ABSTRACT

AUTOMATIC TARGET DETECTION VIA MULTISPECTRAL UWB OFDM RADAR IMAGING

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This research proposes using the multispectral radar imaging methodology for target detection in complicated scenarios. The investigation proposes to extend this concept to ultra-wideband radar by means of employing multi-carrier waveforms based upon Orthogonal Frequency Division Multiplexing (OFDM) modulation. Individual sub-bands of an OFDM waveform can be processed separately to yield range and cross-range reconstruction of a target scene containing both useful targets and clutter. An image based automatic target recognition algorithm has been developed to provide decision making within each sub-band. Target detection in resultant images will be performed and contrasted with the detection performance of a traditional fixed-waveform Synthetic Aperture Radar system. The adaptive removal of clutter from these selected images will result in a system that looks to improve detection performance.
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Acknowledgments

This thesis would not have been possible without the help of numerous individuals. First I would like to thank my advisor Dr. Dmitriy Garmatyuk who provided invaluable encouragement and help when I needed it. The research meetings in which we discussed the problem and possible solutions and the advice he gave to me during my research and future plans was invaluable.

I would like to thank my committee members Dr. Donald Ucci and Dr. Chi-Hao Cheng who were generous enough to read and evaluate my thesis. Their comments and guidance remained an invaluable source in furthering my research. Lastly, I would like to thank my family and friends who patiently put up with my long hours of work. Their patience and advice was greatly appreciated.
Chapter 1

Introduction

1.1 Background

Radar was originally an acronym for RA dio De tection And Ranging, however the acronym has now become a common term used to classify a group of systems that accomplish detection and ranging. Currently, in the late 1970's to the present, the rapid development of digital hardware has accelerated radar systems by allowing for the development of rapid signal processing, higher power transmission capabilities, and advance target detection techniques. Radar is still the dominant technology used for detection and surveillance and has been applied to other areas such as civilian use, radar guns, and weather[1].

The focus of this thesis is to look at a proposed combination of two different concepts, which include Synthetic Aperture Radar (SAR) and Multi-Spectral Imaging (MSI) to form a coherent system for target detection. SAR and MSI each have properties that complement each other and therefore can support a novel system for classifying targets. The motivation behind the research is to provide a unified system capable of detecting targets within a high clutter environment.

SAR is an airborne or space borne imaging based radar first conceived in 1951 by Carl A. Wiley [2]. This type of radar provides its user with detailed images formed from the received responses of the radio frequency waves of an observed scene. The waves reflect off objects and materials present within the scene and the reflectivity is returned to the operator where an image is formed. SAR is able to provide another way to retrieve information in the form of images in addition to using conventional optical methods.

The term synthetic is based upon the implementation of the antenna used to transmit and receive. The resolution of the image formed is dependent on the length of the antenna of the radar which in turn is responsible for the cross range resolution of the image. Normally, for space and airborne SAR systems, the range away from the target scene of interest is fairly large. Therefore, to achieve a very fine resolution a large antenna is required. Having a large physical antenna is not practical and could not be implemented on Unmanned Aerial Vehicles (UAV) or similar sized flying systems; therefore, a synthetic antenna or aperture is
used. The synthetic antenna is formed from the SAR system, by following a set flight path during which the system emits pulses directed towards the target scene. The radar system combines the information received from the return echoes of the pulses coherently to form a very large synthetic antenna.

SAR has some major advantages over other methods used to extract information from a observed scene, including the ability to capture images during the night as well as the day. The signal pulses sent out provide their own illumination due to measuring the reflectivity of the objects. An optical image taken of the same scene at night will appear dark since it cannot provide its own illumination. Another benefit of a SAR system is that it can be used in different weather conditions such as rain because the transmitted signal suffers little attenuation and, therefore, is still able to form images [1].

MSI is, the other focus of interest that pertains to this research. MSI is an imaging process which allows for the capturing of a large amount of information by observing the scene at different frequency bands within the electromagnetic spectrum. The objects within a scene, such as trees, reflect different amounts of a signal depending upon the frequency used [3]. MSI takes snapshots of the target scene of interest, in which images are spaced by a predefined wavelength. Once the images are captured, analysis of the images can be applied by using a number of algorithms such as those found in [4, 5, 6].

