will form the sum and difference of the reflected signal. Recently much attention has been paid to various methods of processing received signals at lower frequencies [89]. The advantage of performing such a task at lower frequencies is that the hardware required to form the sum

and difference channels is readily available and is often made of lumped elements instead of a printed type hybrid. It is also an interesting topic for my future research work.

4.5 Trace Target On The Curve

Unfortunately, there is not a straight road from the start to the end. One of the high false detections of unnecessary objects and non-detections of necessary objects in the traffic often take places when the radar vehicle is running on the curve (Fig.4.4) [90,91]. To prevent it, the radar beam is steered at the location of the target so as to trace it properly. We could set up a mathematics model as follows.

First, the curve radius R of the presently running lane is estimated by the yaw rate and the vehicle speed as Equation 4.17, then the beam steering angle θ is determined accordingly as expressed below:

$$R = \frac{v}{\omega_y} \quad (4.17)$$

where v is the vehicle speed; and ω_y is the yaw rate.

That means if there is a target exists in the running direction on the lane, and the distance of the target detected by the radar is L , θ is determined as expressed below:

$$\theta = \sin^{-1}(L/2R) \quad (4.18)$$

4.5. Trace Target On The Curve

If there is no target exists in the running direction on the lane, the distance L in equation 4.18 is set the same as the warning distance to a stationary vehicle [92].

From the above, the target can be traced even if the distance to the target changes at a curve.

Fig 4.4 Car on the road

4.6 Improve The Azimuth Measurement

From Eq. 4.16 (differential the equation’s two sides), we can get

4.6. Improve The Azimuth Measurement

- 102 -

$$d\phi = \frac{2\pi}{\lambda} d \cos\theta d\theta \quad (4.19)$$

$$d\theta = \frac{\lambda}{2\pi d \cos\theta} d\phi \quad (4.20)$$

From Eq 4.20, we can see that the improvement of azimuth could be realized if we adopt high accuracy phase measurement instrument (to get small $d\phi$), or reduce the value of λ / d .

It also could be concluded that when $\theta = 0$, or the target is located the normal line of the antenna, the error of measuring azimuth $d\theta$ is smallest. The $d\theta$ augment with θ . So as to guarantee high accuracy measuring azimuth, we should limit the value of θ .

Although raise the d / λ could increase the measuring azimuth, from Eq.4.19 we could know that within a certain range of θ (within the azimuth measurement) when the d / λ grow up enough, the value of ϕ may exceed 2π :

$$\phi = 2\pi N + \psi \quad (4.21)$$

where N is integer, $\psi < 2\pi$. The phase measurement instrument actually take the reading of the ψ . Then we could not definite the real ϕ because of the uncertain N.

Fig 4.5 Beam steering logic

In order to solve the ambiguity question and uniquely identify the azimuth ϕ of the target, we propose a precise azimuth measuring method using three antennas shown as Fig 4.6.

From Fig 4.6, we assume the target exists in the running direction at an angle of θ . The distance between antennas 1 and 2 is d_{12} , and antennas 1 and 3 is d_{13} . We need to properly set-up d_{12} to satisfy the Eq.4.19 at the range of the measuring azimuth:

$$\phi_{12} = \frac{2\pi}{\lambda} d_{12} \sin \theta < 2\pi \quad (4.22)$$

where ϕ_{12} is the difference phase of the received signals for antennas 1 and 2. ϕ_{12} is taken directly on the instrument 1.

To meet the measurement demand, design d_{13} bigger enough, then we could get Eq 4.23

$$\phi_{13} = \frac{2\pi}{\lambda} d_{13} \sin \theta = 2\pi N + \psi \quad (4.23)$$

Fig.4.6 Measuring azimuth using three antennas

4.6. Improve The Azimuth Measurement

- 105 -

ϕ_{13} is measured from the instrument 2. The actual reading is ψ , which is less than 2π . So as to make certain N, we could make use of relations as follows:

$$\frac{\phi_{13}}{\phi_{12}} = \frac{d_{13}}{d_{12}}$$

$$\phi_{13} = \frac{d_{13}}{d_{12}} \phi_{12} \quad (4.24)$$

We could obtain ϕ_{13} from ϕ_{12} (the reading of instrument 1), but the ϕ_{12} contains the reading error of the instrument, the error of ϕ_{13} (Eq.4.24) is d_{13}/d_{12} times the amount of the instrument reading error. So ϕ_{13} obtained from Eq 4.24 is just the approximate value of Eq.4.23. $(d_{13}/d_{12})\phi_{12}$ divided by 2π , the integer of quotient is N. So we could make a certain N. Then Eq.4.23 can be used to calculate ϕ_{13} and confirm θ . The value of (d_{13}/λ) is bigger enough to satisfy the demand of the precision measurement of azimuth angle error $d\theta$.

