A Recursive Approach for Adaptive Parameters Selection in A Multifunction Radar

Thesis

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By

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Abstract

A multifunction radar is a modern system that is capable of performing multiple radar functions simultaneously, such as surveillance, target tracking, weather monitoring, etc. This class of radar, multifunction radar (MFR), requires a control function, resource manager, to balance the use of its finite resources among the multiple functions. Hence, the multifunction radar performance is limited by the resource manager intelligent behavior to allocate the system resources. This thesis addresses the challenge of using radar resource management (RRM) to provide the attention element of cognition for radar systems. A recursive form of the radar resource allocation problem is proposed that uses prior knowledge about the target to refine the radar parameters every time the radar revisiting the target. This approach enables the radar system to be more sensitive to the change in the environment and therefore adapt its parameters accordingly.

The approach is applied to the problem of tracking multiple targets with different RCS configurations. The aim is to minimize the dwell time while achieving an acceptable SNR for track maintenance and while simultaneously maximizing the track update time. This control over the SNR and update rate can be thought of as giving the correct attention to the target track task. The main advantage of this approach is the ability to reduce the radar load allocation while maintaining a desirable SNR.
This thesis also describes the design and implementation of a multifunction radar
model that is used to support the development of the adaptive parameters selection
resource allocation approach. The application of the earliest deadline first approach
to schedule track dwells, adaptive update rate, is analyzed in this thesis. It was shown
that this approach of resource allocation can only manage a limited number of targets
and it is sometimes difficult to allocate resources to continue the surveillance task.
Acknowledgments

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I have been privilege to be a part of The ElectroScience Laboratory and meet inspiring and intelligent colleagues. I would like to thank them all.
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## Table of Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract</td>
<td>ii</td>
</tr>
<tr>
<td>Acknowledgments</td>
<td>iv</td>
</tr>
<tr>
<td>Vita</td>
<td>v</td>
</tr>
<tr>
<td>List of Tables</td>
<td>viii</td>
</tr>
<tr>
<td>List of Figures</td>
<td>ix</td>
</tr>
<tr>
<td>1. INTRODUCTION</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Thesis Layout</td>
<td>2</td>
</tr>
<tr>
<td>2. AN OVERVIEW OF RADAR FUNDAMENTALS</td>
<td>4</td>
</tr>
<tr>
<td>2.1 Radar Basics Principles</td>
<td>4</td>
</tr>
<tr>
<td>2.1.1 Radar Ranging</td>
<td>5</td>
</tr>
<tr>
<td>2.1.2 The Radar Equation</td>
<td>5</td>
</tr>
<tr>
<td>2.1.3 Range Resolution</td>
<td>8</td>
</tr>
<tr>
<td>2.1.4 Radar Waveform</td>
<td>9</td>
</tr>
<tr>
<td>2.1.5 Range Ambiguity</td>
<td>11</td>
</tr>
<tr>
<td>2.1.6 The Doppler Effect and Velocity Ambiguity</td>
<td>12</td>
</tr>
<tr>
<td>2.2 Radar Signal and Data Processing</td>
<td>13</td>
</tr>
<tr>
<td>2.2.1 Phased Array Antenna</td>
<td>13</td>
</tr>
<tr>
<td>2.2.2 Monopulse</td>
<td>18</td>
</tr>
<tr>
<td>2.2.3 Detection</td>
<td>20</td>
</tr>
<tr>
<td>2.2.4 Tracking</td>
<td>33</td>
</tr>
<tr>
<td>2.2.5 Data Association</td>
<td>37</td>
</tr>
<tr>
<td>2.2.6 Track Management</td>
<td>39</td>
</tr>
</tbody>
</table>
2.3 Multifunction Radar

2.3.1 Multifunction Radar Modes

2.3.2 Radar Control Parameters

3. RESOURCE MANAGEMENT IN A MULTIFUNCTION RADAR

3.1 Radar Resource Management Architectures

3.2 Methodologies for Radar Resource Management

3.2.1 Heuristic-based Resource Management

3.2.2 Optimization-based Resource Management

3.3 Priority Assignment in Multifunction Radar

3.4 Scheduling In Resource Management

3.5 Conclusion and Discussion

4. MODELING A MULTIFUNCTION RADAR SYSTEM

4.1 Radar Model Overview

4.2 The Environment Model

4.2.1 Modeling The Target

4.2.2 Modeling The Noise

4.2.3 Modeling The Clutter

4.3 The Pulsed Radar Model

4.3.1 Modeling The Phased-Array Antenna

4.3.2 Modeling The Transmitted Signal

4.3.3 Modeling The Received Signal

4.4 Pulsed Radar Data Processing

4.4.1 Doppler Processing

4.4.2 Radar Detection

4.4.3 Monopulse Processing

4.4.4 Multitarget Tracking

5. ADAPTIVE PARAMETERS SELECTION IN MULTIFUNCTION RADAR

5.1 Multifunction Radar in Track While Scan Mode

5.2 Track While Scan with Adaptive Parameters Selection

5.3 Search and Track with Adaptive Parameters Selection

6. CONCLUSIONS and FUTURE WORK

Bibliography

vii
List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>PRF Choices</td>
</tr>
<tr>
<td>2.2</td>
<td>The Swerling Models</td>
</tr>
<tr>
<td>2.3</td>
<td>Multifunction Radar Control Parameters [1]</td>
</tr>
<tr>
<td>3.1</td>
<td>Radar tasks priority ranking [2]</td>
</tr>
<tr>
<td>4.1</td>
<td>Pulsed Radar Parameters</td>
</tr>
</tbody>
</table>
## List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>SNR as a function of range for a single target with $\sigma = 1m^2$</td>
<td>7</td>
</tr>
<tr>
<td>2.2</td>
<td>Matched filtered response of two point targets, whose locations are indicated by the red lines, separated by (a) the Rayleigh resolution, (b) less than the Rayleigh resolution</td>
<td>9</td>
</tr>
<tr>
<td>2.3</td>
<td>An example of (a) unmodulated pulse, (b) linear frequency modulation pulse</td>
<td>10</td>
</tr>
<tr>
<td>2.4</td>
<td>Matched filter response for (a) unmodulated pulse, (b) linear frequency modulation pulse</td>
<td>11</td>
</tr>
<tr>
<td>2.5</td>
<td>A linear phased array with $n$-elements spaced $d$ distance apart</td>
<td>13</td>
</tr>
<tr>
<td>2.6</td>
<td>A $0^\circ$ phase shift produces a beam normal to the array axis, while a constant phase shift across the array produces a beam at angle $\theta_s$</td>
<td>14</td>
</tr>
<tr>
<td>2.7</td>
<td>A beam pattern for an array scanned at $0^\circ$ and $60^\circ$</td>
<td>15</td>
</tr>
<tr>
<td>2.8</td>
<td>The change of beamwidth with steering angle for a phased array antenna with $3^\circ$ at the broadside</td>
<td>16</td>
</tr>
<tr>
<td>2.9</td>
<td>Radiation pattern for an array spaced $1.5\lambda$ apart scanned at $0^\circ$ and $60^\circ$</td>
<td>17</td>
</tr>
<tr>
<td>2.10</td>
<td>Two radiation pattern of an amplitude-comparison monopulse beams with monopulse axis at broadside</td>
<td>19</td>
</tr>
<tr>
<td>2.11</td>
<td>Sum and difference radiation pattern of phase-comparison monopulse</td>
<td>20</td>
</tr>
<tr>
<td>2.12</td>
<td>A threshold example based on Neyman-Pearson criterion</td>
<td>21</td>
</tr>
</tbody>
</table>
4.3 Trajectory for multiple targets ............................................. 67
4.4 Simulated noise statistics using 100,000 samples. The theoretical Rayleigh pdf is also shown ............................................. 69
4.5 A range profile of a simulated radar clutter using the lognormal function ............................................. 71
4.6 Simulated clutter statistics using 12,000 samples. The theoretical Lognormal pdf is also shown ............................................. 72
4.7 The coherent receiver .......................................................... 75
4.8 Example of one CPI intensity plot .......................................... 77
4.9 A range-doppler map of a target moving at a speed 50 m/s .................. 79
4.10 Detection processor block diagram ......................................... 80
4.11 Two Dimensional CA-CFAR Window ..................................... 81
4.12 The output of the CA-CFAR with $P_{FA} = 10^{-6}$, using 16-reference cells as shown in Figure 4.11 .................................. 82
4.13 Plots of two targets grouped together into two clusters ................... 84
4.14 Estimated target position, the output of the detection processor ........... 85
4.15 Example of a radar measurements before (left) and after (right) the binary integration .................................................. 86
4.16 Tracking processor block diagram .......................................... 88
4.17 Example of a target under track ............................................. 90
4.18 Example of an ellipsoidal gate ................................................. 91
5.1 Radar look direction in azimuth for TWS mode .......................... 94
5.2 Fixed radar parameters for every CPI in TWS mode ....................... 95
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.3</td>
<td>Trajectories for high RCS targets and their state estimate</td>
<td>96</td>
</tr>
<tr>
<td>5.4</td>
<td>Position RMS Error for the three target</td>
<td>96</td>
</tr>
<tr>
<td>5.5</td>
<td>Trajectories for low RCS targets and their state estimate</td>
<td>97</td>
</tr>
<tr>
<td>5.6</td>
<td>An adaptive parameters selection radar resource management architecture</td>
<td>102</td>
</tr>
<tr>
<td>5.7</td>
<td>Trajectories for low RCS targets and their state estimate using adaptive parameters selection</td>
<td>103</td>
</tr>
<tr>
<td>5.8</td>
<td>Evolution of radar parameters using adaptive parameters selection</td>
<td>104</td>
</tr>
<tr>
<td>5.9</td>
<td>Evolution of targets SNR using adaptive parameters selection</td>
<td>105</td>
</tr>
<tr>
<td>5.10</td>
<td>Evolution of radar parameters using adaptive parameters selection for high RCS targets</td>
<td>106</td>
</tr>
<tr>
<td>5.11</td>
<td>The radar relative load using adaptive parameters selection method and TWS mode for tracking 3 targets</td>
<td>107</td>
</tr>
<tr>
<td>5.12</td>
<td>The radar relative load using adaptive parameters selection method and TWS mode for tracking 50 targets</td>
<td>108</td>
</tr>
<tr>
<td>5.13</td>
<td>Radar look direction in azimuth for search and track mode</td>
<td>109</td>
</tr>
<tr>
<td>5.14</td>
<td>Radar look direction in azimuth for search and track mode in an overloaded situation</td>
<td>110</td>
</tr>
</tbody>
</table>
Chapter 1: INTRODUCTION

The advances in phased array antennas have made it possible for a single radar system to perform many functions that were previously performed either by individual systems or, at best, by specific modes of conventional radar [5]. Multifunction radars (MFRs) are modern systems that can rapidly steer the beam position and adapt the radar parameters to perform different functions. As consequence, a MFR has to share its finite resources between the multiple functions. This means that under certain situation the radar has insufficient resources to perform all its functions. To maximize efficiency it is therefore desirable to minimize the amount of time taken to conduct each task and to seek parameter sets that allow multiple tasks to be undertaken together. As a result, a new radar problem arises, resource management. The MFR resource management problem can be summarized as how to allocate the radar’s time and energy resources in the optimal way to ensure all tasks are achieved to acceptable performance levels.

Several techniques of radar resource management been developed with the aim of optimizing radar resources usage. Some of these techniques uses heuristics rules [6], [7], while others formulate the radar resource management problem and solve it using optimization methods [8], [9] or information based approaches [10]. These approaches are essentially deterministic in nature, even thought their learning and/or
statistical nature prevent analytic rules from being written for them. This deterministic approach is in contrast to natural systems. Humans and animals also have to balance finite personal resources to accomplish a variety of tasks ranging from the simple, such as walking, to the complex, such as designing and building a radar. With these biological systems it is the cognitive processes, and specifically the concept of attention, that are responsible for managing the bodies resources [11].

This thesis addresses the challenge of using radar resource management (RRM) to provide the attention element of cognition for radar systems. In addition, this thesis develops a recursive form of the radar resource allocation problem that uses prior knowledge about the target to refine the radar parameters every time the radar revisiting the target. The aim is to minimize the dwell time while achieving an acceptable SNR for track maintenance and while simultaneously maximizing the track update time. This control over the SNR and update rate can be thought of as giving the correct attention to the target track task. The thesis secondary objective is to create a multifunction radar model that will be used to develop a radar resource allocation approach.

1.1 Thesis Layout

The thesis is organized as follows.

Chapter 2 provides a background theory to the topics that are relevant to the work present here. Radar system basics and radar signal and data processing are presented in this chapter as well as the theory of phased array antenna. Finally a description to the tasks performed by multifunction radar and the system control parameters is given.
Chapter 3 surveys through the current literature on radar resource management. A multifunction radar resource management architectures are given, followed by a review on different methodologies radar resource management. In addition, relevant research in the area of priority assignment and scheduling are discussed.

Chapter 4 describes a multifunction radar model that is used to support the development of radar resource management approach. The design and implementation of every component in the model is described.

Chapter 5 introduces a recursive approach to adaptively refine the radar parameters. The approach is described in details and its application to the multifunction radar resource management problem is presented.

Finally the conclusion of the work and the plan for future work is presented in Chapter 6.
Chapter 2: AN OVERVIEW OF RADAR FUNDAMENTALS

The purpose of this chapter is to provide an introduction to radar basic principles as well as an overview of phased array antennas, detection theory, and multiple target tracking. These topics are the foundation of any modern radar, especially a multifunction radar (MFR). This section draws on material in [12], [13], [14] and [15] in which the basic radar theory is expanded upon. Further references will not be made in this chapter unless a non-standard aspect of theory is being discussed. This chapter is concluded with an introduction to the multifunction radar and its main functions and parameters.

2.1 Radar Basics Principles

Radar is a sensing system that uses a directive antenna to transmit electromagnetic (EM) waves toward an area of interest. A small echo of the EM waves is scattered back from different objects in the environment towards the radar antenna. This echo signal is then processed to determine the presence of targets and to find their position.
2.1.1 Radar Ranging

The EM waves propagate in the space at the speed of light, $c$, allowing the radar to measure the location of an object remotely in range. This range can be calculated by measuring the time $\Delta t$ for the EM waves to propagate to a target at range $R$ and back to the radar, by the following expression:

$$ R = \frac{c \Delta t}{2} $$  \hspace{1cm} (2.1)

2.1.2 The Radar Equation

The radar equation expresses the signal-to-noise (SNR) ratio at the receiver in terms of system, target and the environment parameters. It gives an indication of the maximum detectable range that the radar can provide and it is a common tool for radar system design. The received target signal power can be calculated as:

$$ P_r = \frac{P_t G^2 \lambda^2 \sigma}{(4\pi)^3 R^4} $$  \hspace{1cm} (2.2)

where,

$P_t$ is the peak transmitted power in Watts.

$G_t$ is the gain of the antenna.

$\lambda$ is the carrier wavelength in meters.

$R$ is the range from the radar to the target in meters.

$\sigma$ is the mean radar cross section (RCS) of the target in square meters.
The receiver noise power is given by:

\[ P_n = kT_0FB \]  \hspace{1cm} (2.3)

where,

\( K \) is Boltzmann’s constant (1.38 \times 10^{-23} \text{ W/K/Hz}).

\( T_0 \) is the noise reference temperature (290 K).