MSI looks for targets via their spectral signature which is graphed over the frequency bands are used to form the images. The spectral data can be matched to targets from a spectral library in order to identify whether or not a target is present, or additional operations can be performed such as anomaly detection [4] to alienate pixels which do not belong to the background and, therefore, can be classified as areas of interest.

This research delves in the question of incorporating the features of multi-spectral imaging into SAR, as well as the development and implementation of an algorithm for detection of the presence of targets. The question of combining the two will be solved by using Ultra-Wide-Band (UWB) SAR with Orthogonal Frequency Division Multiplexing (OFDM) to divide the bandwidth into multiple sub-bands. The sub-bands will then be processed separately to yield range and cross range reconstructed images. In radar, UWB OFDM signaling and system architecture has not been explored as much the OFDM coding structure was first used to create a multi-frequency complementary phase-coded radar signal concept [7, 8]. Incorporating the two technologies would result in a UWB SAR system that is capable of forming multiple pictures of the observed scene for target analysis.

The bandwidth used within the SAR will be separated into sub-bands of various lengths; this will allow the receiver to maintain a database of images received from the observed scene. The assumption that the clutter within the scene is frequency dependent implies the sub-images formed contain different strengths of clutter returns. A target of interest would stand out in a sub-image that contains a smaller clutter response, rather than a single image comprised of using the full bandwidth, which would contain clutter responses from all frequencies.
1.2 Problem Statement

In summary the problem being researched and solved is the successful detection of targets within a clutter environment such as objects buried within a foliage environment. This is a problem of high interest [9, 10]. The use of SAR and MSI will be used to exploit the frequency dependence of clutter within an observed scene.

1.3 Goals

Below we delineate the questions and topics discussed within this thesis. The goals stated below will show the benefit, novelty, and understanding of the topic being researched. We will:

- show and demonstrate that incorporating MIS techniques into UWB SAR will lead to a viable target detection system.
- develop an algorithm to be used for detection of targets buried in clutter.
- provide detection results with comparison of full image bandwidth vs. sub-images.
- provide results in environments of known and unknown clutter

1.4 Overview

The approach used within this thesis will be based upon computer simulation and modeling of clutter environments. The remainder of the thesis is organized as follows. Chapter 2 will provide the background information on detection theory. Chapter 3 will discuss the SAR image reconstruction algorithm and the environment variables. Chapter 4 will detail the different algorithms researched for target detection. Chapter 5 will focus on the novel automatic target detection algorithm implemented for targets within clutter. Chapter 6 will demonstrate the results from the case studies of targets in known and unknown clutter. Lastly, the conclusion of the research and future work will be discussed in chapter 7 and chapter 8 respectively.
Chapter 2

Detection Theory Review

This chapter provides the reader with information regarding detection and expands into other methodologies researched. The areas researched include statistical analysis, template matching, and mathematical operators such as the gradient [11, 12]. The understanding of each topic provides the reader with the necessary information to understand the development of detection algorithms presented in the later chapters.

2.1 Statistical Detection Theory

The section outlines the ground work of the statistical approach by looking at a simple example, as well as defining terms for the reader’s understanding. Detection with the use of statistical analysis is often used to distinguish between signals within noise or clutter through the use of hypothesis based testing. A more in-depth discussion on the topic can be found in the literature [11, 12]. The statistical approach used in this thesis is based upon the commonly used philosophy of the Neyman-Pearson (NP) theorem. The NP approach is based upon two competing hypothesis defined as follows; $H_0$ is the null hypothesis and $H_1$ is the alternate hypothesis.

\[ H_0 : \text{Clutter Only hypothesis} \quad (2.1) \]
\[ H_1 : \text{Signal plus Clutter hypothesis} . \quad (2.2) \]

The radar, when observing a scene of interest, first acquires information through the use of training pulses directed towards the ground. Let us define the response of the training pulses in terms of a vector \( x \), where \( x \) contains the responses from the received echoes and is defined as,

\[ x = [x(0), x(1), x(2), \ldots x(n)] . \quad (2.3) \]
The values within Eq. 2.3 can either belong to the clutter or to the signal of interest. Deciding whether or not an observation is from a signal or target depends heavily on our two hypotheses. An example demonstrates the NP approach. Suppose we observe a scene wherein the response can belong to either one of the following Probability Density Functions (PDF).