4.7 Results

The simulation results (Fig 4.7) shows the calculations relationship between the azimuth measuring error and the target azimuth angel θ at different d/λ . Where d is the distance between the detective antennas (shown in Fig 4.3), and λ is the radar

transmitted wavelength. It can be seen that when $\theta = 0$, i.e. the target is located at the normal line of the antenna, the error of the measuring azimuth $d\theta$ is the smallest.

The error $d\theta$ augments with θ (from 0 to $\pm \frac{180^\circ}{\pi}$). When d/λ increase, the error $d\theta$ reduced rapidly.

Fig 4.7 Azimuth measuring error $d\theta$ versus target azimuth θ at different d/λ

4.8 Conclusion

In this chapter, we developed a new beam steering logic method and a novel antenna configure technology. From the simulation results, we could observe that the false detections of unnecessary objects and failures to detect necessary objects, which used to be major problems in anti-collision radar detection performance especially when a car is on the curve, had been substantively reduced.

Chapter 5

CFAR Radar Sensors for Collision Avoidance

5.1 Vehicular Application

In collision avoidance systems a radar system warns the operator of the vehicle when it is too close to an adjacent vehicle or when the closing speed to the next vehicle exceeds a prescribed rate. Such systems are currently available in up-scale cars such as Cadillac, Lexus, and Mercedes [93]. These installations consist of simple radar systems that look out of front of the car. An automated cruise control system may be an extension of a collision avoidance system. The current state of cruise control in vehicles is limited to speed control. The operator sets a computer to a desired speed once the speed is achieved [94]. The computer then adjusts the accelerator to keep the vehicle at a constant speed irregardless of whether the car is on a hill or on a flat road. Future automated cruise control systems will integrate radar systems with current cruise control technology to make driving safer and more comfortable. A radar system may be implemented in an

automated cruise control system in order to feed closing rate vehicle proximity information to a decision making computer. The computer would then make speed adjustments accordingly. While such systems are still some way in the future, research is currently being performed on related topics [95-97].

The radar detection properties depend basically on the waveform design. In our research activities we focused on continuous wave frequency modulated (FM) transmit signals [98]. The main requirement is to measure target range and velocity simultaneously in multi-target situations [99]. To meet the requirements for reliability (extreme low false alarm rate) and reaction time (extreme short delay) we discussed the specifics of the radar system's requirements, side looking surrounding and forward looking the car. An illustration of this type of application is given in Fig.1.2. The signal from the systems are considered simultaneously for target detection and tracking in a data fusion process.

5.2 Application of Novel CFAR Detectors

The novel CFAR strategy was selected for the calculation of the adaptive thresholds in the Anti-collision radar systems. In FMCW radars (shown in Fig 5.1) that use frequency-coded waveforms to measure simultaneously range and speed of a number of objects, these advantages become significant. The structure of the applied CFAR detector is shown in Fig 5.2.

The calculation of a decision threshold in this case is carried out in the frequency domain. Hence, the random variables $X_1 \dots X_N$ do not represent time samples, but bins in the power spectrum. For each cell in the considered window the measured value at the FFT output will be described as random variables X_i . In the pure noise case H_0 , these random variables and the value Y of the cell under test are assumed to be independent and identically exponentially distributed with the probability density function (PDF)

$$P_{y0}(x) = P_{xi}(x) = \begin{cases} \frac{1}{\mu} e^{-x/\mu} & x \geq 0 \\ 0 & \text{Otherwise} \end{cases} \quad (5.1)$$

where μ stands for the average clutter power.

$$Y_0 = Y / H_0 = \{Noise\} \quad (5.2)$$

If a target situation H_1 occurs in the test cell the random variable Y_1 is assumed to be distributed according to the following Rice PDF:

$$P_{Y_1}(x) = \begin{cases} \frac{1}{\mu} e^{-\left(\frac{x}{\mu} + G^2\right)} * I_0\left(2G\sqrt{\frac{x}{\mu}}\right) & x \geq 0 \\ 0 & \text{Otherwise} \end{cases} \quad (5.3)$$

$$Y_1 = Y / H_1 = \{\text{Noise}\} + \text{Signal} \quad (5.4)$$

where G^2 describes the S/N ratio and G is assumed to be Rayleigh-distributed for targets with fluctuating amplitude (Swierling case II).

$$P_G(x) = \begin{cases} \frac{2x}{G_0^2} e^{-\frac{x^2}{G_0^2}} & x \geq 0 \\ 0 & \text{Otherwise} \end{cases} \quad (5.5)$$

where $G_0^2 = E\{G^2\}$

The parameter μ stands for the average clutter power and is unknown. μ has to be estimated based on the cells in the reference window. A value for the decision threshold $S = T * Z$ is composed of the estimation Z , depending on μ and a scaling factor Z , which is selected so as to ensure the desired false alarm rate.