\( B \) is the receiver bandwidth in Hz.

\( F \) is the receiver noise figure.

Therefore, the SNR is the ratio of the received target signal power over the noise power given by:

\[ SNR = \frac{P_r}{P_n} = \frac{P_tG^2\lambda^2\sigma L}{(4\pi)^3R^4kT_0FB} \]  \hspace{1cm} (2.4)

where \( L \) is the total system loss factor, which include:

- Transmit losses.
- Propagation losses.
- Receive or losses.
- Beamshape losses.
- Signal processing losses.
The radar equation can be rearranged to show the maximum detectable range, given a minimum signal-to-noise ratio $SNR_{min}$ required for detection as:

$$R_{max} = \left[ \frac{P_tG^2\lambda^2\sigma L}{(4\pi)^3R^4kT_0FB(SNR_{min})} \right]^{1/4}$$ (2.5)

Figure 2.1 shows the SNR versus range for a point target with $\sigma = 1\ m^2$ using typical radar parameters at X-band. A typical SNR for reliable target detection is about 13 dB, which is at range approximately 40 km. The blue line shows the SNR outcome of simulating a point target at different ranges, while the red line shows the theoretical SNR using 2.4. The two lines starts to deviate after the 13 dB point. The blue line settles around the 13 dB point, since when the target range is greater than 40 km only the noise signal is measured at the target location, while the red line continued to show the SNR for long ranges. The figure illustrates the difficulty to detect targets with low SNR (less than 13 dB) because at this level it is not possible to discriminate between noise and signal.

Figure 2.1: SNR as a function of range for a single target with $\sigma = 1\ m^2$
2.1.3 Range Resolution

Radar range resolution is defined as the ability to separate between two targets in range. The range resolution of the radar is proportional to the bandwidth $B$ of the transmitted pulse given by:

$$\Delta r = \frac{c}{2B}$$  \hfill (2.6)

The two common ways to define range resolution are:

- The mainlobe width of the target response at the $-3$ dB point.

- When the peak of a target matched filtered response falls on the first null of the second target matched filtered response, which known as Rayleigh resolution. For un-modulated pulse the Rayleigh resolution is at $-6$ dB crossing.

Two targets separated by more than the Rayleigh resolution provide two peaks in the receiver output as shown in Figure 2.2, part (a). If the two targets are separated by less than the Rayleigh resolution, then the two peaks are merged together into single peak and it would not be possible to resolve the targets as shown in part (b) of 2.2.

For simple, unmodulated pulse $B = 1/\tau$, where $\tau$ is the pulse length. High range resolution for simple pulses requires shorter pulses, but good detection performance requires high transmit pulse energy. Therefore, it is important to increase the pulse width to achieve good detection performance. These conflicting requirements are resolved by applying pulse compression techniques. Pulse compression is achieved by
Figure 2.2: Matched filtered response of two point targets, whose locations are indicated by the red lines, separated by (a) the Rayleigh resolution, (b) less than the Rayleigh resolution modulating longer pulse to increase the waveform bandwidth in order to obtain the resolution of shorter pulse.

2.1.4 Radar Waveform

There are several types of pulse compression waveform that can be used, but the most commonly used waveform is linear frequency modulation (LFM). The instantaneous frequency of this waveform changes linearly over the duration of the transmitted pulse. The frequency can be linearly increasing or decreasing, which is then called up-chirp down-chirp respectively. An example of (a) unmodulated pulse and (b) linear frequency modulation pulse is shown in Figure 2.3
The problem of detecting a weak signal embedded in noise is addressed by applying a filter to the received signal to maximize SNR and thus improve the detection performance. The filter that maximize the SNR has properties matched to the transmitted waveform and is known as *matched filter*. The matched filter impulse response in time domain is a delayed, conjugated and time-reserved version of the transmitted waveform, i.e.

\[ h(t) = Ku^*(t_0 - t) \]  

(2.7)

Therefore, The matched filter output response is the cross correlation of the received signal with the transmitted waveform. The output of the matched filter is a peak response at a time corresponding to the target time delay. The matched filter responses of the two waveforms given in Figure 2.3 are shown in Figure 2.4.

The matched filter response of the unmodulated pulse is a triangle function with a width that is twice the pulse width. Therefore, only targets separated by 1 pulse width can be distinguished by the radar when using this waveform. The matched filter response of the LFM waveform is sinc function with $-13.2$ dB peak sidelobes as shown in Figure 2.4, part (b). The width of the response at the 3 dB point corresponds...
Figure 2.4: Matched filter response for (a) unmodulated pulse, (b) linear frequency modulation pulse

to the range resolution provided by the waveform. It is clear from the figure that the LFM waveform provide much finer resolution than the unmodulated pulse.

2.1.5 Range Ambiguity

Pulses are usually transmitted with sufficient time interval to allow the radar to receive echo signals reflected from objects in the environment. This interval is known as pulse repetition interval (PRI). As a consequence is that, a range ambiguity occurs when the two-way propagation delay is larger than the PRI. Therefore, the maximum unambiguous range is given by:

$$R_{max} = \frac{cPRI}{2} \text{ or } \frac{c}{2PRF}$$

(2.8)

where $PRF$ is the pulse repetition frequency, which is the inverse of the PRI. Range ambiguity can be resolved by lowering the PRF. However, low PRF can cause Doppler ambiguity since the PRF must be sampled at twice the highest Doppler frequency to avoid aliasing, a consequence of the Nyquist sampling theorem.

Alternatively, varying the PRF from pulse-to-pulse is sometimes used to avoid range and Doppler ambiguities. This technique is sometimes called PRF agility or
PRF jitter and it is also used to prevent jammers. Staggered PRF is one form of PRF agility which is used to overcome the blind speeds problem when applying the Moving Target Indication (MTI) filter.

2.1.6 The Doppler Effect and Velocity Ambiguity

Any relative movement between the radar and the target causes a change in the frequency of the transmitted signal. Therefore, the Doppler frequency is defined as the change of the frequency between the transmitted and received signal. A coherent system must be used in order to measure the rate of phase change or Doppler frequency shift. The formula for the Doppler frequency shift for moving target with radial velocity $v$ is:

$$ f_D = -\frac{2vf_c}{c} $$

where $f_c$ is the frequency of the transmitted signal. The minus sign in $2.9$ has been introduced to obtain a positive Doppler frequency for a target moving toward the radar, while a negative Doppler frequency occurs for a target moving away from the radar. Often, one cannot find a PRF that can resolve both range and Doppler ambiguity, but three PRF intervals is defined to help choosing the appropriate PRF. Table 2.1 illustrates the three PRF choices.

<table>
<thead>
<tr>
<th>PRF</th>
<th>Frequency</th>
<th>Range</th>
<th>Doppler</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>250 Hz to 4 KHz</td>
<td>Ambiguous</td>
<td>Unambiguous</td>
</tr>
<tr>
<td>Medium</td>
<td>10 KHz to 20 KHz</td>
<td>Ambiguous</td>
<td>Ambiguous</td>
</tr>
<tr>
<td>High</td>
<td>100 KHz to 300 KHz</td>
<td>Unambiguous</td>
<td>Ambiguous</td>
</tr>
</tbody>
</table>
2.2 Radar Signal and Data Processing

2.2.1 Phased Array Antenna

A phased array antenna consists of a number of identical radiating elements connected together to form a single larger antenna. These elements are usually simple devices such as dipoles, patches or small horns. The radiating elements can be arranged geometrically in a straight line (linear array) or on a plane surface (planer array). An example of a passive linear array of $n$ radiating elements with $d$ spacing between each element is showing in Figure 2.5. An electronically controlled phase shifter is located behind each radiating element of the antenna and it is connected to a central feed to combine elements into one antenna.

![Figure 2.5: A linear phased array with $n$-elements spaced $d$ distance apart](image)

The beam pattern is shaped by summing the signal radiated from each element of the antenna array, which is written as

$$E_a(\theta) = \frac{1}{\sqrt{N}} \sum_{n=1}^{N} e^{-j \left( \frac{2\pi}{\lambda} nd \sin \theta - \phi_n \right)}$$

(2.10)
where $\theta$ is the look angle, $n$ is the element number, $d$ is the inter-element spacing, and $\phi_n$ is the phase shift per element. The direction of the beam is steered by electronically adjusting the phase of the signal radiated from each element, which requires a phase shifter at each element of the antenna. If all of the phase shifters are set to 0°, then the beam will be generated normal to the array axis. Applying a constant phase difference between elements produces a beam pointing away from the normal array axis. This is shown in Figure 2.6.

**Figure 2.6:** A 0° phase shift produces a beam normal to the array axis, while a constant phase shift across the array produces a beam at angle $\theta_s$. 
The phase difference required at each element to form a look angle \( \theta_s \) depends on the path difference, \( d \sin \theta_s \), and given by:

\[
\phi_n = \frac{2\pi}{\lambda} nd \sin \theta_s \quad (2.11)
\]

The antenna pattern in 2.10 can be rewritten as

\[
E_a(\theta) = \frac{1}{\sqrt{N}} \sum_{n=1}^{N} e^{-j \frac{2\pi}{\lambda} nd (\sin \theta - \sin \theta_s)} \quad (2.12)
\]

An example of a simulated beams scanned at the broadside and 60° after applying a constant phase difference between elements using 2.12 is shown in Figure 2.7.

Beam agility is the main advantage of the phased array antenna, since the beam can steer to any position at any time without the need to mechanically positioning the antenna, but when the beam pointing at angle \( \theta_s \) is off-broadside, the effective aperture area in the direction of the main beam is reduced by \( \cos \theta_s \) as shown in Figure 2.6. This causes an increase in the radar beamwidth and decrease in the...
antenna gain. Recall that the 3 dB beamwidth of the pattern at the broadside is inversely proportional to the aperture size $L$ and the transmitted wavelength $\lambda$ given by:

$$\theta_3 = \frac{0.886\lambda}{L} \quad (2.13)$$

As the beam is steered away from the broadside by angle $\theta_s$, the effective aperture is then given by:

$$L_{\theta_s} = \frac{L}{\cos \theta_s} \quad (2.14)$$

Therefore, the beamwidth at scan angle $\theta_s$ is:

$$\Delta \theta_s = \frac{\theta_3}{\cos \theta_s} \quad (2.15)$$

![Radar beamwidth Vs Scan Angle](image.png)

Figure 2.8: The change of beamwidth with steering angle for a phased array antenna with 3° at the broadside
The off-broadside steering effect on the beamwidth ($3^\circ$) is plotted in Figure 2.8. At $60^\circ$ scan angle the main beam will be double the width as it is at broadside.

The antenna gain is related to the effective area by:

$$G = \frac{4\pi A_e}{\lambda^2} = \frac{4\pi K_a A}{\lambda^2} \quad (2.16)$$

where $\lambda$ is the wavelength, $A_e$ is the effective antenna aperture, $K_a$ is the antenna aperture efficiency and $A$ is the aperture physical size. The aperture efficiency depends on the distribution of the illumination across the aperture.

As a result of beam scanning at angle $\theta_s$ off-broadside, the achieved SNR at that angle, is smaller than the SNR at broadside.

Figure 2.9: Radiation pattern for an array spaced $1.5\lambda$ apart scanned at $0^\circ$ and $60^\circ$

The dashed pattern in Figure 2.9 shows a phased array electronically scanned to $60^\circ$ degrees and an additional beam at $-30^\circ$ degrees. This undesired beam is called a grating lobes and occur as a function of antenna element spacing. The electric field $E_a(\theta)$ is maximum whenever:
\[
\frac{d}{\lambda}(\sin \theta - \sin \theta_s) = n
\]  \hspace{1cm} (2.17)

where \(n\) is an integer. The main beam appears at \(n = 0\), while grating lobes correspond to nonzero integers and have maxima at an angle other than \(\theta_s\). Grating lobes can be avoided if the element spacing \(d\) satisfies:

\[
d = \frac{\lambda}{(1 + \sin \theta_s)}
\]  \hspace{1cm} (2.18)

If the main beam is steered to \(+90^\circ\) degrees then the element spacing should not be greater than a half wavelength. Practical phased array antenna cannot scan \(\pm 90^\circ\), Therefore the element spacing \(d\) must be less than \(\lambda/2\) to avoid grating lobes.

### 2.2.2 Monopulse

Without further processing, radar provides a measurements of the target angular position with a precision that of the order of the antenna 3 dB beamwidth. This is not sufficient for target tracking, that requires finer precision. Higher accuracy target angular measurements are commonly made using the monopulse technique. Monopulse is a techniques for measuring the target angular position from a single pulse by forming multiple simultaneous receive beams from the same antenna and then contrasting their response. A thorough account of monopulse is given in [16].

Amplitude-comparison monopulse forms two overlapping antenna beams that are symmetrically offset around the antenna boresight as shown in Figure 2.10. This form of monopulse obtains a null on the monopulse axis, as shown in Figure 2.10, and uses the difference beam \((\Delta)\) to measure the target angular position. The sum beam \((\Sigma)\) peak is on the monopulse axis and is used for transmission. In reception the sum
channel is used for detection and range measurements. The monopulse error signal is the ratio of the difference beam to the sum beam:

\[
e(\theta) = \frac{\Delta(\theta)}{\sum(\theta)}
\]  

(2.19)

Figure 2.10: Two radiation pattern of an amplitude-comparison monopulse beams with monopulse axis at broadside

Another monopulse technique is the phase-comparison monopulse. This technique uses two antennas or divide the antenna into two halves, in case of a phased array antenna, with a small distance \(d\) between them. Both antennas generate a beam that is pointing in the same direction, therefore, the received echo from each beam has the same amplitude but can be different in phase. The sum and difference beam patterns for the two beams used in the phase-comparison monopulse is shown in Figure 2.11. Since both beams have similar amplitude, their sum beam will have higher amplitude and their difference beam will determine the monopulse error signal, after scaling by the sum channel. If the return echo arrives at both antennas at the same time, the
phase difference will be $0^\circ$. If the target is at $\theta$ with respect to the antenna broadside, then the two echo will arrive at a different time and the phase difference will be:

$$\Delta \phi = \frac{2\pi d \sin \theta}{\lambda}$$  \hspace{1cm} (2.20)

Figure 2.11: Sum and difference radiation pattern of phase-comparison monopulse

Figure 2.11 also shows the monopulse error signal for phase-comparison monopulse. This error signal is used in 2.20 to obtain the angular location of the targets. In the amplitude-comparison monopulse, the error signal magnitude corresponds to the difference between the target angle location and the monopulse axis, while the sign of the error signal indicates the angle error direction relative to the monopulse axis.

2.2.3 Detection

Almost all radars use threshold detection to decide whether a target is present or not in the presence of noise, clutter and interference. The detection problem can be formulated in terms of a binary hypothesis test, where the null hypothesis,
$H_0$, represent the target absent and the second hypothesis, $H_1$, represent the target present. Radar detection decisions are commonly based on the Neyman-Pearson optimization criterion. This rule sets a fixed probability of false alarm, and then maximizes the probability of detection for a given SNR. The Neyman-Pearson test leads to a likelihood ratio:

$$\frac{p(y|H_1)}{p(y|H_0)} \overset{H_1}{\gtrsim} V_T \quad (2.21)$$

where $V_T$ is a detection threshold that is chosen to maximize the probability of detection for a fixed probability of false alarm. Applying Neyman-Pearson criterion produces a detection threshold illustrated in Figure 2.12. The Neyman-Pearson detection threshold is constant for all range bins. Any scatter exceeds the detection threshold is considered to be a target of interest and often referred to as detection or plot.