Fig. 5.1 Anti-collision FMCW radar block diagram

Fig 5.2 The structure of the applied CFAR detector
(where I stands for in-phase and Q stands for quadrature)

5.3 Conclusion

To make use of the significant advantages of the novel CFAR algorithm, we introduce an application on the vehicular technology of collision avoidance. The Anti-collision FMCW Radar Block Diagram and the structure of the applied CFAR detector are also presented in this chapter. The novel CFAR strategy will play a more and more important part for improving the performance of the anti-collision radars.

Chapter 6

Conclusion and Recommendation

6.1 Conclusion

Heavy responsibility lies upon vehicle researchers to develop an obstacle detection sensor, especially an anti-collision radar which has high expectations for active safety, since it is not easy to decrease the traffic accidents in number by using a conventional technology.

The millimeter-wave radar has excellent characteristics to correspond with the social demands for promoting safety-driving and reduce traffic collision accidents. It would be Certainly that the radar systems should play a more and more important role in industrial field and commercial applications [100].

It is emphasized in this thesis that the novel And-Ca-Os, And-Ca-Os-Os, And-Os-Os, And-Os-Os-Os CFAR detectors have been proposed and show high performance in Anti-collision radar detection measurement accuracy about the target range and velocity

information. We also have obtained the analytical expressions for the detection probability and false alarm probability.

The performance of the novel CFAR detectors have been examined in details and then compared with that of the traditional Ca-CFAR and Os-CFAR detectors . From the simulation results we could see that the novel CFAR detectors have a better detection probability than the classical CFAR detectors under different designed false alarm probabilities.

Based on the novel CFAR detectors, a anti-collision frequency-modulated-continuous-wave (FMCW) radar model has been presented.

We also developed a new beam steering logic method and a novel antenna configure technology. By using this, the false detections of unnecessary objects and failures to detect necessary objects, which used to be major problems in anti-collision radar detection performance especially when a car is on the curve, can be substantively reduced.

Hence, the summary of major contributions of this thesis is as follows:

- 1.) Four new types of CFAR detector models are proposed to obtain better results on anti-collision radar CFAR data fusion. Simulation results show that approach is effective and flexible, and provides a universal way to solve the high false alarm problem for anti-collision radar systems.

- 2.) The derivation of equations for the novel CFAR detection system is presented. Cases are considered where weak random signals are observed in additive Gaussian noise-plus-clutter of unknown power.
- 3.) For these four new CFAR detectors we obtain analytic expressions of the false alarm rate, the detection probabilities and the measure ADT under the Swerling case 2 assumption. Comparing to the conventional CFAR detectors in homogeneous background and in the presence of strong interfering targets, the new CFAR detectors have better detection performance.
- 4.) A novel method on Secant Line iteration (Appendix C) is proposed for obtaining better results on calculating the threshold of CFAR detector for a given constant false alarm rate. It combats the problem of heavy and complicated work resulting from divide line method and Newton iteration method.
- 5.) A new proposal of antenna design to improve the anti-collision radar detection performance when car is on the curve.

6.2 Recommendation and Future Work

We have made good performance progress by using the novel CFAR detectors with Swerling II model.

Furthermore, we would be interested in examining the Novel CFAR detectors performance in a more generic environment, such as Weibull model and Swerling case I, III and IV models.

We will check that under these environments, the performance of the novel CFAR detectors will be superior to the traditional Os-CFAR and Ca-CFAR detectors.

Considering the practice applications in traffic avoid collision affairs, the performance of the novel CFAR detectors will be examined under multi-target situation and at the clutter edge.

We will also study the novel CFAR detector's detection loss features in detail. Especially in the simulation traffic environment. Such as 1) regions of clutter power transition; 2) multiple target environments; 3) closely spaced target environment.

In the majority of Anti-collision radar applications, the primary factor limiting detection accuracy is interference [101]. Interference cannot be represented analytically, rather, it is modeled as a random process. In recent years, neural networks have been considered for signal detection primarily because a neural network may be trained to operate with acceptable performance, in an environment under which the optimum signal detector is not available. So implement the CFAR scheme as a part of a fuzzy data fusion scheme by choosing an appropriate membership function to represent the CFAR threshold. Once the threshold membership function of the Fuzzy Integrator has been set up, the false alarm rate of the scheme is independent of fluctuation in interference mean power and depends

only on the number of signals integrated by the data fusion unit and the required false alarm rate.

Fig 6.1 The basic diagram of a proposal fuzzy-neural network detector for anti-collision radar systems

So it is interesting to design a novel Fuzzy-neural network detector for improving the performance of the neural network detector. The proposal diagram is shown as Fig 6.1.