![Figure 2.12: A threshold example based on Neyman-Pearson criterion](image)

Figure 2.12: A threshold example based on Neyman-Pearson criterion
In a coherent receiver, the I and Q channels are independent and identically-distributed (i.i.d.) zero-mean Gaussian random process with identical variances. The thermal noise is also a Gaussian with zeros-mean and a variance $\sigma^2$. The amplitude of the complex noise signal $\sqrt{I^2 + Q^2}$ follows a Rayleigh distribution:

$$p(x) = \frac{x}{\sigma^2} \exp\left(-\frac{x^2}{2\sigma^2}\right)$$

when a target is present, the output of the envelope detector for the signal plus Gaussian noise is characterized by the Rician distribution:

$$p(x) = \frac{x}{\sigma^2} \exp\left(-\frac{x^2 + A^2}{2\sigma^2}\right) I_0\left(\frac{xA}{\sigma^2}\right)$$

where $I_0$ is the modified Bessel function of the first kind with order zero and $A$ is the amplitude of the complex signal. Figure 2.13 shows the noise only and signal plus noise PDF. The $P_{FA}$ area represents the probability that the signal crosses the threshold when there is no target, while the $P_D$ area represents the probability that the signal crosses the threshold when there is a target. It can be noticed that increasing the threshold $V_T$ reduces the false alarm but also reduces the probability of detection for given SNR. To achieve high probability of detection and lower probability of false alarm at the same time, the two PDFs must be well separated to place the threshold between them. This separation is achievable by improving the SNR as shown in Figure 2.13.

The probability of false alarm and probability of detection can be computed by integrating the area under the curves:

$$P_{FA} = \exp\left(-\frac{V_T^2}{2\sigma^2}\right)$$
Figure 2.13: Probability density function of the noise and target plus noise

\[ P_D = Q_m(\sqrt{2SNR}, \sqrt{-2\ln P_{FA}}) \]  

(2.25)

where \( Q_m \) is known as Marcum’s Q-function. The probability of detection versus SNR for a nonfluctuated point target point is plotted in Figure 2.14. This curve is one form of the receiver operating curve (ROC), which is a plot of two of \( P_D, P_{FA}, \) and \( SNR \) with the third as a parameter. From the figure, it can be seen that a 13.2 dB SNR is needed for 0.9 probability of detection with probability of false alarm equal to \( 10^{-6} \).

2.2.3.1 Pulse Integration

The SNR can be improved by combining several received pulses from the target and noise from the same look direction. This improvement occurs because the noise from pulse-to-pulse tends to be uncorrelated, thus the noise averages out, while target pulses tend to be correlated and add-up. There are three types of integration: coherent integration, noncoherent integration and binary integration. Adding the complex
signal improves the SNR by coherent integration gain $n$, where $n$ is the number of pulses, but it requires the phase of the received signal to be known across the coherent processing interval (CPI).

The noncoherent integration gain is obtained by adding the magnitude of the signal only. This gain typically varies between $n^{0.8}$ to $n^{0.7}$ and can be reduced more as $n$ becomes larger. The improvement in SNR can be defined as

$$SNR_n = n^\alpha SNR_1$$

(2.26)

where $SNR_1$ is the signal to noise ratio for single pulse, $SNR_n$ is the signal to noise ratio for $n$ number pulse, and $\alpha$ is an integration exponent. For coherent integration, $\alpha = 1$. Figure 2.15 illustrates the effect of integration on detection performance for a nonfluctuating target.
Figure 2.15: ROC of coherently integrated pulses, $N$, $P_{FA} = 10^{-6}$

Binary integration or $M$-of-$N$ integration is performed after $N$ detection process, out of this $N$ binary decision a minimum of $M$ number of detection is required to declare the target. Binary integration can increases the probability of detection and reduces the probability of false alarm.

2.2.3.2 Target Fluctuation

Real targets can be considered as collections of individual scattering centers and each scatterer has an echo that is independent of the echo from other scatterers. The RCS of the target is the sum of the scattering from all of these scatterers and varies as function of time, aspect angle and the transmitted signal wavelength. Therefore, the combined RCS of the scatterers is treated as random variable that has a specified probability density function (PDF). The simplest and most traditional method for representing the echo fluctuation of a complex targets was defined by Swerling. These four models are a combination of two different PDFs of the target RCS and two decorrelation classes as shown in Table 2.2.
Table 2.2: The Swerling Models

<table>
<thead>
<tr>
<th>PDF of RCS</th>
<th>Uncorrelated from</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Scan-to-scan</td>
<td>Pulse-to-pulse</td>
</tr>
<tr>
<td>Rayleigh/exponential</td>
<td>Case 1</td>
<td>Case 2</td>
</tr>
<tr>
<td>chi-square with degree 4</td>
<td>Case 3</td>
<td>Case 4</td>
</tr>
</tbody>
</table>

Swerling case 0 or 5: The echo pulses received from the target are assumed to be unchanging from pulse-to-pulse and scan-to-scan. Here the scatterers response is assumed to be independent of orientation. The PDF of the RCS $\sigma$ is given by:

$$p(\sigma) = \delta(\sigma - \sigma_0) \quad (2.27)$$

Swerling case 1: The echo pulses received from the target are assumed to be unchanging from pulse-to-pulse, but vary from scan-to-scan. The scan-to-scan fluctuation or slow fluctuation for this case described by an exponential PDF (sometimes called Rayleigh because corresponding voltage PDF is Rayleigh):

$$p(\sigma) = \frac{1}{\bar{\sigma}} \exp\left(-\frac{\sigma}{\bar{\sigma}}\right) , \sigma \geq 0 \quad (2.28)$$

where $\bar{\sigma}$ is the mean value of the RCS $\sigma$. This PDF correspond to a target consisting of a large number of equal size scatterers.

Swerling case 2: The echo pulses received from the target are independent from pulse-to-pulse. This case is known as fast fluctuation and described by the same PDF as that of Swerling case 1. The probability density function and histogram of an exponential distribution is shown in Figure 2.16.
Swerling case 3: Similar to Swerling case 1, the echo pulses received from the target are uncorrelated from scan-to-scan, but follow a PDF described by chi-square with 4-degree of freedom:

\[ p(\sigma) = \frac{4\sigma^2}{\bar{\sigma}} \exp\left(-\frac{2\sigma}{\bar{\sigma}}\right), \sigma \geq 0 \] (2.29)

This PDF correspond to a target consisting of one dominant scatterer and a number of smaller scatterers.

Swerling case 4: The echo pulses received from the target are independent from pulse-to-pulse and described by the same PDF as that of Swerling case 3. The probability density function and histogram of a 4-degree chi-square distribution is shown in Figure 2.17.

The choice of PDF requires some knowledge of the target RCS characteristics, whether there is a dominant scatterer or not. Choosing the rate of variation depends on the change of the aspect angle and the frequency of the transmitted pulse over
a CPI. The pulse-to-pulse variation is very important when multiple pulses are integrated and used in detection decision. A pulse sequence for (a) Swerling case 1 or 3 and (b) Swerling case 2 or 4 are illustrated in Figure 2.18.

2.2.3.3 Radar Clutter

Clutter is defined as an echo signal from an object or multiple objects that have no interest to the radar’s objective. If the radar’s objective changes, these objects could become the targets of interest. Radar clutter is normally a return echo from either natural or man-made objects such as buildings, sea or vegetation. These echoes can degrade the performance of the radar and makes detection and tracking of targets more difficult.

A common way of describing the radar cross section of the clutter is by defining a clutter cross section per unit area, which is given by:

\[ \sigma^0 = \frac{\sigma_c}{A_c} \]  

(2.30)
Figure 2.18: An example of (a) Scan to Scan, (b) Pulse to Pulse decorrelation

where $\sigma_c$ is the radar cross section of the clutter within an area $A_c$. $\sigma^0$ is unitless quantity and expressed in decibel units dBsm/sm. The area $A_c$ of illuminated clutter by a radar beam at a given grazing angle $\psi_g$ is showing in Figure 2.19 and given by:

Figure 2.19: The area of illuminated clutter by a radar beam at grazing angle
where $\theta_3$ is the azimuth beamwidth of the antenna. The radar cross section of the clutter $\sigma_c$ is then:

$$\sigma_c = R \Delta r \theta_3 \sec(\psi_g) \sigma^0$$  \hspace{1cm} (2.32)

Therefore, the radar equation for the received power from surface clutter is:

$$P_c = \frac{p_t G^2 \lambda^2 \Delta r \theta_3 \sec(\psi_g) \sigma^0}{(4\pi R)^3}$$  \hspace{1cm} (2.33)

The received echo power $P_c$ from surface clutter is inversely proportional to $R^3$ rather than $R^4$, as in the case for point targets. Radar clutter is normally described by a specified PDF because of the high variation of the received clutter echo. This variation is caused by the movement of the scatterers within the radar resolution cell. The clutter model depends mostly on the radar operating frequency and grazing angle. There are several distributions to be used when modeling radar clutter. One of the first models that was used to fit non-Rayleigh clutter was the lognormal distribution. The lognormal distribution is given by:

$$p_\sigma(\sigma) = \frac{1}{\sigma s \sqrt{2\pi}} \exp\left(-\frac{(\ln \sigma - \bar{\sigma})^2}{2s^2}\right)$$  \hspace{1cm} (2.34)

where $\bar{\sigma}$ is the mean RCS and $s^2$ is the variance of $\sigma$. The lognormal distribution is a better representation of rough clutter since it has longer tail than Rayleigh and Weibull distribution. Figure 2.20 shows a log-normal distribution for $\bar{\sigma} = 0$ and $s^2 = 0.5$. 

30
2.2.3.4 Constant False Alarm Rate

Using a fixed threshold to detect a target in the presence of changing interference allows too many false alarms. To avoid this it is necessary to estimate the statistics of the interference level and adapt the detector threshold to maintain a constant false alarm rate (CFAR). CFAR determine the presence of a target at a particular test cell. It uses a set of reference cells near to the test cell to estimates the interference level, then apply a threshold multiplier to this estimate to compute the threshold. If the magnitude exceeds the threshold, a detection is declared. Normally a number of guard cells are specified to avoid counting the target in the reference cells. One major from of CFAR is the cell averaging CFAR (CA-CFAR) illustrated in Figure 2.21.

CA-CFAR computes a threshold based on an estimate of the mean interference power in the reference cells. The CA-CFAR is implemented for Rayleigh distributed interference and assumes that the interference in the reference cells are independent.
and identically distributed (i.i.d.). Figure 2.22 shows a simulated return with CA-CFAR and Neyman-Pearson threshold. The length of the CFAR window is chosen to be 16 and the probability of false alarm is $10^{-6}$.

From Figure 2.22, it can be seen that the CA-CFAR threshold appears to be higher than Neyman-Pearson threshold. Higher threshold reduces the probability of detection as shown in Figure 2.23. CFAR loss is defined as the additional SNR
needed to achieve the same detection performance as that associated with a fixed threshold detector where the interference level is known. The CFAR loss decreases as the number of reference cells increases and increases as the probability of false alarm decreases as shown in Figure 2.24. In the figure, three curves are plotted for three different values of $P_{FA}$, assuming a desired $P_D = 0.9$. Both figures show approximately 2 dB loss in SNR when the CFAR window size is equal to 16 for a $P_D = 0.9$.

![Figure 2.23: ROC for a Neyman-Pearson detector and CA-CFAR](image1.png)

![Figure 2.24: CFAR loss as a function of CFAR reference cells](image2.png)

### 2.2.4 Tracking

Tracking is the process of estimating the target state trajectory from a set of measurements that have been associated with that target. The target state trajectory, which typically includes position and velocity, is used to predict the target future position and therefore the beam position for the next dwell. Tracking can be viewed as a stochastic state estimation problem by assuming a stochastic model for the target motion. This section is based on the following well known text books: [1] and [17]
2.2.4.1 Target Dynamic Model

The target dynamic motion model is commonly described by a stochastic linear system given by:

\[ x_{k+1} = A_k x_k + B_k u_k + w_k \]  (2.35)

The terms of 2.35 are defined as follows. \( x_k \) is the target state vector containing the position and velocity of the target at discrete time \( k \). The target motion state can be described by a 2D motion model in Cartesian coordinate given by

\[ x_k = \begin{bmatrix} x_k & y_k & \dot{x}_k & \dot{y}_k \end{bmatrix}' \]  (2.36)

where \((x_k, y_k)\) and \((\dot{x}_k, \dot{y}_k)\) are the target position and velocity, respectively, in the 2D plane. Equation 2.36 can be extended to 3D when the target motion modeled has the following form:

\[ x_k = \begin{bmatrix} x_k & y_k & z_k & \dot{x}_k & \dot{y}_k & \dot{z}_k \end{bmatrix}' \]  (2.37)

The following equations are based on the assumption that the target motion model has a state described by 2.36.

\( A_k \) is the state transition matrix:

\[
A_k = \begin{bmatrix}
1 & 0 & T & 0 \\
0 & 1 & 0 & T \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]  (2.38)

where \( T \) is the sampling interval. It is desirable to track target with an update rate that is less than the target maneuver time in order to maintain a level of track quality. 

\( B_k \) is the input matrix:
\[
B_k = \begin{bmatrix}
T^2 & 0 \\
0 & T^2 \\
T & 0 \\
0 & T
\end{bmatrix}
\] (2.39)

\(u_k\) is the target acceleration vector and \(w_k \sim \mathcal{N}(0, Q_k)\) is the process noise, where \(Q_k\) is the process noise covariance matrix given by:

**Discrete White Noise Acceleration Model**

\[
Q_k = \begin{bmatrix}
T^4/4 & 0 & T^3/2 & 0 \\
0 & T^4/4 & 0 & T^3/2 \\
T^3/2 & 0 & T^2 & 0 \\
0 & T^3/2 & 0 & T^2
\end{bmatrix} \sigma_v^2
\] (2.40)

where \(\sigma_v^2\) is an acceleration error.

The linear measurement model is given by:

\[
y_k = C_k x_k + v_k
\] (2.41)

where \(y_k\) is the target position measurement vector at time \(k\) and \(C_k\) is the measurement matrix.

\[
C_k = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0
\end{bmatrix}
\] (2.42)

\(C_k\) can be modified to include the target Doppler velocity measured by the radar. \(v_k \sim \mathcal{N}(0, R_k)\) is the measurement noise, where \(R_k\) is the measurement noise covariance matrix.

\[
R_k = \begin{bmatrix}
\sigma_x^2 & \sigma_{x_0 y_0}^2 \\
\sigma_{x_0 y_0}^2 & \sigma_y^2
\end{bmatrix} \sigma_v^2
\] (2.43)

where,
\[
\sigma_{x_0}^2 = \sigma_{R_0}^2 \cos^2 \eta_0 + \sigma_{\eta_0}^2 R^2 \sin^2 \eta_0
\] (2.44)

\[
\sigma_{y_0}^2 = \sigma_{R_0}^2 \sin^2 \eta_0 + \sigma_{\eta_0}^2 R^2 \cos^2 \eta_0
\] (2.45)

\[
\sigma_{x_0y_0}^2 = \frac{1}{2} \sin^2 2\eta_0 [\sigma_{R_0}^2 - R^2 \sigma_{\eta_0}^2]
\] (2.46)

where, \(\sigma_{R_0}^2\) and \(\sigma_{\eta_0}^2\) are range and azimuth angle measurement variance, respectively.