References

- [1] Stove, A.G. "Linear FMCW radar techniques," Radar and Signal Processing, IEE Proceedings F , Volume: 139 Issue: 5 , Oct. 1992 pp. 343 –350.
- [2] Peyton Z.Peebles, JR., "Radar principles" ISBN 0-471-25205-0 John Wiley & Sons, 1998, pp. 289.
- [3] M.I.Skolnik, "Introduction to radar systems," McGraw Hill, New York, NY,1980.
- [4] M.Wallman, "Disturbance detection and suppression in FMCW radar signals," Royal Inst. Of Technology, Signal Processing, Stockholm Swedden, 1996. pp. 378.
- [5] Hidayet.M, and P.A. McLannes, "On the Specification of an Antenna Pattern for a Synthetic Aperture Radar," International Conference RADAR-77, Oct. 25- 28, 1977, IEE (London) Conf. Publ., no.155. pp.391-395.
- [6] Nicholls, M.R. "Millimetre wave collision avoidance radars" Millimetre-Wave Radar, IEE Colloquium on , 1990 pp. 3/1 -3/7.

- [7] GANDHI, and KASSAM, S.A., "Analysis of CFAR processors in nonhomogeneous background nonhomogeneous background," IEEE Trans., 1988, AES-24,(4), pp.427-445.
- [8] Stove, A.G. "Obstacle detection radar for cars," Electronics & Communication Engineering Journal, Volume: 3 Issue: 5 , Oct. 1991 pp. 232 –240.
- [9] Griffiths, H.D. "New ideas in FM radar," Electronics & Communication Engineering Journal, Volume: 2 Issue: 5, Oct. 1990 pp. 185 –194.
- [10] ROHLING, H. "Radar CFAR threshold in clutter and multiple target situations," IEEE Trans., 1983, AES-19, (4), pp. 608-621.
- [11] RICKARD, J.T., and DILLARD, G.H. "Adaptive detection algorithms for multiple target situations," IEEE Trans., 1977, AES-13, (14), pp.338-343.
- [12] HIMONAS, S.D. and BARKAT, M., "A robust radar CFAR detector for multiple target situations," Proceeding of IEEE National Radar Conference, 1989, pp.85-90.
- [13] HIMONAS, S. D. and BARKAT, M., "Automatic censored CFAR detection for nonhomogeneous environments," IEEE Trans., 1992, AES-28, (1), pp.286-304.
- [14] HANSEN, V.G. "Detectability loss due to greatest of selection in a cell-averaging

- 121 -

- CFAR,” IEEE Trans., 1980, AES-16,(1), pp.116-118.
- [15] ELIAS-FUSTE, A. R., DE MERCADO, M. G. and DAVO, E.R. “Analysis of some modified order statistic CFAR: OSGO and OSSO CFAR,” IEEE Trans., 1990, AES-26,(1), pp. 197-202.
- [16] RITCEY, J. A. and HINES, J. L. “Performance of max family of order-statistic CFAR detectors,” IEEE Trans., 1991, AES-27, (1), pp. 48-57.
- [17] DAVID, H. A. “Order statistics,” (Wiley,1991), pp. 478.
- [18] PAPOULIS, A. “Probability, random variables, and stochastic processes,” (McGraw-Hill, New York, 1984), pp. 34.
- [19] M. GRECO, F. GINI, A.FARINA and J. B. BILLINGLEY, “Validation of windblown radar ground clutter spectral shape,” IEEE Trans., 2001, AES/37/2/06328, pp. 38-41.
- [20] Skolnik, M. I. “Introduce to radar systems,” McGraw-Hill, Inc, 1962. pp 2-3.
- [21] Gini. f, Montanari, M., and Verazzani, L. (2000). “Estimation of chirp radar signals in compound-Guassian clutter: A cyclostationary approach,” IEEE Transactions on Signal Processing, 48,4 (Apr.2000), pp.1029-1039.

- 122 -

[22] Barlow, E. J., "Doppler Radar," Proc. IRE, April, 1949. vol. 37, pp. 340-355.

[23] Raffaelli, L. "Millimeter-wave automotive radars and related technology"

Microwave Symposium Digest, 1996., IEEE MTT-S International , Volume: 1 , 1996

vol.1. pp. 35-38.

[24] Saunders, W. K., "Radar Handbook," McGraw-Hill Book Co., New York, 1970. pp

173-179.

[25] Hyltin, T. M. "Radar Handbook," McGraw-Hill Book Company, New York, 1970.

Chap. 30. pp 146-148.

[26] Mumford, W. W., and E. Scheibe " Noise: performance factors in communication

systems," Horizon House Microwave, Inc., Dedham, Mass. 1968. pp 14-19.

[27] Crispin, J. W., Jr., and K. M. Siegel, "Methods of radar cross section analysis,"

Academic Press, New York, 1968. pp. 21-24.

[28] Skolnik, M. I. "Introduce to radar systems," McGraw-Hill, Inc. International Edition

1981. pp. 44.

[29] Kendall, Sir., A. Stuart, "The advanced theory of statics," Vol. 2, Macmillan, New

York, 1979, pp 34-42.

- [30] Lehmann, E. L., "Testing statistical hypotheses," J. Wiley, New York, 1959, pp. 68-74.
- [31] You He, "Performance of some generalised modified order statistics CFAR detectors with automatic censoring technique in multiple target situations," Radar, Sonar and Navigation, IEE Proceedings - , Volume: 141 , Issue: 4 , Aug. 1994, pp.205 – 212.
- [32] Iskander, D.R., Zoubir,A.M., and Boashash, B (1999) "A method for estimating the parameters of the K-distribution" IEEE Transactions on Signal Processing, 47,3 (1999), pp. 880-884.
- [33] Mashade M.B.El, "M-sweeps detection analysis of cell-averaging cfar processors in multiple-target situations," IEE Proc. –Radar, Sonar Navig., vol. 141, Apr. 1994, pp. 259-266.
- [34] Peterson, W. W., T.G. Birdsall, and W.C. Fox, "The theory of signal detect ability," IRE Trans., Sep. 1987, pp 48-54.
- [35] Mashade M. B. El, " Detection performance of trimmed-mean cfar processor with noncoherent integration," IEE Proc.- Radar, Sonar Navig., vol;. 142, Feb. 1995, pp. 18-24.

- [36] Mashade M. B. El, "Monopluse detection analysis of the trimmesd mean cfar processor in nonhomogeneous situations," IEE Proc.- Radar, Sonar Navig., vol/ 143, Apr. 1996, pp. 87-94.
- [37] Shnidman, D. A., "Radar detection probabilities and their calculation" Aerospace and Electronic Systems, IEEE transactions. Pp. 928-950.
- [38] Fuller, W., "An introduction to probability theory and its applications," 2d ed., John Wiley & Sons, Inc., New York, 1957. vol.1, pp. 23-38.
- [39] Woodward, P. M. "Probability and information theory with applications to radar," McGraw-Hill Book Company, New York, 1953. pp12-21.
- [40] Dillard, G. M., "A moving -window detector for binary integration," IEEE Trans., vol. IT-13, January, 1967. pp. 2-6.
- [41] Hansen, V. G., "Optimization and performance of multilevel quantization in automatic detectors," IEEE Trans., vol. AES-10, March, 1974. pp. 274-280.
- [42] Fulvio Gini and Fabrizio Lombardini, "On distributed signal detection with multiple local free parameters," IEEE Trans. On Aerospace and Electronic System, vol. 35, Oct. 1999, pp. 1457-1466.

- [43] Han Y.I. and Kim T., "Performance of excision go-cfar detectors in non-homogeneous environments," IEE Proc,-Radar, Sonar Navig., Apr. 1996, vol 143, pp.105-112.
- [44] Abenz K. and Wohlhauser A., "Advanced Mathematics for Practicing Engineers," Deham, MA: Artech House, 1986. pp. 35-47.
- [45] David, H. A. "Order statistics" (Wiley, 1981), pp. 38-43.
- [46] RITCEY, J. A., and HINES, J. L., "Performance of max family of order-statistic CFAR detectors," IEEE Trans., 1991, AES-27, (1), pp.48-57.
- [47] Smith, M.E., Varshney, P.K., "Intelligent CFAR processor based on data variability," Aerospace and Electronic Systems, IEEE Transactions on , Volume: 36 , Issue: 3 , July 2000, pp.837 – 847.
- [48] Liu. Zhoufeng, Ping. Qingwei and He Peikun, "An improved algorithm for the detection of vehicle group targets in high-resolution SAR images," Microwave and Millimeter Wave Technology, 2002. Proceedings. ICMMT 2002. 2002 3rd International Conference on , 17-19 Aug. 2002 pp:572 – 575.
- [49] Himonas, S.D. and Barkat, M., "An adaptive CFAR signal detector for spatially correlated noise samples," Decision and Control, 1990., Proceedings of the 29th IEEE Conference on , 5-7 Dec. 1990, pp.3540 – 3545.

- [50] Kaplan, L.M. and Murenzi, R., "Evaluation of CFAR and texture based target detection statistics on SAR imagery," Acoustics, Speech, and Signal Processing, 1998. ICASSP '98. Proceedings of the 1998 IEEE International Conference on , Volume: 4 , 12-15 May 1998, pp.2141 – 2144.
- [51] Hong. Yi, Li. Ji-Yun and Ruan. Xin-Chang, "OSEXCA-CFAR processor on nonhomogeneous background," Radar 97 (Conf. Publ. No. 449) , 14-16 Oct. 1997 pp.734 – 737.
- [52] Lampropoulos, G.A.; Gigli, G.; Seigniny, L.; Beaudoin, A.; Secker, J.; "Detection of targets from electro-optical and SAR data using chaotic predictors and optimal CFAR detectors," Geoscience and Remote Sensing Symposium, 2002. IGARSS '02. 2002 IEEE International , Volume: 1 , 24-28 June 2002 pp.107 – 109.
- [53] Goldman, H., "Performance of the excision CFAR detection in the presence of interferers." Radar and Signal Processing, IEE Proceedings F, Volume: 137, Issue:3, June 1990. pp. 163-171.
- [54] Hensen, V. G., "Constant false alarm rate processing in search radars," Proc of IEE International Radar Conference, (London, U.K.), 1973. pp. 325-332.
- [55] Di. Vito, A.; Morreti, G., "Probability of false alarm in CA-CFAR device downstream from linear-law detector," Electronics Letters , Volume: 25 , Issue: 25 , 7 Dec. 1989, pp.1692 – 1693.
- [56] M.B. Mashade, "Analysis of censored-mean level cfar processor in multiple target and nonuniform clutter," IEE Proc.-Radar, Sonar Navig., Oct. 1995. vol. 142, pp. 103-108.
- [57] J.D. Kraus, " Antennas since Herze and Marconi," IEEE Trans. Antennas Propagate.,