The dynamic motion model described in this subsection define a Kalman filter to track targets in \(x-y\) plane. The model can be extended to include the vertical position \(z_k\) and velocity \(\dot{z}_k\).

2.2.4.2 Kalman Filter

Kalman filter is a recursive state estimator that minimizes the mean square error estimate. The Kalman filter is often used to filter the position measurement for estimating the target position, velocity, and acceleration. It provides minimum mean square estimate of the target state when the target motion and measurement models are linear and the measurement and processes noise are Gaussian.

Given the target dynamic motion model and measurement model from 2.36 and 2.41, the Kalman filter equations are given by:

- Prediction Update

Predicted state: \(\hat{x}_{k/k-1} = A_{k-1}\hat{x}_{k-1}\) (2.47)

Predicted state covariance: \(P_{k/k-1} = A_{k-1}P_{k-1}A_{k-1}^T + Q_{k-1}\) (2.48)
Predicted innovation covariance: \[ S_{k|k-1} = C_k P_{k|k-1} C_k^T + R_k \] (2.49)

- Measurement Update

Kalman gain: \[ K_k = P_{k|k-1} C_k^T S_{k|k-1}^{-1} \] (2.50)

Estimated state: \[ \hat{x}_k = \hat{x}_{k|k-1} + K_k [y_k - C_k \hat{x}_{k|k-1}] \] (2.51)

Estimated state covariance: \[ P_k = [I - K_k C_k] P_{k|k-1} \] (2.52)

The above equations provides a recursive way to estimate the target state and covariance matrix from linear measurements corrupted by additive Gaussian noise (2.51 and 2.52). It also computes the target prediction state as well as the target prediction state covariance and predicted measurement covariance (2.47-2.49).

While the equations of motion are readily modeled as a linear system in cartesian coordinates, the radar produces measurements in spherical/polar coordinates. Thus, either the system matrix \( A_k \) or the measurement function \( C_k \) will be nonlinear. Also the noise terms cannot be assumed to be Gaussian when the measurement is transformed to cartesian coordinates. One potential approach is to keep the measurements in the original form and use Extended Kalman filter to approximates the nonlinear function. Another approach is to transform from polar coordinates to cartesian and use the measurement covariance from 2.43 to perform linear filtering. Due to the great computational advantages associated with the use of decoupled filters the second approach will be used to develop the tracking filter.

### 2.2.5 Data Association

A radar measurement could be from a target under track, a nearby existing target, a new target not seen before, or be a false alarm. The first part of the tracking
operation is to use a data association technique to accurately assign measurements to tracks.

2.2.5.1 Gating

Gating is a technique of eliminating unlikely measurement to track pairings in order to reduce the computational cost of the data association. A gate is formed by placing the center of the gate at the predicted target location, based on the existing track, and only considering measurements that falls within the gate for track update. Gating can be accomplished by using coarse gate, rectangular gate and ellipsoidal gate. Ellipsoidal gate defines a gate size $G$, such that a measurement is accepted if it falls within the normalized statistical distance $d^2$.

$$d^2 = (\tilde{y}_k)^T S_k^{-1} \tilde{y}_k \leq G$$  \hspace{1cm} (2.53)

where $\tilde{y}_k$ is the residual or innovation vector, which is the difference between measurement and the track.

2.2.5.2 Global Nearest Neighbour (GNN)

Global Nearest Neighbor (GNN) method for measurement to track association is the most widely applied method of data association. This method assigns the closest measurement to the measurement prediction in the gate. The assignment is based on the minimum statistical distance of all the measurements and the track. For a situations where there is more than one measurement in track gate or an measurement in more than one track gate, an measurement to track assignment matrix is formed to find the optimal solution. GNN is typically used with systems that uses simple $M/N$ rule for confirmation and $N_D$ consecutive misses for track deletion.
2.2.6 Track Management

Track management refers to the function of track initiation, confirmation, and deletion. Each new incoming measurement should either be an update for an existing track or form a tentative track. Tentative tracks are normally generated to confirm or deny that a sequence of measurements comes from an actual target. Once a tentative track is formed a logic method is usually required to maintain the tracks. Track confirmation is accomplish by using a $M/N$ decision rule, where $M$ is number of correlating measurements and $N$ is number of scans. Track deletion happens after $N_D$ consecutive scans have produced no updating measurement.

2.3 Multifunction Radar

A multifunction radar is a modern system that is capable of performing multiple radar functions simultaneously, such as search or independent track. This class of system uses phased array antenna with its inherent beam agility to implement many functions. A radar resource manager is always needed in a multifunction radar system to balance the use of the finite resources among the multiple functions. To decide upon which radar parameters, the resources, can be controlled by the resource manager it is necessary to consider what functions are undertaken. [5] and [18] presented a comprehensive description of the multifunction radar.

2.3.1 Multifunction Radar Modes

A multifunction radar can be configured, depending on the application, to perform many different types of radar functions. A brief description of the basic radar functions
is given in this section. These functions are applicable to any multifunction radar system.

2.3.1.1 Surveillance

The primary goal of many radars is to survey a given volume of interest within a time-frame to detecting new targets. The surveillance task is normally perform under a set of operational requirements which includes number of false alarm and detection performance. When the radar is in surveillance mode, it can form tracks using the measurements from multiple surveillance scans, which is known as track-while-scan (TWS) mode. The surveillance mode is function of the total search volume, the dwell time and the antenna beamwidth.

It is desirable to implement surveillance tasks with using as few resources as possible. Optimizing the dwell time spent at each beam position reduces the amount of radar timeline that the surveillance function uses.

2.3.1.2 Plot Confirmation

Plot confirmation function is implemented to conform whether a detection is a target or a false alarm. Typically, the update rate or revisit time for this function is short in order to avoid the target decorrelation and therefore loosing the detection. The waveform remain the same during plot conformation to reduce the chance of decorrelation. This function uses the predicted target position from the tracking filter to associate the new detection to the target.

2.3.1.3 Tracking

The main goal of the tracking function is to use the measurements from the target to estimate its trajectory. The output target state of the tracking function/manager is
more accurate over time than the radar measurements. This improvement is achieved by using a tracking filter similar to the one discussed in 2.2.4.2. Tracking mode has four primary component:

*Track Initiation*: This function initiates a candidate track for each confirmed detection. Track initiation requires several rapid revisit to the target to establish an accurate track.

*Track Update*: This function uses new measurements to update the target track, a tracking filter task.

*Track Merging and splitting*: False alarms and missed detections can establish multiple tracks for a single target or form one track for multiple targets. This function solves track merging and splitting by connecting or deleting tracks.

*Track Maintenance*: The aim of track maintenance is to insure that all tracks are stable by requesting revisits to the target when needed.

The tracking mode may require a revisit rate higher than the surveillance rate to achieve sufficient accuracy to maintain the tracks. This requirement can introduce an extra demand on the radar timeline. It is clear that the optimum configuration for tracking and surveillance modes are different, which illustrates the need for radar resource management in multifunction radar.

### 2.3.1.4 Target Classification

Radar target classification extracts distinguishing features from a target and then uses those features to obtain more information about that target. It is necessary for the radar to determine the detected target before taken any high risk action. This
mode is important to determine the radar’s future objectives and can help to improve the resource allocation. Target classification often depends on the radar waveform, dwell time and the incident angle.

Other radar functions include missile guidance and missile communication for air or ground defense as well as other functions relating to electronic warfare, which involves jamming and electronic counter-countermeasures.

2.3.2 Radar Control Parameters

A multifunction radar is an agile system that typically operates using a large number of different controllable parameters. For each radar mode, there is an optimal set of control parameters that would typically be used in a dedicated radar. These optimal parameters are desired but are often difficult to employ due to the radar resources limitation. Table 2.3 defines the parameters which can be controlled in a multifunction radar system and their impact on the radar performance.
Table 2.3: Multifunction Radar Control Parameters [1]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Transmitted Power (W)</td>
<td>• Increasing the transmit power increases the SNR.</td>
</tr>
<tr>
<td>Pulse Repetition Frequency (Hz)</td>
<td>• Increasing PRF increases energy on target.</td>
</tr>
<tr>
<td></td>
<td>• Increasing PRF decreasing doppler ambiguity and increases range ambiguity.</td>
</tr>
<tr>
<td>Pulse Width (sec)</td>
<td>• Increasing pulse width increases energy on target but increases the blind range.</td>
</tr>
<tr>
<td>Pulse Compression Ratio</td>
<td>• Increasing pulse compression ratio improves range resolution and increases the SNR.</td>
</tr>
<tr>
<td>Dwell Time (sec)</td>
<td>• Increasing dwell time improves the detection performance.</td>
</tr>
<tr>
<td>Revisit Time (sec)</td>
<td>• Increasing revisit time improves the tracking performance but degrades the detection performance ($P_D$).</td>
</tr>
<tr>
<td>Integration Interval (sec)</td>
<td>• Increasing the coherent integration interval (CPI) improves the detection performance and improves Doppler resolution.</td>
</tr>
<tr>
<td>Beam Pointing</td>
<td>• Controlled by the radar resource management to direct the radar at a target or an area of interest.</td>
</tr>
<tr>
<td>Detection Threshold</td>
<td>• The choice of the number of reference cells and guard cells can increase the probability of detection while maintaining an acceptable probability of false alarm.</td>
</tr>
<tr>
<td>Tracking Filter</td>
<td>• The choice of the tracking filter, target model and data association method improves the tracking performance.</td>
</tr>
</tbody>
</table>
Chapter 3: RESOURCE MANAGEMENT IN A MULTIFUNCTION RADAR

This chapter focuses on a number of literatures that are of direct interest to the radar resource management problem. Section 3.1 discusses multifunction radar resource management architecture and describes some of the recently developed architectures. Methodologies for radar resource management are described in Section 3.2. Sections 3.3 and 3.4 outlines several method that have been proposed for priority assignment and scheduling in multifunction radar.

3.1 Radar Resource Management Architectures

The architecture of radar resource management represents the processing interaction between different component in the system. Radar resource management architecture is one form of a general sensor manager architecture which can be mapped in various ways:

Centralized Architecture: Mapped to have a central unit that collects all the information about the environment and makes radar scheduling decisions.

Decentralized Architecture: In this architecture, each task is represented by an agent that is responsible to negotiate with other agents for the radar resources.
Hierarchical Architecture: This architecture consists of several processing levels, where the lowest level makes a decision then propagates it upwards to higher level to generate a global radar scheduling decisions.

Any of the mentioned architectures can be used in the multifunction radar systems. While the centralized architecture is simplest to realize, it demands high computational processing compare to the other architectures.

[1] proposed Macro-level/Micro-level hierarchical architecture for multi-sensor system. The Micro-level manager is located at each sensor and it is responsible of finding the best way to employ the high-level tasks. The Macro-level is a high-level centrally located manager that collect inputs from the Micro-level managers to form resource utility decisions to achieve the sensor objectives. This architecture is more suitable for resource allocation in a network of multifunction radar systems.

Figure 3.1 shows a radar resource management architecture proposed by [3]. This architecture contains two major components: priority assignment and task scheduler. The human operator in this architecture is responsible of defining the mission objectives and requirements. The surveillance and tracking manager forms a list of task requests which is then prioritized and fed to the scheduler to generate a timeline of tasks to be executed by the radar.

Another radar resource management architecture is given by [19]. In this architecture, the task manager forms a list of tasks with an assigned priority and update rate based on the current environment and the radar load. The list of tasks is fed to the dwell manager to generate a dwell request for each task with an appropriate waveform. The burst manager receives the dwell requests and then passes them to the space-time manager to be carried out by the radar.
An example of a decentralized architecture proposed by [4] is shown in Figure 3.2. Each agent in this architecture represents a radar function, such as tracking or surveillance. Agents negotiate with each others based on an auction mechanism managed by the auctioneer agent. Tasks requests are formed by the resource manager and then passed to the scheduler for execution. The most basic advantages of this architecture is the ability to modify the decision-making process and the computational processing efficiency.

### 3.2 Methodologies for Radar Resource Management

In this section, several radar resource management methodologies are described. The approaches described in this section have specific constraints and objectives, depending on the application, but with much wider utility. There are two main classes of radar resource management problem: heuristic and optimization-based resource management. A common way to evaluate a radar resource management technique is
Figure 3.2: Decentralized radar resource management architecture [4]

to test it under stressed condition. A radar is said to be under stressed condition when it has to track a large number of target along with other different tasks.

3.2.1 Heuristic-based Resource Management

The resource allocation in this methodology is driven by a set of rules that is defined based on descriptive scheme. Heuristics-based radar resource management approaches are often used in operational systems due to there simplicity of implementation and low computational complexity. These approaches provide sub-optimal global solution since they selects the system parameters to address a desirable set of tasks without considering the system overall constrains and performance. Therefore, it is difficult to predict their overall performance.

A benchmark problems [20] and [21] were developed to compare various tracking and resource allocation algorithms. The benchmark problem in [22] included a maneuvering target with different radar cross section and the presence of false alarm and electronic counter measures (ECM), which include a standoff jamming (SOJ) and
range gate pull of (RGPO). The goal of the resource manager was to select the waveform parameters and the operating detector to minimize the radar energy and time. [23] and [24] presented a solution for a benchmark problems using interacting multiple model with probabilistic data association filter and multiple hypothesis tracking respectively. Both authors gave a heuristic approach for resource management based on the track predicted covariance matrix.

[6] presented an approach for adaptive revisit time to efficiently maintain existing targets track with minimum radar resources. In this approach, an update time $t_{N+1}$ is required when the predicted covariance reaches an threshold given by

$$G(t_{N+1}/N) = V_0 B$$

where $B$ is the beamwidth and $V_0$ is a dimensionless track sharpness. Once the threshold is reached the beam is pointed towards the space where the predicted track position is. In case of a miss-detection, the beam is directed around the target original location until the target is detected. This criteria allows the radar to spend more time searching for targets and also to track high number of targets. It was concluded that the minimum required resources allocation is independent of the target maneuver parameters, range and antenna beamwidth, and it can be found by the proper choice of $V_0$, $SNR$ and $P_{FA}$. A range of optimal choices for $V_0$, $SNR$ and $P_{FA}$ was provided to minimize the radar energy resources allocation and to achieve good tracking performance.

[1] proposed a radar resource allocation approach to handle multiple radar functions, mainly searching for new targets and updating an existing tracks. A utility theory or expert system approach is used to assign priorities to different radar tasks.
Task utilities can be computed using situation assessment function whose purpose is to analyze the information about the environment to determine track and search region priorities. The sensor manager is responsible for generating a queue of tasks based on information given from external inputs such as track importance and the tasks priorities, as defined by the figure of merit. The task queue is then sent to the dwell scheduler whose purpose is to select the radar waveform parameters and to execute a beam position commands. A data preprocessor was set to assess the queue generator when a missed detection occur by providing a request to the sensor manager for another track update. The data preprocessor also assess the plot confirmation function by determining whether the new detection correlates with an existed target track or not.

3.2.2 Optimization-based Resource Management

The primary goal of the optimization approaches is to find a decision that achieves a global optimum resource allocation over a finite time horizon. These approaches involve complicated formulation and high computation demands. Recent advances in computer processing power have facilitated investigation of different optimization methods. Some of the recent developed techniques are presented in this section.