- 127 -

Vol. AP-33, No.2, February 1985, pp. 131-137.

[58] C.A.Balanis, " Antenna Theory: A Review," Proc. IEEE, Vol. 80, no. 1, January 1992, pp. 7-23.

[59] C.A.Deschamps, " Part II-Geometrical Representation of the Polarization of a Plane Electromagnetic Wave," Proc. IRE, Vol. 39, May 1951, pp.540-544.

[60] D.M. Pozar, " Directivity of Omnidirectional Antennas," IEEE Antennas and Propagation Magazine, Vol.35, No.5, October 1993, pp. 50-51.

[61] S.A. Schelk, "Mathematical Theory of Linear Arrays," Bell System Tech. J., January , 1943, vol.22, pp.80-107.

[62] J.D. Kraus, "Antennas," McGraw-Hill, New York, 1988. pp. 65-68.

[63] J. Romeu and R. Pujol, "Array," Software Book in Electromagnetics, Vol. II, Chapter 12, CAEME Center for Multimedia Education, University of Utah, 1995,pp. 467-481.

[64] A.Z.Elsherbeni and P.H. Ginn. " Interactive analysis of Antenna Arrays," Software Book in Electromagnetics, Vol. II, chapter 6, CAEME Center for Multimedia Education, University of Utah, 1995, pp. 337-366.

- [65] A.Z. Elsherbeni and C.D. Taylor Jr., "Interactive Antenna Pattern Visualization,"
Software Book in Electromagnetics, Vol. II, Chapter 8, CAEME Center for
Multimedia Education, University of Utah, 1995, pp.367-410.
- [66] W.R. Scott Jr., " A General Program for Plotting Three-dimensional Antenna
Patterns," IEEE Antennas and Propagation Society Newsletter, December
1989, pp. 6-11.
- [67] J.S. Hollos, T. J. Lyon, and L. Clayton Jr.(eds.), "Microwave Antenna
Measurements," Scientific-Atlanta, Inc., July 1970, pp. 345-348.
- [68] A.Z. Elsherbeni and C.D. Taylor Jr., " Antenna Pattern Plotter," Copyright@ 1995,
Electrical Engineering Department, The University of Mississippi, University, MS,
pp.36-38.
- [69] W.A. wheeler, " Small Antennas," IEEE Trans. Antennas Propagate., Vol. AP-23,
No.4, July 1975, pp.462-469.
- [70] W.R. Scott, Jr., " A General Program for Plotting Three-Dimensional Antenna
Patterns," IEEE Antennas and Propagation Society Newsletter, December
1989, pp. 6-11.

- [71] C.A. Balanis, "Advanced Engineering Electromagnetics," John Wiley & Sons, Inc., New York, 1989. pp.87-89.
- [72] R.Mitra(Ed.), "Computer Techniques for Electronmagnetics, Pergamon," New York, 1973, pp.57-59.
- [73] J. Moore and P. Pizer (Eds.), "Moment Methods in Electromagnetics: Techniques and Applications," Letchworth, UK: Research Studies Press,1984, pp. 465-468.
- [74] J. J. Wang, "Generalized Moment Methods in Electromagnetics," John Wiley & Sons, Inc., New York, 1991, pp. 98-101.
- [75] K. Fujimoto and J.R. James, "Mobile Antenna Systems Handbook," Artech House, Norwood, MA, 1994, pp. 45-48.
- [76] M. A Jensen and Y. Rahmat-Samii, "Performance Analysis of Antennas for Hand-Held Transceivers Using FDTD," IEEE Trans. Antennas Propagate., Vol.42, No. 8, august 1994, pp. 1106-1113.
- [77] M.A Jensen and Y. Rahmat-Samii, "EM Interaction of Handset Antennas and a Human in Personal Communications," Proc. IEEE, Vol. 83, No.1 January 1995, pp. 7-17.

- [78] C. A. Balanis, K. D. Katsibas and P.A. tirkas, " Antenna Considerations for wireless Communication systems and Networks," 5th International Conference on Advances in Communication and Control , June 26-30,1995, Rethymnon, Crete, Greece, pp.38-43.
- [79] D. Decarlo, " automation of In-Flight Antenna Measurements," MSEE Problem report, dept. of Electrical engineering, west Virginia University, July 1980, pp. 34-35.
- [80] S. A. Schelkunoff, " A Mathematical theory of Linear Arrays," Bell System Technical Journal, Vol.22, 1943, pp. 80-107.
- [81] H. G. Booker and P. C. Clemmow, " The concept of an Angular spectrum of Plane waves, and Its relation to That of Polar Diagram and Aperature distribution,,: Proc. IEE (London), Paper No. 922, Radio section, Vol. 97, pt. III, January 1950, pp. 11-17.
- [82] P. M. Woodward, " A Method for Calculating the Field over a Plane Aperture Requored to Produce a Given Polar Diagram," J.IEE, Vol. 93, pt. IIIA, 1946, pp. 1554-1558.

- 131 -

- [83] T. T. Taylor, "Design of Line-Source antennas for Narrow Beamwidth and Low Side-Lobes," IRE Trans. Antennas Propagat., Vol. AP-3, No. 1, January 1955, pp. 16-28.
- [84] R. Tang and R.W. Burns, "Array Technology," Proc. IEEE, Vol. 80, No.1, January 1992, pp 173-182.
- [85] R. S. Elliott, "On Discretizing Continuous Aperture Distributions," IEEE Trans. Antennas Propagat., Vol. AP-25, No. 5, September 1977, pp. 617-621.
- [86] R. C. Hansen (ed.) Microwave Scanning antennas. Vol. I, Academic Press, New York, 1964, pp.56.
- [87] J. Ruze, "Physical Limitations on antennas," MIT Research Lab., Electronics Tech. October 30, 1952, pp. 248.
- [88] H. J. Orchard, R.S. Elliott, and G. J. Stern. "Optimizing the Synthesis of Shaped Beam Antenna Patterns," IEE Proceedings, Part H, 1985, pp. 63-68.
- [89] R. S. Elliott, "Design of line Source Antennas for Narrow Beamwidth and Asymmetric Antenna Patterns." IEE Proceedings, Part H, 1985, pp. 63-68.
- [90] S. Silver (ed.), "Microwave antenna Theory and Design," MIT Radiation

- 132 -

Laboratory Series, Vol.12, McGraw-Hill, New York, 1965, Chapter 6, pp. 169-199.

[91] D. M. Pozar, "Microwave Engineering," Addison-wesley, Reading, MA, 1993.

pp.68.

[92] R. C. Johnson and H. Jasik (eds.), "Antenna Engineering Handbook," 2nd. Ed.,

McGraw-Hill, New York, 1984, pp. 2-14 to 2-41.

[93] Woll, J. D. "Monopulse Doppler radar for vehicle applications" Intelligent

Vehicles '95 Symposium., Proceedings of the , 1995, pp. 42 –47.

[94] Watterson , J. W., "An optimum multilayer perception neural receiver for signal

detection," IEEE Trans. Neural Networks, vol. 1, 1990, pp. 298-300.

[95] Lippmann, R. P. and Beckman, P., "Adaptive neural net preprocessing for signal

detection in non-gaussian noise," Advance Neural Inform. Process. Syst.,

vol.1,1989. pp. 1431-1435.

[96] Michalopoulou, Z., Nolte, L. and Alexandrou, D., " Performance evaluation of

multilayer perceptions in signal detection and classification," IEEE Trans. Neural

pp. 56-58.

[97] Gandhi P.P. and Ramamurti V., "Nerval networks for signal detection in non-

- 133 -

gaussian noise,” IEEE Trans. On signal Processing, vol. 45, 1997, pp. 2846-2851.

- [98] Eriksson, L.H.; As, B.-O. “Automotive radar for adaptive cruise control and collision warning/avoidance,” Radar 97 (Conf. Publ. No. 449), 1997 pp. 16 – 20.
- [99] Nishi, T., Takagi, T., “A proposal of collision avoidance algorithm for driving support system” Industrial Electronics Society, 2001. IECON '01. The 27th Annual Conference of the IEEE , Volume: 1 , 2001 pp. 80 -83 vol.1.
- [100] Nicholls, M.R. “Millimetre wave collision avoidance radars” Millimetre-Wave Radar, IEE Colloquium on , 1990 pp. 3/1 -3/7.
- [101] Fikkema, P.G., Johnson, S.G., “Vehicle collision warning and avoidance system using real-time FFT” Vehicular Technology Conference, 1996. Mobile Technology for the Human Race., IEEE 46th , Volume: 3 , 1996 vol.3, pp. 1820 – 1824.