3.2.2.1 Q-RAM

[8] applied the quality of service based resource allocation (Q-RAM) model [25], [26] on a multifunction radar resource management problem. The goal of this model is to maximize the overall system utility by allocating resources to tasks while maintaining two major constrains: the maximum resources for any task cannot exceed an upper bound and each task must meet its minimum needs. In this paper, the Q-RAM
model solves the radar resource allocation problem with four adjustable variables for each track or search task (dwell period, dwell time, transmission power and tracking filter algorithm) subject to radar energy and time constraints. The dwell time for each radar task is modeled as transmit power, transmit period, wait time and receive period.

Four different preference aspects were considered in this model: QoS dimensions, environmental dimensions, operational dimensions, and resource dimensions. QoS dimensions represents the user satisfaction on the task quality, such as target tracking estimation error. Environmental dimensions represents the set of tasks that affect the QoS level, but are outside of the radar control such as target speed. Operational dimensions the set or parameters that can be control by the user such as dwell time or transmit power and resource dimensions are the available radar resource that must be distributed among tasks, such as radar time.

The Q-RAM model assumed that the utility function of the radar resource management problem is concave and hence a concave majorant process is used in the Q-RAM model to reduce the number of setpoints considered for a task. However, when the number of the setpoints is high, which is the case for a highly configurable system such as radar, the Q-RAM model uses fast traversal techniques in order to reduce the number of set points that must be considered. The Q-RAM model has a centralized mechanism that makes it computationally expensive even when the fast traversal is used.

3.2.2.2 CDAPS

[4] developed an agent based auction algorithm for selecting the optimum parameters for radar tasks to maximize the radar global utility. The continuous double
auction parameter selection (CDAPS) algorithm is a bidding strategy that allows autonomous agents to participate in trading market by buying or selling radar resources. Agents in this algorithm represent radar tasks, such as individual target tracks or surveillance, and aims to achieve maximum performance by utilizing as much radar resources as possible.

The radar resource management problem in this algorithm is formulated similar to the Q-RAM algorithm. The parameters that the radar has a direct control on (operational parameters), such as the bandwidth and pulse width, is mapped to quality and utility functions for a given environmental parameters. The environmental parameters affects the radar loading and performance but they are outside the radar control. Each agent has the ability to evaluate the quality, utility and radar loading for every parameters selection as the resources changes. The parameters selection that gives the best ask and bid offers is local and hence it is found by using a hill climbing search.

The CDAPS algorithm was applied to different simulated scenarios for radar surveillance [27] and multi target tracking [9]. A comparison between the CDAPS and a conventional rule-based approach in a static and dynamic scenarios is addressed in both papers. It was concluded that the CDAPS algorithm achieve global resource optimization, which is an improvement over the locally optimum rule-based approach. The decentralized mechanism makes the CDAPS algorithm computationally efficient and therefore it can be implemented in real-time.

3.2.2.3 Information Theoretical-based Resource Management

In [28],[29], [30] an information theoretical approach for sensor management is proposed. This approach uses the Rényi Information Divergence to estimate the
information gain for each possible action and then choose the action that produces the maximum expected information gain. The expected information gain can be found by calculating the divergence between the current PDF and the predicted PDF after an action is taken. A great reduction in uncertainty provided by a measurement indicates that this measurement contains large information which implies a high quality of an action. [29] suggested the need to schedule extra dwell time for a target that will become invisible to the radar for a period of time, in order to reduce the uncertainty about the target kinematic state.

A comparison between task driven and information driven resource allocation approaches for target tracking is given in [31]. It was concluded that the task driven approach performs marginally better than the information driven approach when the performance is defined by a given task. However, in the present of multiple competing performance criteria the information driven approach performs better by balancing the different desired performance.

[4] investigated the information-based approach using the mutual information or Kullback-Leibler divergence for radar resource allocation to track multiple targets. It was found that allocating resources to seek a great mutual information gain drive the radar to focus on strong targets only without given any attention to weaker targets, which is undesirable behavior.

3.3 Priority Assignment in Multifunction Radar

Task prioritization is one of the primary element that is normally taken into account when scheduling tasks under insufficient resources. Hence, priority assignment
has major benefits when the system is in stressed conditions. Most scheduling techniques depend heavily on the priority assignment to resolve conflict between tasks that have almost similar due time. Task prioritization can be selected in many different ways and it is always application dependent. However, a typical method of assigning priorities is to rank the radar tasks at design time based on their importance. When the radar is under overload situation, only high priority tasks are carried out and low priority ones are dropped, which can cause performance degradation.

Different priority order tables can be found in literature [32], [2] and [33]. All these tables have some common features. For example, track maintenance always has the highest priority to ensure that all tracks are stable and to avoid losing the target under track. The second highest priority is assigned to plot conformation, which is required to avoid the target decorrelation and therefore losing the detection. Track initiation has higher ranking than track update since it requires several updates to provide accurate track information. An example of a fixed priority ranking is given in table 3.1.

<table>
<thead>
<tr>
<th>Priority</th>
<th>Radar Task</th>
<th>Priority Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>Track Maintenance</td>
<td>Highest Priority</td>
</tr>
<tr>
<td>6</td>
<td>Plot Confirmation</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Track Initiation</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Track Update</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Surveillance</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Slow Track Map/Surface Picture</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Receiver Calibration</td>
<td>Lowest Priority</td>
</tr>
</tbody>
</table>

Table 3.1: Radar tasks priority ranking [2]
Some effort has been spent on developing dynamic methods to task ranking by using fuzzy logic or neural networks. These two methods improves the resource allocation by continuously adapting the task prioritization based on the evaluation of the environment. An overview of fuzzy logic and its use for situation assessment and sensor management is given in [1]. [34] used fuzzy logic with an assessment of the target membership to continuously adjust the priorities of the radar tasks before scheduling. [35], [36] proposed a method that prioritize detected targets with learning ability using neural networks. The model used five features to represent the state of the detected target. The five features are: target radial range to the radar and its radial velocity, acceleration, azimuth and membership.

[3], [37] proposed a fuzzy logic based prioritization method for ranking targets and surveillance sectors in a continuously changing environment. A set of fuzzy variables were defined to represents important aspects of the target tracks and surveillance sectors. A fuzzy values were assigned to each fuzzy variables and a set of if-then rules were formed to assign prioritize to target tracks and surveillance sectors. Different target trajectories and target distributions in surveillance sector was used to evaluate the validity of this method. The paper provided a comparison between the fuzzy logic approach and two other less computationally demanding priority approaches. One approach is based on a fixed ranking method and the second has similar rules as the fuzzy logic approach but only one rule is allowed to be fired at a time. It was shown that the fuzzy logic approach provides smooth transition characteristics. This characteristics along with dynamic behavior in the fuzzy logic approach lead to significant improvement in the resource allocation. It is therefore concluded that the fuzzy logic approach is more efficient than the other approaches.
3.4 Scheduling In Resource Management

The task scheduler is a subsystem of the multifunction radar resource manager. It is a process of forming a timeline for a set of tasks to be performed by the radar according to the importance of the tasks and the radar available resources. [1] described two general approaches for scheduling tasks, brick packing and best first.

- **Brick packing**

Brick packing is a local optimum approach that subdivides the scheduling timeline into smaller time intervals and then schedule tasks in this time interval according to some criteria. As the schedule is being executed by the radar, the scheduler formulates the schedule for the next time period. Figure 3.3 shows an example of brick packing timeline, where a set of radar tasks is planned over a time interval $\Delta T$ ahead of the execution time $t_0$. The main goal of brick pack scheduling is to schedule the hard deadline tasks very close to their desired time of execution. To do that, the hard deadline tasks are placed first into the schedule and then other tasks are placed around it.

![Figure 3.3: Brick packing scheduler time line](image)
The brick packing technique assumes that no urgent tasks need to be scheduled before the next time frame. Therefore, the brick packing approach cannot handle pop-up tasks.

- **Best First**

Best first scheduler uses a shorter time frame than the brick packing approach to allow urgent tasks to be executed without delay. All tasks are queued every time interval $\Delta T$ according to the priority or deadline of each task as shown in Figure 3.4. Similar to the brick packing method, the hard deadline task is selected and scheduled first, then the next task at the top of the queue is executed. The best first technique is computationally efficient, since it needs less computation to maintain the queue. The sequential execution mechanism in the best first scheduler ensures that the radar time is fully utilized at all time. A drawback of using the best first approach is that it is difficult to execute tasks that rapidly appear without delaying other tasks.

![Figure 3.4: Best first scheduler time line](image)

Many authors have worked on the radar scheduling problem in order to design efficient scheduling algorithms. [38] developed a local optimum scheduling method
and used neural network to interleave tracking and surveillance tasks within the dead times between the transmitted and the received pulses.

[33] presented five heuristics approaches to schedule coupled tasks. A coupled task is a job consisting of transmission period $t_i$ and reception period $r_i$ separated by idle interval $L_i$ as shown in Figure 3.5. The aim of the approach is to schedule the tracking jobs as close as possible to their due time, and then use the idle interval within a job to schedule other radar tasks. As suggested, the idle interval for tracking and surveillance tasks needs to be estimated by using the target distance away from the radar, and the inner and outer points of the surveillance region to avoid scheduling larger task and to improve the usage of the radar time. The five heuristics includes highly constrained heuristics, which execute each tracking task when due and does not allow interleaving of the tasks, to more flexible heuristics where tracking and surveillance tasks could be interleaved. It was concluded that adjusting the tracking tasks slightly from their due time increases the radar utilization by 70% without effecting the tracking performance.

![Figure 3.5: An example of a coupled-task job](image)

[2] extended the approach taken in [39] to schedule tasks based on the concept of time-balance. The time-balance was modified to represent the earliness and lateness of a task rather than the amount of time the radar owed to each task. A positive time-balance means that the task is late, zero time-balance means that the task is on
its due date and a negative time-balance indicates that the task is early. Therefore, the next task to be executed is the task with highest priority and largest delay. New tasks are inserted to the job table with negative time-balance representing their due time. Once a task is scheduled the time-balance is decremented either by the task revisit time or by resetting the time-balance to minus the revisit time. The first approach was used for surveillance tasks, because scheduling these tasks as soon as possible improves the detection performance, while the second approach is used for tracking tasks since the tracking filter updates the target information every revisit time.

[40] studied the prioritized scheduling of interleaved and non-interleaved coupled tasks. It was concluded that the interleaved case improves the radar utility especially when the radar is under overload situations. Furthermore, more tracking tasks can be executed when interleaving is performed.

[41] addressed the problem of scheduling radar tasks with hard time constraint and priority. Hard time constraint tasks are defined as a tasks that cannot be executed before their due time and cannot be delayed by more than some constant from their due time. The aim was to schedule some high priority tasks with a very high accuracy. Therefore, a task is rejected if it cannot be processed before its deadline. The proposed method forms a frame of radar tasks from a sequence of hard time constraint tasks and soft time constraint tasks. The algorithm uses the fact that hard time constraint tasks cannot be executed before their due time to determine which task to be inserted into the frame. Therefore, if the current time is within the hard time constraint task time interval, then this task is selected otherwise a soft time constraint task is inserted into the frame.
[42] developed a scheduling technique called the Two-Slope Benefit Function (TSBF) to schedule a tracking update looks. This technique uses a benefit function to decide which looks are to be scheduled. Each look request has a required time to complete, desired start time, earliest and latest start time, peak benefit, slope for early scheduling and slope for late scheduling. The benefit function measures the benefit of selecting start time to schedule an update look. Looks with high peak benefit have a high chance of being scheduled, while high slope looks have a better chance of being scheduled as close to their desired time. If two look requests have to start at the same time, the scheduler will decide either to shift the start time or to drop one of the looks. When the radar is overloaded, this method schedules the looks which have higher priority. The goal of this technique is to maximize the radar tracking performance while utilizing the radar resources. This technique was compared to [33] and it was shown that the TSBF schedule tasks with small deviation around their due to.

[43] provided a comprehensive comparison of the scheduling algorithms from [33] and [2]. It was concluded that both schedulers produce similar performance under overload situations, especially when examining their ability to allocate radar resources and to schedule tracking tasks as close as possible to their desired due time. The main difference between the two scheduling algorithms is that the approach of [33] does not occupy the entire radar time even when the radar is under stressing condition. However, the scheduler used in [2] does occupy the entire radar time, but at the expense of placing tasks away from their desired due time.
3.5 Conclusion and Discussion

Current approaches to radar resource management considers modeling the radar system either as an output of a tracking filter, target state estimate and covariance matrix, or as set of tasks with a pre-defined task length, start and end time. However, this neglects a large degree of freedom in controlling the radar system parameters and considers the radar resource management problem to be a control problem that could be solved using an optimization methods or logic-based approach. Therefore, the first objective of this work is to develop a high fidelity radar simulation to support the development of a cognitive radar resource management approach.

[11] introduced the concept of cognitive radar and highlighted five fundamental components based on Fuster’s model for cognition: perception-action, memory, attention, intelligence and language. Following Haykin and setting language aside, a simplified block diagram of a cognitive radar architecture is shown in Figure 3.6. The potential for cognition to improve the radar resource management techniques is worth further investigation. The first objective of generated a detailed simulation will be
addressed in Chapter 4. The perception-action component of the cognitive model will be investigated in Chapter 5 in the form of an adaptive parameter selection approach.
Chapter 4: MODELING A MULTIFUNCTION RADAR SYSTEM

A model of a multifunction phased array radar is developed in this chapter. The aim of developing a radar model is to support the development of radar resource allocation approaches that will adjust the radar controlled parameters based on the radar's perception of the environment. This chapter describes the design and implementation of every component in the radar model.

An overview of the radar model is given in Section 4.1. This overview consists of the functional block diagram of the main radar component and a table lists the selected radar parameters. Section 4.2 describes the environment modeled that is used to generate the radar data. The modeled environment is composed of clutter, targets and radar receiver noise. The radar model is provided in Section 4.3. The radar is modeled as pulsed Doppler phased array radar operating in X-band. Section 4.4 contains a details description of the radar data processing. The data processing involves target detection and multiple target tracking.

4.1 Radar Model Overview

The main purpose of developing a radar model is to investigate the impact of changing the radar controlled parameters on the system performance. Radar resource
management can be considered as a parameter selection task given a set of available radar resources. The simulation was designed to allow the radar resource manager to be integrated directly at all levels of the radar system. The simulation consists of two main components: the environment model and the radar system model. The radar system model includes emulating the radar received signals and processing the received signals to detect and track targets of interest. The environment model is used to generate a radar perception of the world, which include radar system noise and returns from targets and clutter. Each function in the simulation was modeled directly to allow any necessary modification or replacement of the function. The block diagram of the radar model is given in Figure 4.1.

The radar is modeled as a X-band phased array pulsed radar using phase-comparison monopulse. Table 4.1 list the radar parameters that were used in the simulation. Parameters such as, number of pulses, PRF and uncompressed pulse width can be adjusted from dwell to dwell by the human operator or the radar resource manager.

4.2 The Environment Model

This section describes the environment model that is used to generate the radar returned signal. The aim of modeling a radar environment is to generate a realistic scenarios under different real-world constrains, which will allows us to examine the radar resource management problem. An environment from the radar perspective is typically consist of a number of targets of interest and different unwanted objects known as clutter. Other external environment factors, such as atmospheric attenuation and multi path interference can affect the radar received signal but are not considered here for simplicity.
The environment model presented consists of a maneuvering targets with RCS fluctuations according to the Swerling model as well as uncorrelated sea clutter and radar receiver noise. Only effects relate to target fluctuation, miss detection, false alarm and target maneuvers are considered in this model.
Table 4.1: Pulsed Radar Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transmitted Frequency</td>
<td>$f_c$</td>
<td>10 GHz</td>
</tr>
<tr>
<td>Transmitted Power</td>
<td>$P_t$</td>
<td>25 KW</td>
</tr>
<tr>
<td>Radar Height Above Sea Level</td>
<td>$h$</td>
<td>0 m</td>
</tr>
<tr>
<td>Radar Grazing Angle</td>
<td>$\psi_g$</td>
<td>0°</td>
</tr>
<tr>
<td>Antenna Length</td>
<td>$L$</td>
<td>1.2 m</td>
</tr>
<tr>
<td>Antenna Gain</td>
<td>$G$</td>
<td>35 dB</td>
</tr>
<tr>
<td>Antenna Beamwidth on Braodside</td>
<td>$\theta_3$</td>
<td>1°</td>
</tr>
<tr>
<td>Antenna Azimuth Angle sweep range</td>
<td>$\phi$</td>
<td>120°</td>
</tr>
<tr>
<td>Antenna Elevation Angle</td>
<td>$\theta$</td>
<td>0°</td>
</tr>
<tr>
<td>Uncompressed Pulse Width</td>
<td>$\tau$</td>
<td>10 µs</td>
</tr>
<tr>
<td>compression Pulse Width</td>
<td>$\tau_c$</td>
<td>10 ns</td>
</tr>
<tr>
<td>pulse Compression Ratio</td>
<td>$r_c$</td>
<td>1000</td>
</tr>
<tr>
<td>Range Resolution</td>
<td>$\Delta r$</td>
<td>1.5 m</td>
</tr>
<tr>
<td>Pulse Repetition Frequency</td>
<td>$PRF$</td>
<td>10 KHz</td>
</tr>
<tr>
<td>Blind Range</td>
<td>$R_b$</td>
<td>1500 m</td>
</tr>
<tr>
<td>Maximum Unambiguous Range</td>
<td>$R_{max}$</td>
<td>15 km</td>
</tr>
<tr>
<td>Number of Pulses per CPI</td>
<td>$N$</td>
<td>32</td>
</tr>
<tr>
<td>Reference Temperature</td>
<td>$T_0$</td>
<td>290 K</td>
</tr>
<tr>
<td>Losses</td>
<td>$L$</td>
<td>10 dB</td>
</tr>
<tr>
<td>Noise Figure</td>
<td>$F$</td>
<td>5 dB</td>
</tr>
<tr>
<td>Boltzmann’s Constant</td>
<td>$K$</td>
<td>$1.38 \times 10^{-23}$ W/K/Hz</td>
</tr>
</tbody>
</table>

4.2.1 Modeling The Target

4.2.1.1 Target RCS

Real world targets are very complicated and as a result their RCS fluctuates over time. A good representation to the target RCS fluctuation was developed using the statistical models discussed in subsection 2.2.3.2. The target is modeled as a single isotropic scatterer that is independent of aspect angle. All of the Swerling cases discussed in Subsection 2.2.3.2 are implemented in the simulation and can be used to represents the target amplitude fluctuation. The targets average RCS are always
chosen to be large enough in order to achieve at least 18 dB SNR. An example of the target RCS variation over multiple pulses is shown in Figure 4.2 for a fluctuating target follows Swerling 2 model and a non-fluctuating target.

![Figure 4.2: Comparison of the target RCS for fluctuating and non-fluctuating with mean RCS $\sigma = 1 \text{ m}^2$](image)

**4.2.1.2 Target Trajectories**

Since most targets of interest are non-stationary objects, moving targets with different trajectories are generated in the simulation. The target dynamical motion model given in Subsection 2.2.4.1 is used to generate $n$ number of targets with different velocity and bearing. Target location is defined in Cartesian coordinates but only on 2-D surface and thus, the targets has $0^\circ$ elevation angle. The target initial range and speed can be chosen arbitrary regardless the range and doppler ambiguity constraints,
while the target azimuth angle can varies from $-60^\circ$ to $60^\circ$. It is required to specify the target initial location and speed for every target in the simulation.

Figure 4.3 shows two target trajectories that were generated using 2.35. Target 1 is an inbound target travel at a constant speed of 55 m/s, which represents a large moving target, such as a guided missile destroyer. Target 1 initialized at a range of 18 km, an azimuth of $-45^\circ$ and the trajectory ends at a range of 7 km. The second target initialized at a range of 18 km, an azimuth of $-45^\circ$ and travels away from the radar with a speed of 70 m/s. Target 2 travels with an acceleration variance $\sigma_v^2 = 25$ m/$2^2$ and it represents a small highly maneuverable target, such as a fast boat.
4.2.2 Modeling The Noise

The noise spectrum at the radar receiver input is white. Therefore the radar receiver noise power in the I and Q signal sample can be modeled as an identically-distributed (iid) zero-mean Gaussian random process with identical variance. The output noise power by the radar receiver can be characterized by the receiver noise figure $F$, the receiver bandwidth $B$ and the noise reference temperature $T_0$. Equation 2.3 is used to determine the receiver noise power $P_n$, which is the variance of the complex-valued white Gaussian noise process. The receiver output noise is generated as:

$$N_{out} = \sqrt{\frac{P_n}{2}} (N^I + jN^Q)$$ (4.1)

where $N^I$ and $N^Q$ are Gaussian random numbers with zero mean and unit standard deviation, and $j$ is the imaginary number. The amplitude of the noise signal is Rayleigh distribution as shown in Figure 4.4 and the phase angle is uniformly distributed on $[0, 2\pi)$.

A comparison between the probability density function of the simulated noise sequence and the Rayleigh function is shown in Figure 4.4. The red line represents the probability density function of the Rayleigh function calculated using the statistical parameters from the simulated data. The histogram shows the probability density function of the simulated noise sequence using 100,000 samples. Figure 4.4 shows that the statistics of the amplitude of the noise signal generated in the simulation are the Rayleigh distribution.
Figure 4.4: Simulated noise statistics using 100,000 samples. The theoretical Rayleigh pdf is also shown

4.2.3 Modeling The Clutter

A realistic model of the clutter is extremely useful to improve the radar detection performance. However, the intent of modeling the clutter in this simulation is not to characterize the clutter to improve the radar detection performance, but to generate simulated radar data with higher false alarm rate to examine the radar resource management problem. Modeling the radar backscatter from a real surface in terms of its dynamics and structure would beyond the scope of the current research objectives. A preferable approach to model a clutter is to use a statistical model to represent the clutter backscatter temporal and spatial variation.

Clutter amplitude can be modeled as Rayleigh distribution similar to the radar receiver noise for low resolution radar, since a one range cell contains a large number of scatters. However, for high resolution radar, only few number of scatters exist within
a range cell and therefore the clutter tends to have a probability density function with a longer tail. Distributions such as Weibull, lognormal and k are commonly used to represent clutter in a high resolution radar. The lognormal model with probability density function given in 2.34 is selected to simulate the surface clutter. Clutter backscatter tends to have a strong temporal and spatial correlation, which is the primary cause of detection performance degradation. A realistic clutter model falls outside the scope of this research, hence for simplicity it is assumed that the lognormal distribution is spatially and temporally uncorrelated. The radar clutter is generated spatially as

\[ C = \sqrt{\frac{P_c}{2}} e^{-j\phi_c} \]

where \( \phi_c \) is the clutter phase and its random across 0 to \( 2\pi \) and \( P_c \) is the received power from the clutter given by 2.33. The radar is located at the sea level and therefore the grazing angle \( \psi_g = 0 \). The normalized clutter scattering coefficient \( \sigma^0 \) follows lognormal distribution given in 2.34 with mean RCS \( \bar{\sigma} = -20 \text{ dBSm/sm} \).

An example of a simulated radar clutter as a function of the radar range bin is shown in Figure 4.5. The clutter power is higher at a shorter range and reduces as the distance to the radar increase. This indicates that the returned signal at a far range exhibit noise-like statistics. A comparison between the probability density function of the simulated radar clutter sequence and the lognormal function is shown in Figure 4.6. The read line represents the probability density function of the lognormal function calculated using the statistical parameters from the simulated data. The histogram shows the probability density function of the simulated clutter sequence.
using 100,000 samples. Figure 4.6 shows that the statistics of the amplitude of the radar clutter generated in the simulation is lognormal distribution.

![Image showing a range profile of a simulated radar clutter using the lognormal function.](image)

Figure 4.5: A range profile of a simulated radar clutter using the lognormal function

### 4.3 The Pulsed Radar Model

Radar systems generally operate as Continues wave (CW) radar or a pulsed radar. The transmitter and receiver in a CW radar are operating all the time. The receiver is continuously listening to the returned echo while the transmitter is sending the signal. The pulsed radar transmits only for a finite duration, pulse width $\tau$, and receives the returned echo while the transmitter is off. Pulsed radar uses a sequences of pulses separated by the $PRI$ with transmit power that much higher then the CW radar.
The main benefits of a pulsed radar are the ability to measure the target radial velocity and range simultaneously, and the ability to separate targets from clutter in the Doppler domain. Clutter energy is typically much larger than target energy and it is normally concentrated around zero doppler. Thus, it is much easier to separate clutter from a moving target when using Doppler processing.

The pulse radar has some drawbacks such as range and Doppler ambiguity as well as blind zones over the range interval. This section illustrates modeling the phased array antenna, and the transmitted and received signal.

### 4.3.1 Modeling The Phased-Array Antenna

Beam agility provided by the phased array antenna enables the radar to perform different radar functions. Therefore, modeling a phased array antenna is essential in any multifunction radar simulation. The radar antenna is modeled as a linear phased
array where each element is isotropic in the forward direction but with no response
to the rear. The electric-field amplitude and phase of \( N \) number of idealized array
elements are simulated and then summed to generate the antenna directivity pattern
as described in 2.10. A phase shift is induced at each element of the array to steer the
beam away from the broadside angle. The amplitude and phase across the antenna
aperture are equal, i.e. rectangular window, which provides the highest achievable gain.
A weighted amplitude, such as Taylor window can be used to improve the sidelobe
level, but at the expense of broadening the beam. The amplitude distribution is not
considered here.

The array is 1.7 m long and consist of 115 individual elements. The antenna
broadside is directed at 0° and the beam scans from 60° to −60° in azimuth only.
The antenna 3 dB beamwidth at the broadside is 1° and increases as the beam steers
away from the broadside. The increase in the beamwidth caused by scanning off the
broadside direction is described by 2.15 and shown in Figure 2.8. If the beamwidth at
the broadside is 3° then the beamwidth at a scan angle 60° is 6° as shown in Figure
2.8. Figure 2.7 illustrates the effects of beam broadening as the beam steers off the
broadside for the phased array antenna modeled here. The blue line represents the
antenna pattern for the beam directed at the broadside with 1° beamwidth, while
the read dotted line represents an antenna pattern with wider, 2°, beamwidth that is
directed at 60° angle. The antenna gain is modeled to have a 35 dB at the broadside.
The decreases in the antenna gain caused by scanning off the broadside direction is
not considered in the simulation.
4.3.2 Modeling The Transmitted Signal

The waveform is a primary factor in determining the radar performance and measurements accuracy. The transmitted waveform is modeled as a linear frequency modulated (LFM) waveform to improve range resolution. The LFM waveform is the simplest and most commonly used waveform in modern radars. The improvement is achieved by frequency modulating the transmitted signal along the pulse duration. The LFM signal in baseband is defined as

\[ x(t) = \exp(j\pi B \frac{t^2}{\tau}), \quad -\frac{\tau}{2} \leq t \leq \frac{\tau}{2} \]  

(4.3)

where \( B \) and \( \tau \) is the signal bandwidth and pulse-width respectively. An example of a LFM waveform is shown in Figure 2.3(b). The waveform parameters such as pulse-width \( \tau \) and the \( PRF \) can be varied from pulse to pulse and from dwell to dwell. A dwell consists of multiple pulses separated by the \( PRI \) and is sometimes called coherent processing interval (CPI). The number of pulses within a dwell can be varied depends on the desired doppler resolution and the target RCS.

4.3.3 Modeling The Received Signal

The key benefit of pulsed radar is the ability to measure the target radial velocity and range simultaneously, which enables it to separate targets from stationary clutter. In order to measure the radial velocity of the target the radar needs to measure the phase of the received signal. Measuring the phase of the received signal enables the radar to perform functions such as Doppler processing, synthetic aperture radar (SAR) imaging and space-time adaptive processing (STAP). The advantage of knowing the phase information illustrates the need to use a coherent receiver. A block
diagram of coherent receiver is shown in Figure 4.7. The coherent receiver determines the amplitude and phase informations by converting the received signal to in-phase and quadrature signals.

![Diagram of Coherent Receiver](image)

**Figure 4.7:** The coherent receiver

Echoes from a point target have similar characteristics as the transmitted signal. Thus,

\[
r(t) = A(t) \sin(\omega_0 t + \varphi(t))
\]  

(4.4)

where \( \omega_0 \) is the angular carrier frequency and \( \varphi \) is the phase modulation. The received signal \( r(t) \) is split into two identical signals. Both signals are mixed with two local oscillator signals that have equal gain but one has a 90° phase delay compared to the other. The outputs of the mixer are passes through a low-pass filter (LPF) to pass the baseband signal and reject the higher frequency components. The outputs of the
LPF are the in-phase ($I$) and quadrature ($Q$) components. The received complex baseband signal is formed by combining the $I$ and $Q$ signals

$$y(t) = \cos(\varphi(t)) + j \sin(\varphi(t))$$

(4.5)

An equivalent representation to the received complex baseband signal after coherent demodulation is given by

$$y(t) = \sqrt{P_r} \exp(j[\varphi(t - t_0) - 2\pi f_c t_0]) + N_{out}(t)$$

(4.6)

where $P_r$ is the received signal power given by Equation 2.2 and $t_0$ is the delay corresponds to the target range. The term $-2\pi f_c t_0$ represents the received signal phase due to target motion. Equation 4.6 is used to create an artificial received complex baseband signal assuming that the process of transmitting the radar signal at the carrier frequency, $f_c$, receiving the reflected echo as well as converting the received signal to the $I$ and $Q$ signals are already performed.

4.4 Pulsed Radar Data Processing

Each range bin in the received data is represented by one complex number, which indicates the measured voltage and phase at a point in range. The first step after a burst of data has been received is to filter that data using the matched filter to maximize the SNR to increase the probability of detecting a target. The output of the matched filter is a sequence of complex samples of the corresponding received signal response over a range interval. The range interval starts at the radar blind range, $\frac{cT}{2}$, and continues to the maximum unambiguous range. The output of the matched filter is referred to as a range profile.
To gain the maximum benefits of the pulse radar, the data should be collected such that the Doppler processing can be applied. Therefore, radar data is collected over multiple pulses and from the same look direction to form 2-D data, where the first dimension represents the range (or fast time) and the second represents the pulses (or slow time). A 2-D data matrix after matched filtering for 128 pulses illuminating a target at 10 km away from the radar is shown in Figure 4.8. The plot shows the intensity of the radar returns over multiple pulses and range interval. The high intensity at 10 km represents the return from the target, which appears to be stationary over the illumination time.