Appendix A

Minimum Bayes Risk detection Binary

Hypothesis

We minimize R as given by (3.17). note that if $C_{00}=C_{11}=0$, $C_{01}=C_{10}=1$, then $R=P_e$ and so our derivation also applies to the minimum P_e problem. Now

$$R = \sum_{i=0}^1 \sum_{j=0}^1 C_{ij} P(H_i | H_j) P(H_j)$$

Let $R_1=\{x: \text{decide } H_1\}$ be the critical region and R_0 denote its complement (decide H_0).
Then,

$$R = C_{00}P(H_0) \int_{R_0} P(X | H_0) dx + C_{01}P(H_1) \int_{R_0} P(X | H_1) dx + C_{10}P(H_0) \int_{R_1} P(X | H_0) dx + C_{11}P(H_1) \int_{R_1} P(X | H_1) dx$$

- 135 -

But

$$\int_{R_0} P(X | H_0) dx = 1 - \int_{R_1} P(X | H_0) dx + C_{11}$$

Since R_1 and R_0 partition the entire space. Using this we have

$$R = C_{01}P(H_1) + C_{00}P(H_0) + \int_{R_1} [(C_{10}P(H_0) - C_{00}P(H_0))P(X | H_0) + (C_{11}P(H_1) - C_{01}P(H_1))P(X | H_1)] dx P(X | H_0) + C_{01}$$

We include x in R_1 only if the integrand is negative or we decide H_1 if

$$(C_{10} - C_{00})P(H_0)P(x | H_0) < (C_{01} - C_{11})P(H_1)P(x | H_1).$$

Assuming $C_{10} > C_{00}$, $C_{01} > C_{11}$, we have finally

$$\frac{P(x | H_1)}{P(x | H_0)} > \frac{(C_{10} - C_{00})P(H_0)}{(C_{01} - C_{11})P(H_1)} = \gamma$$

Appendix B

Neyman-Pearson theorem

We use Lagrangian multipliers to maximize P_D for a given P_{FA} . Forming the Lagrangian

$$\begin{aligned} F &= P_D + \lambda(P_{FA} - \alpha) \\ &= \int_{R_1} P(x; H_1) dx + \lambda \left(\int_{R_1} P(x; H_0) dx - \alpha \right) \\ &= \int_{R_1} (P(x; H_1) + \lambda P(x; H_0)) dx - \lambda \alpha \end{aligned}$$

To maximize F we include x in R_1 if the integrand is positive for that value of x or if

$$P(x; H_1) + \lambda P(x; H_0) > 0$$

When $P(x; H_1) + \lambda P(x; H_0) = 0$, x may be included in either R_0 or R_1 . since the probability of this occurrence is zero (assuming that the PDFs are continuous), Hence, the

- 137 -

> sign in 3A.1 and the subsequent results can be replaced with $\geq$ if desired. We choose to retain the > sign in our development. We thus decide H_1 if

$$\frac{P(x; H_1)}{P(x; H_0)} > -\lambda$$

The Lagrangian multiplier is found from the constraint and must satisfy $\lambda < 0$. Otherwise, we decide H_1 if the likelihood ratio $P(x; H_1)/P(x; H_0)$ exceeds a negative number. Since the likelihood ratio is always nonnegative, we would always decide H_1 , irrespective of the hypothesis, resulting in $P_{FA}=1$. we let $\gamma = -\lambda$ so that finally we decide H_1 if

$$\frac{P(x; H_1)}{P(x; H_0)} > \gamma$$

Where the threshold $\gamma > 0$ is found from $P_{FA} = \alpha$.

Appendix C

```
%..... Divide line method code.....

function y=erfen(fun,a,b,esp)

if nargin<4 esp=1e-4;end

if feval(fun,a)*feval(fun,b)<0

    n=1;

    c=(a+b)/2;

    while c>esp

        if feval(fun,a)*feval(fun,c)<0

            b=c; c=(a+b)/2;

        elseif feval(fun,c)*feval(fun,b)<0

            a=c; c=(a+b)/2;
```

- 139 -

```
    else y=c; esp =10000;

    end

    n=n+1;

end

y=c;

elseif feval(fun,a)==0

    y=a;

elseif feval(fun,b)==0

    y=b;

else disp('these, may not be a root in the intercal')

end

n
```

$$X_{k+1} = X_k - \frac{f(X_k)}{f'(X_k)}$$

- 140 -

% Newton iteration method code.....

function y= newton(x0)

x1=x0-fc(x0)/df(x0);

n=1;

while(abs(x1-x0)>=1.0e-4)&(n<=100000000)

x0=x1;

x1=x0-fc(x0)/df(x0);

n=n+1;

end

x1

n

$$X_{k+1} = X_k - \frac{f(X_k)(X_k - X_{k-1})}{f(X_k) - f(X_{k-1})}$$

- 141 -

%..... Secant Line iteration code.....

function y=ger(x0,x1)

x2=x1-fc(x1)*(x1-x0)/(fc(x1)-fc(x0));

n=1;

while(abs(x1-x0)>=1.0e-4)&(n<=100000000)

x0=x1;x1=x2;

x2=x1-fc(x1)*(x1-x0)/(fc(x1)-fc(x0));

n=n+1;

end

x2

n