![Cine CPI of Pulsed Radar Data](image)

Figure 4.8: Example of one CPI intensity plot

The aim of the data processing scheme developed here is to detect and track multiple targets. The following subsections describes the data processing algorithms and their application on the radar data.
4.4.1 Doppler Processing

The relative velocity between the target and the radar induces a phase shift in the received signal. This phase shift causes a change in the frequency of the received signal. The frequency different between the transmitted and received signal is known as the Doppler shift. The radar is normally stationary, therefore only moving targets will produces a Doppler shift in the returned signal. A pulsed radar uses the benefits of measuring the Doppler shift to detect moving targets in the middle of strong stationary clutter.

Every range profile represents a radar realization of the environment with a sampling rate equal to the $PRF$. The Doppler shifted can be measured by applying a spectrum estimation technique on the ensemble data, i.e. slow time axis. The spectrum estimation is achieved by using a bank of multiple narrowband filters each centered at frequency sample (Doppler bin). The use of the filter bank is mathematically equivalent to computing the Periodogram on the ensemble signal. The Periodogram is a classical spectrum estimation technique that can be easily computed using the Discrete Fourier Transform (DFT),

$$\hat{P}_{\text{per}}(e^{j\omega}) = \frac{1}{N} |X(e^{j\omega})|^2$$  \hspace{1cm} (4.7)

where $X(e^{j\omega})$ is the Discrete-Time Fourier Transform (DTFT) of the slow-time signal with length $N$. A range-Doppler map of a scenario generated using the radar simulation is shown in Figure 4.9. The data was generated using a total of 128 pulses in one CPI sampled at $PRF = 10\text{kHz}$. The high intensity returns at zero Doppler represents the backscatter from the stationary clutter. The high intensity returns
at 50 m/s corresponds to a moving target. The target response exhibits high peak sidelobes which can be reduced by windowing.

The maximum velocity that can be observed when using a radar operates at 10GHz with $PRF = 10\text{KHz}$ is $\pm \lambda PRF/4 = \pm 75\text{m/s}$. A Doppler ambiguity occurs when a target moves at a speed higher than 75m/s. Therefore, to avoid Doppler ambiguity the slow-time sampling rate must be

$$PRF = \frac{4v}{\lambda} \quad (4.8)$$

### 4.4.2 Radar Detection

The aim of the detection processor in the radar modeled developed in this thesis is to detect targets of interest in the presence of unwanted interference. Before the
radar can establish a target track, the received signal has to be processed to determine the presence of a target. The processing involves calculating a threshold, applying the threshold to filter the data, clustering neighboring plots and forming a measurement for the target. Figure 4.10 shows a block diagram of one approach from many approaches that can be used to perform radar target detection. This approach will be used since it is the most straightforward to implement. Detecting targets among background interference can be achieved using different signal processing techniques. A typical technique is used in this model and described in the following subsections.

4.4.2.1 2D-CFAR

A one-dimensional cell-averaging constant false alarm rate (CA-CFAR) is described in Section 2.2.3.4. Figure 2.23 and 2.24 illustrates performance evaluate to the (CA-CFAR) used in the radar model. A (CA-CFAR) detector with 16-reference cells produces 2 dB loss in its performance when compared to a perfect detector as shown in Figure 2.23. Here, a 16-reference cells are used to discriminate targets from
background interference in the range-doppler map but with a different configuration as shown in Figure 4.11.

![Two Dimensional CA-CFAR Window](image)

**Figure 4.11: Two Dimensional CA-CFAR Window**

Application of the 2D-CFAR on the range-doppler map is showing in Figure 4.12. The red dots are the scatters that exceeded the CFAR threshold and are referred to as *plots*. The threshold is an estimation of the interference power from the reference cells and a threshold multiplier is used to scale the detection threshold. The threshold multiplier is calculated using equation under the assumption that the interference has a Rayleigh distributed. The threshold multiplier is a function of the number of reference cells and the selected probability of false alarm. Although the targets considered in this model are point targets, target power separation over multiple range bins or multiple doppler bins may occur, which necessitates the use of guard cells in the CFAR window. The CFAR in the radar model is implemented in an independent function that requests the radar data in a form of range-doppler map, probability of
false alarm, number of reference and guard cells, and the output of this function is a binary image.

![Image of a radar screen with plots and colors representing detections.](image)

**Figure 4.12:** The output of the CA-CFAR with $P_{FA} = 10^{-6}$, using 16-reference cells as shown in Figure 4.11

### 4.4.2.2 Clustering

Clustering is the process of grouping one or more connected plots into a single target. This process runs under the assumption that all connected plots belong to a single target of interest. Clustering is a necessary element in any operating radar since real targets typically produce multiple plots. Clustering is used in the detection processor to cover the possibility of having multiple plots originated from the same target, which is possible when the antenna is scanning over the target and when the target moves over multiple range bins or multiple doppler bins.
A wide range of algorithms for data clustering are available in textbooks and literature. The algorithm implemented here uses both the position and velocity of the connected plots to form a cluster. The minimum number of plots in a cluster is 1 and there is no limit on the size of the cluster. The fact that a large cluster could be formed from a large clutter patch such as an island is ignored here. Another cluster is formed even if the Euclidian distance between the two plots is more than 1. All clusters are time independent, i.e. new clusters are generated for every range-doppler map and there is no association between clusters among different range-doppler maps. The clustering algorithm implemented here suffers from the effect of doppler ambiguity. A target at maximum observable velocity can appear at two different locations in the range-doppler map and hence the algorithm will generate two different clusters.

Figure 4.13 shows plots for two targets moving with speed of 50m/s at a distance 4000m and 4040m away from the radar. It is clear from the figure that the target energy was spread over multiple range and Doppler bins which is why the CA-CFAR produced two plots around each target position. Since these plots were adjacent, they were considered as a detection for the same target and they were grouped into a cluster. Plots with the same color code at a distance 4000m and 4040m indicates an independent cluster.

4.4.2.3 Measurements

For each cluster, a centroid mechanism is used to estimate the position of the target, which is referred to here as *measurements*. The method used to estimate the actual location of the target is based on weighted arithmetic mean:
where \( \bar{x} \) is the estimated target position, \( w_n \) and \( x_n \) are the plots amplitude and positions respectively. Equation 4.9 is applied to the clustered plots and it is implemented independently in range and in doppler. The measurements are the output of the detection processor and the input to the data association in the tracking processor. An estimated position, cyan dots, of the two target in Figure 4.13 was calculated using 4.9 and the result is shown in Figure 4.14.

**4.4.2.4 Binary Integration**

Since the CFAR algorithm does not eliminate all false alarms, a binary logic is used to remove the remaining false alarm. The simulated lognormal clutter has a direct impact on the performance of the CFAR, i.e. the CFAR will provide an actual
Figure 4.14: Estimated target position, the output of the detection processor

probability of false alarm higher than the specified value. One possible way is to create a measurements map for each radar channel, 2-channels in this model, and use 2 out of 2 logic to eliminate the false alarm and to conform the presence of the target. The probability of false alarm for a $M$ out of $N$ pulses is given by:

$$P_{FA} = \sum_{n=M}^{N} \binom{N}{n} P_{FA}^n (1 - P_{FA})^{(N-n)} \quad (4.10)$$

Equation 4.10 is simplified for a $N$ out of $N$ to be:

$$P_{FA} = P_{FA}^N \quad (4.11)$$

From Equation 4.11, the probability of false alarm for a 2 out of 2 binary integration in the detection processor is $10^{-12}$. The binary integration does not improve the detection performance but it helps eliminating the false alarms that are mostly
produced by the clutter. Figure 4.15 shows an example of a radar measurements before and after the binary integration.

Figure 4.15: Example of a radar measurements before (left) and after (right) the binary integration

4.4.3 Monopulse Processing

Monopulse processing is a single pulse lobing technique that is used to improve the accuracy of the target angular position measurements. In order to achieve a better estimate of the target angular position, a phase-comparison monopulse is used. The phased array antenna is split into two halves with a small separation between the two antennas. Both antennas produce a beam that is directed at the same angle and has a beamwidth that is double the full antenna beamwidth. The phased array monopulse radar system is modeled with 2 received channel for the 2 phased array antennas. The detection process described earlier is performed on each channel as well as the sum channel. Once a measurement is declared after the binary integration
process, the monopulse ratio is formed using the corresponding measurements from the 2 received channels. The ratio is calculated by dividing the difference channel measurements by the sum channel measurements as

$$e(\theta) = \frac{M_1 - M_2}{M_1 + M_2}$$

(4.12)

where \(M_1\) and \(M_2\) are the measurements in channel 1 and channel 2, respectively, corresponds to the measurement that passes the binary integration function. The phase difference between the two received measurements is computed via

$$e(\theta) = j \tan\left(\frac{\phi(\theta)}{2}\right)$$

(4.13)

Using the phase difference between the two measurements computed above, the measured angle of arrival \(\theta\) can be determined using 2.20.

### 4.4.4 Multitarget Tracking

The main objective of the tracking processor in the radar model is to establish and maintain a track on all of the detected targets. The processing involves track initiation, measurements to track association, updating the target track, and conforming and deleting tracks. The track processor block diagram is shown in Figure 4.16. The input to the tracking process is the measurements created by the detection processor and the output of the tracking processor is a targets track which can help the operator to observe the environment and make decisions regarding waveform selection and antenna beam pointing.

The tracking processor plays a major role in the development of an efficient radar resource allocation technique. Minimizing the time on target is a desirable radar
action that can create free resources, which can be used to maximize the number of targets in track and to perform surveillance functions. Hence, many authors have proposed a radar resource allocation techniques based on calculating the predicted estimation error to schedule tracking tasks in order to maintain a certain track quality. Therefore, high quality data association, track filtering and maintenance may improve the efficiency of a multifunction radar.

4.4.4.1 Track Initiation

The track initiation function is responsible for establishing candidate tracks for all the measurements received from the detection processor. It is a very important radar function because it determines the initial estimate of the target kinematic state from a few radar measurements. At the start, all the measurements created by the detection processor are used to establish the candidate tracks. After the first scan, measurements to track association is first performed, then new candidate tracks are created only for measurements that are not associated with any existing tracks.
A track is promoted from a candidate track to a valid track only after receiving a successive number of track updates during a specified number of scans. Track confirmation check is determined in the track deletion function.

4.4.4.2 Tracking Filter

The main objective of the tracking filter is to estimate the target kinematic state and to predicted future target position which used for measurements to track association. An improved estimate of the target kinematic state is obtained every time the track is updated. The received measurements are filtered to reduce the uncertainty caused by either the receiver noise and/or antenna beam position which is referred to as measurements noise.

The Kalman filter described in Subsection 2.2.4.2 is used in the tracking processor. A target motion model given in Subsection 2.2.4.1 is used to derive the filter equations. The filter uses the measurement assigned to the track to compute the Kalman gain which is then used estimate the target kinematic state using equation 2.51 and the estimated target state covariance. The second step is to compute the target predicted state and the predicted innovation covariance which is used by the data association function to assign measurements to tracks. In case of miss detection, the filter uses the previous predicted position to update the track and calculate the new predicted position. Figure 4.17 shows an example of an outbound target under a track. It can be seen in Figure 4.17 that the estimated target state is closer to the true target position than the measured position.
4.4.4.3 Data Association

Data association, in the context of target tracking, refers to the process of assigning measurements to tracks. All the received measurements from the detection processor are first fed to the data association algorithm before updating existed tracks or creating new tracks. Data association uses the target predicted position and innovation covariance to determine if the measurements belong to any tracks. The data association approach implemented here creates a gate around the target predicted position to reduce the number of measurements that must be considered. The normalized distance is calculated using equation 2.53 and then compared to a specified gate threshold $G$. Only measurements falling inside the gate are considered in the data association algorithm. An example of an ellipsoidal gate around the target predicted position is shown in Figure 4.18. The new measurement, black dot, is considered to be a valid measurement from the target since it falls inside the predicted
gate. This measurement is then used by the tracking filter to update the target state estimate.

![Example of an ellipsoidal gate](image)

**Figure 4.18: Example of an ellipsoidal gate**

The data association algorithm implemented in the tracking process is the Global Nearest Neighbour (GNN) described in Subsection 2.2.5.2. If more than one measurements fall inside the gate, the GNN will select the measurement that has the shortest normalized distance to the target predicted position. If multiple tracks competes for one measurements then again, the GNN will associate the measurement to the closest track based on the normalized distance between the measurement and the target predicted position. A more difficult situation, when multiple gates overlap containing multiple measurements. In this situation, a normalized distance matrix is formed and the minimum normalized distance define which measurements should be assigned the tracks. In the case when no measurement falls inside the gate, the filter
uses the previous target predicted position to estimate the target state. New tracks are created for the measurements that falls outside the specified gate.

4.4.4.4 Track Deletion and Conformation

The track deletion function is responsible for determining whether the candidate track is a true target track or it was established by a false target. The conformation is accomplished here by using the $M$ out of $N$ decision rule, where $M$ is the number of received track updates and $N$ is the number of scans or scheduled track looks. If the value of $M/N$ is below a specified value, the track deletion function will terminate the track. A similar method can be used to confirm the track, when the value of $M/N$ exceeds a specified value after a certain number of scans. The track predicted covariance can be used to conform the validity of the track. If the track predicted covariance exceeds a specified threshold, the track is then declared as a false track and it can be deleted.

The stability of the track relies on the reliability of the measurements to track association and on the performance of the detection processor. The possibility that the target will no longer exist after a period of time affects the track stability, which would happen when a target moves behind a clutter. This problem can be solved via track merging which is not considered in the model presented here.
Chapter 5: ADAPTIVE PARAMETERS SELECTION IN MULTIFUNCTION RADAR

This chapter presents a recursive form of the radar resource allocation problem by adapting the radar parameters every time the radar revisiting the target. The chapter begins by addressing the problem when a multifunction radar operates in track while scan (TWS) mode. It is shown that a multifunction radar operating in TWS mode only has many limitation. For example, tracks only updates when the radar finish a complete scan. Section 5.2 introduces a recursive approach to adaptively refine the radar parameters. The method is examined through simulated scenario consisting of multiple targets with different RCS configurations. Then, in Section 5.3, an earliest deadline first approach to adaptively pointing the radar beam is analyzed.

5.1 Multifunction Radar in Track While Scan Mode

The TWS mode is the easiest and widely implemented multifunction radar approach in which the system is designed to continually scans an area in a predefined scan pattern [13]. In a conventional TWS, the scan rate and scan pattern along with the radar parameters do not change without operator interaction. TWS mode represents a multifunction radar that has a resource management with fixed radar parameters and beam pointing scheme. An example of TWS scan pattern using an
electronically scanned antenna is shown in Figure 5.1. The antenna scans from 60° to −60° in discrete steps, one beamwidth (1°) apart, with 120 dwell in azimuth. The TWS mode can be performed without the use of electronically scanned antenna. In fact, it is often operates using mechanically scanned antenna.

![Figure 5.1: Radar look direction in azimuth for TWS mode](image)

Figure 5.1: Radar look direction in azimuth for TWS mode

Figure 5.2 shows some of the radar control parameters that could be modified for every CPI, as discussed in Table 2.3. These parameters are normally fixed when the multifunction radar is under TWS mode.

A typical TWS radar system can perform surveillance and track simultaneously. The TWS keeps searching with a constant scan rate and once a new target is detected, a track is established for that target. The target track is only updated once per scan when the antenna points the beam towards the target. Therefore, the system updates every track with constant update rate regardless the target maneuver and membership.

Track accuracy is poor when using TWS mode which leads to a high chance of loosing the tracks especially when tracks are initiated. This approach is suitable for air traffic control since high update rate is not a major requirement for this
application. Since the system scans at a fixed rate, it illuminates each area with fixed dwell time. This is another limitation in TWS system which leads to major degradation in detection performance, especially with low RCS targets. All of the mentioned limitations shows that the TWS system has an elementary radar resource management.

The model presented in Chapter 4 was used to demonstrated the limitations when a multifunction radar operates in TWS mode. The electronically scanned antenna was adjusted to have a scan pattern similar to the one shown in Figure 5.1. Three fluctuated point targets were generated according to Swerling case 2 model. Targets were traveling at different acceleration and bearing toward the radar. The radar parameters in Table 4.1 were used in this simulation.
Figure 5.3 shows the three targets with their true position as blue lines and the target state estimate as the purple lines. The red dot indicates the last positions of the targets. The radar system was able to detect and track all target successfully. This is due to the fact that the three targets were generated with high RCS, thus higher SNR and probability of detection \( P_D \). The root mean square (RMS) error for every target is shown in Figure 5.4. The RMS error is higher at the initialization stage but as the filter receives more measurement its estimation to the target true position becomes more accurate.

Another case is presented in Figure 5.5, where the three targets have low RCS which makes them harder to detect and track. Since the radar illuminates each target
with fixed dwell time, only one target has been tracked using TWS mode. Tentative tracks were initiated for the other two targets but they were terminated when no updated measurements were received. Track merging could be used to connect the multiple tentative tracks and associate them to the target. However, an increase in the number of pulses is a better option to prevent loosing the track. The analysis of Figure 5.3 and Figure 5.5 demonstrated the need to adaptively changing the radar parameters to accommodate the change in the environment.

Figure 5.5: Trajectories for low RCS targets and their state estimate

### 5.2 Track While Scan with Adaptive Parameters Selection

In this section, an adaptive parameters selection approach is developed for a multifunction radar. The aim of this section is to develop an approach that uses prior
knowledge about the target to refine the radar parameters every time the radar revisiting the target. As a secondary objective, the approach has to be computationally efficient and therefore it can be implemented in real-time.

The radar initial goal is to detect and track targets with minimum resource, time on targets, which allows more tasks to be conducted by the system. In order to optimize the radar resources it is necessary to formulate the radar resource allocation problem. The radar resource loading $l$ can be expressed in terms of dwell time $T_d$ and the revisit interval $T_s$

$$l = \frac{T_d}{T_s} \quad (5.1)$$

For a TWS system the resource loading is the dwell time divided by the scan time and is fixed. In a more adaptive system a high loading occurs at a longer dwell time and a short revisit time.

The primary goal is to minimize the dwell time, while achieving an acceptable SNR, for track maintenance, while simultaneously maximizing the track update time such that the radar resource loading is minimized. The dwell time is a function of the number of pulses $N_r$ in a CPI devoted to the target and the pulse repetition frequency $PRF$.

$$T_d = \frac{N_r}{PRF} \quad (5.2)$$

To minimize the dwell time, i.e. minimizing the system loading, less pulses need to be sent to illuminate the target or a high PRF must be used. The radar resource management problem becomes
\[ \min \quad T_d(N_r, PRF) \]
subject to \[ N_r \geq n_r, \]
\[ PRF \leq \frac{c}{2R_t} \]
(5.3)

where \( R_t \) is the target range and \( n_r \) is minimum number of pulses allowed. It is assumed here that only the number of pulses, pulsewidth, and PRF can be controlled every CPI, therefore an increase in SNR can only be accomplished through an increase in the number of pulses or the pulsewidth

\[
SNR = 10 \log \gamma + 10 \log N_r + 10 \log \tau
\]
(5.4)

where \( \gamma \) represents all of the radar parameters from the radar equation, including noise, except for \( N_r \) and \( \tau \). Since the goal is to minimize the number of pulses in a dwell, the pulsewidth is increased first then the number of pulses is computed accordingly. The estimated pulsewidth is given by

\[
\hat{\tau} = \frac{2\hat{R}_b}{c}
\]
(5.5)

where \( \hat{R}_b \) is the estimated blind range found by solving

\[
\hat{R}_b = \max\{\min\{R_t, R_u - R_t, r_{b_{\max}}\}, r_{b_{\min}}\}
\]
(5.6)

where \( R_t \) is the target range and \( R_u \) is the maximum unambiguous range. The \( r_{b_{\max}} \) and \( r_{b_{\min}} \) are the maximum and minimum blind ranges associated to the maximum and minimum allowable pulsewidth in the radar system. The maximum and minimum pulsewidth values are chosen such that their difference provides 12 dB increases in SNR, which is the amount of reduction caused when the target range increases twice.
Therefore it is assumed here that the minimum and maximum allowable pulsewidth are 1µs and 20µs respectively. It is essential to have a gap between the target range and the maximum unambiguous range so that the received target energy do not fall in the blind range of the second transmitted pulse.

Equation 5.3 is solved using a set of recursive equations for each parameter. A recursive estimate of the pulsewidth is computed as

\[ \tau = \tau + \alpha (\hat{\tau} - \tau) \]  

(5.7)

where \( \hat{\tau} \) is the estimated pulsewidth and \( \alpha \) is given by

\[ \alpha = \begin{cases} 
0 & K < 0 \\
1 & K > M \\
\frac{K^2}{\beta S} & 0 \leq K \leq M 
\end{cases} \]  

(5.8)

where \( K \) represents the number of times the target was detected, \( S \) is the number of scans or scheduled track looks and \( \beta \) is an acceptance threshold. A recursive estimate of the number of pulses can be computed in a similar manner

\[ 10 \log N_r = 10 \log N_r + \alpha ((SNR_d - SNR_m) - (10 \log \tau - 10 \log \hat{\tau})) \]  

(5.9)

where \( SNR_d \) and \( SNR_m \) are the desired and measured SNR in dB. To ensure that \( N_r \) is within the constraint set

\[ N_r = \max\{N_r, n_r\} \]  

(5.10)

The PRF is bounded by the maximum unambiguous range and hence the target range will be used to adjust the maximum unambiguous range. The estimated PRF is given by
\[ PRF = \frac{c}{2\hat{R}_u} \]  

where \( \hat{R}_u \) is the estimated maximum unambiguous range given by

\[ \hat{R}_u = R_t + \hat{R}_b \]  

where \( \hat{R}_b \) is giving by 5.6 and \( R_t \) is the target range. The recursive estimate of the PRF is

\[ PRF = PRF + \alpha(P\hat{RF} - PRF) \]  

The architecture for the adaptive parameters selection resource manager is shown in Figure 5.6. The resource manager receives the target location, velocity and SNR from the radar data processor and then calculates the waveform parameters and number of pulses for every target under track. The resource manager adjust the transmitted waveform only when the radar revisits the targets location. In Section 5.3, another radar parameter will be controlled, beam pointing, that will be function of the target update time. Therefore, the revisit time is not fixed and the antenna beam position will be directed at any position in time.

The above approach for adapting the radar parameters is examined against the two cases presented in Figure 5.3 and Figure 5.5. The low RCS targets situation is addressed first. Figure 5.7 shows the resulting tracks for all the three targets as the purple lines with their true position as blue lines. The use of the adaptive parameters selection enabled the radar system to detect and track all target successfully. This
Figure 5.6: An adaptive parameters selection radar resource management architecture.

is due to the fact that the radar system is more sensitive to the change in the environment when using prior knowledge about the targets. Thus, the system attention were different for each target.

The evolution of the radar controlled parameters (azimuth angle, number of pulses, Pulsewidth, and PRF) using the adaptive parameters approaches are shown in Figure 5.8. The desirable SNR was set to 25 dB. The SNR is increased first by using a waveform with longer pulsewidth. Once the pulsewidth is selected, the number of
Figure 5.7: Trajectories for low RCS targets and their state estimate using adaptive parameters selection

The resource manager calculates the pulsewidth and number of pulses needed to achieve the desirable SNR. The increase in pulsewidth was limited to 20\(\mu\)s, which could be higher depending on the system capability. If the pulsewidth reaches its limit before satisfying the desirable SNR, then the number of pulses will be increased. The minimum number of pulses was set to 14 pulses.

The figure shows that after the targets have been detected, the resource manager calculates the pulsewidth and number of pulses needed to achieve the desirable SNR. At the beginning, the pulsewidth increases partially to avoid increasing the blind range before the target is confirmed as a true target. Therefore, the desired SNR is achieved, during the initiation period, through an increase in the number of pulses.
This explains the results of number of pulses during the first 1500 CPI. Once the target are declared as a true target, the maximum pulsewidth is used and the number of pulses is decreased to reduce the system load. Target 1 and target 3 were declared as a true targets earlier than target 2, which explains the fast transition to the maximum pulsewidth. The PRF follows similar pattern as the pulsewidth. At the beginning, the PRF increases partially to avoid range ambiguity before the target is confirmed as a true targets. Once the targets are declared as a true target, the PRF evolves as a function of the target location only. It can be seen that the system starts to have almost stable behavior after 3000 CPI.
The resulting SNR for each low-RCS target when using the adaptive parameters approaches are shown in Figure 5.9. The blue line indicates the desired SNR at 25 dB. Initially, the SNR for each target is lower than the desired SNR and increases as the number of pulses and pulsewidth increases. The maximum SNR occurs at 5 s which is in the target confirmation period where the pulsewidth and number of pulses increases simultaneously. The SNR for target 2 decreases below the desired SNR around 23 s, which explains the increase in the number of pulses in Figure 5.8 around 3800 CPI. The method proposed in this thesis ensures that each target will converge around the desired SNR but can never reaches it, since the SNR is highly dynamic and depends on other variables beside pulsewidth and number of pulses.

![Figure 5.9: Evolution of targets SNR using adaptive parameters selection](image)

Another advantage of the adaptive parameters selection method is the reduction in the radar load allocation. The reduction in the radar load become significant when the targets under tracks have a high RCS i.e. easier to illuminate. In this case, the
number of pulses can be decreased and the desired SNR can be achieved through an increase in pulsewidth only. Figure 5.10 shows the evolution of the radar controlled parameters using the adaptive parameters approaches for high RCS targets. It can be seen that the number of pulses is always decreasing in this situation until it reaches the minimum limit of number of pulses. It can also be seen that the parameters for every target converges faster in this situation due to the fact that target confirmation is easier for high RCS targets.

Figure 5.10: Evolution of radar parameters using adaptive parameters selection for high RCS targets
Figure 5.11 presents the radar relative load using adaptive parameters selection method and TWS mode. The figure shows the radar load allocation using adaptive parameters selection, where the load is normalized by the radar load using TWS mode. The radar load allocation using TWS mode is always fixed and it is also normalized. The radar load allocation using adaptive parameters selection decreases as the number of pulses decreases and the PRF increases until around 10 s. At 10 s, the radar load start to become fixed as the number of pulses becomes 14 for each target and the PRF started to follow the target range. The effect in the radar load is not significant when only three targets are been tracked because the radar parameters are optimized only for 3 beam positions out of 120.

Figure 5.11: The radar relative load using adaptive parameters selection method and TWS mode for tracking 3 targets
To show a significant reduction in the radar load allocation, 50 targets were generated with high RCS. The result of the radar load allocations using adaptive parameters selection for tracking 50 targets is shown in Figure 5.12.

![Graph showing radar load allocation](image)

Figure 5.12: The radar relative load using adaptive parameters selection method and TWS mode for tracking 50 targets

### 5.3 Search and Track with Adaptive Parameters Selection

The beam agility provided by the phased array antenna enables the system to search for targets, and once a target is detected then a track dwell will be established for this target while continue to search for new targets to track. This mode can only operate using an electronically scanned antenna since its required rapid revisit to every target under track at different locations, therefore beam pointing can be arbitrary and a mechanically scanned antenna cannot provide that [13]. Search and track mode is a typical approach for modern multifunction radar systems since it
provides very accurate tracks as the radar acquire measurements update for every target when needed [13]. Figure 5.13 shows an example of the beam position for a radar system searching and tracking three targets. The red dots indicates a track dwells that are assigned to each target. It is clear from the figure that the update rate for the azimuths where the targets are present is higher than than for the angles where there is no target.

![Figure 5.13: Radar look direction in azimuth for search and track mode](image)

The system started by performing search pattern and then targets were detected from the first scan. Thus, tracks dwells were inserted in the search pattern at different location and time as shown in the figure. The duration of track dwells is based on the target SNR while the starting point of the track dwell is based on the target maneuvers and is computed using the target predication state covariance.

This form of resource allocation can only manage a limited number of targets and it is sometimes difficult to allocate resources to continue the surveillance task. To
demonstrate this limitation 70 targets were generated, each with a desired update interval of 120 ms. The tracking dwell length was obtained using the approach presented in Section 5.2. All targets were generated with low RCS in order to stress the system. The resulting beam pointing is shown in Figure 5.14. Initially, the radar operates in search mode, the blue markers, and during the first scan several targets are detected. Before the first scan has been completed there is a requirement to perform track update dwells and, because of the number of targets, this mode of operation quickly dominates the radar time line. From the 140 CPI onwards no time is scheduled to search. The analysis of Figure 5.14 suggests that a rule based approach is insufficient as a resource manager in a multifunction radar.

Figure 5.14: Radar look direction in azimuth for search and track mode in an overloaded situation
A radar system with an electronically scanned antenna is an agile system that has the ability to execute tasks that were carried out by a group of dedicated radars. This class of radar, multifunction radar (MFR), requires a control function, resource manager, to balance the usage of its finite resources among the multiple functions. Hence, the multifunction radar performance is limited by the resource manager intelligent behavior to allocate the system resources. Therefore, the multifunction radar capabilities can only be achieved through a cognitive radar resource management approach.

It has been identified in the literature review the need to investigate the potential for cognition to improve the radar resource management techniques. This thesis addressed the challenge of using cognitive radar resource management to provide the attention element of cognition for radar systems.

To support the investigation of a cognitive radar resource management techniques, a model of a multifunction phased array radar was developed. The radar resource management problem was formulated and a recursive form of the radar resource allocation problem was developed. The prior knowledge about the target was used to refine the radar parameters every time the radar revisiting the target. The aim was to minimize the dwell time while achieving an acceptable SNR for track maintenance.
and while simultaneously maximizing the track update time. The main advantage of this approach is the ability to reduce the radar load allocation while maintaining a desirable SNR. Therefore, the adaptive parameters selection approach provide better utilization to the radar resources.

It was shown that the radar became more sensitive to the change in the environment when using prior knowledge about the target. The use of the prior knowledge about the target is equivalent to the perception-action component of the cognitive model in Figure 3.6.

To demonstrate the scheduling challenges in a multifunction radar, an earliest deadline first approach was implemented to schedule track dwells when the tracks update time reaches a pre-defined value. It was shown that this approach of resource allocation can only manage a limited number of targets and it is sometimes difficult to allocate resources to continue the surveillance task.

This research extends our knowledge of linking cognition to radar resource management. These findings can serve as a base for future studies that could involves investigating the rule of memory to perform anticipation. This involve determining whether a heuristic approach with a long-term memory provide a learning methods to the radar resource manager. Another possible area of future research would be to determine a lower bound to the number of pulses to include the minimum separation between the target and the clutter.
Bibliography