**Example 1**

\[
H_0 = \mathcal{N}(0, 1), \text{ with } \mu = 0 \text{ and } \sigma = 1 \tag{2.4}
\]
\[
H_1 = \mathcal{N}(1, 1), \text{ with } \mu = 1 \text{ and } \sigma = 1. \tag{2.5}
\]

Where \( \mathcal{N}(\mu, \sigma) \) is a normal distribution with mean \( \mu \) and standard deviation \( \sigma \). Figure 2.1 represents the above normally distributed PDF’s.

![Figure 2.1: Two Competing PDF’s](image)

Every observation must be characterized as one of the defined PDF’s by making use of a decision threshold. Figure 2.1 has set the threshold at 1/2 (via the dashed line). We decide an observation is part of \( \mathcal{N}(1, 1) \) if the value received is greater than or equal to 1/2; otherwise, we decide the value belongs to \( \mathcal{N}(0, 1) \).

Notice, however, that two types of errors can be made. The right shaded portion of Fig. 2.1 decides an observation, \( x[0] \), belongs to \( H_1 \) when it actually belongs to \( H_0 \); this results in a false alarm or (deciding a target or signal is present when it actually is not). The left shaded portion of Fig. 2.1 decides the observation belongs to \( H_0 \) when it belongs to \( H_1 \),
(this is known as a missed detection or deciding a target is not present when it actually is present).

The two types of errors cannot be reduced together; instead, the NP approach commonly constrains the false alarm rate to a fixed value $\alpha$, while trying to minimize the probability of a missed detection. Equivalently, this is the same as maximizing the probability of detection for a given false alarm rate.

The NP approach allows for the development of detectors that take into consideration the PDF models of the data. The detectors that have been researched and implemented are the Likelihood Ratio Test (LRT) and the Generalized Likelihood Ratio Test (GLRT) [11]. The description of each of the detectors is as follows.

The LRT is described in Eq. 2.6 and is implemented when all parameters of the underlying PDF are known. The parameters include but are not limited to mean and variance.

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

The variable $x$ is the vector of observation values called the test statistic. The test statistic is put into the PDF’s of the null and alternative hypothesis in Eq. 2.6, which produces a ratio and the decision is based on the threshold $\gamma$. The LRT assumes that the PDF’s for the clutter and target are fully known and, therefore, an optimal detector can be designed. The threshold $\gamma$ is then found from Eq. 2.7, which constrains the false alarm rate: $P_{fa}$

$$P_{fa} = \int_{\gamma}^{\infty} \rho(x; H_0)dx = \alpha.$$ (2.7)

A more realistic scenario, and one that is more relevant to the research, is that some parameter of the clutter or target PDF is unknown, such as the mean. This problem now relies on estimating the unknown parameters and is implemented by modifying the LRT to make use of estimated parameters. The new detector is the GLRT with the definition defined as follows.

$$L_G(x) = \frac{\rho(x; \hat{\theta}, H_1)}{\rho(x; \hat{\theta}, H_0)} > \gamma.$$ (2.8)

Here, $\hat{\theta}$ represents the estimate of the unknown parameter. Since the parameters are estimates, there is no guarantee that the designed detector is optimal; however they do provide reasonable performance.

In summary the NP Theorem allows for the implementation of a statistical detector that takes into account the probability distribution of the clutter and signal classes through the use of hypothesis based testing. The design of a detector is not a simple task and some aspects include deciding upon the best model for the particular situation. A detector that is designed with a particular PDF would not be adaptive and, therefore, would not be suitable
for all scenarios. The research looks at specific scenarios and employs detectors designed for those situations. The following sections are a review of the different techniques used for PDF modeling.

## 2.2 Parametric and Non-Parametric

The two hypothesis, $H_0$ and $H_1$, depend upon the underlying PDF that is chosen as the clutter model. Two different approaches can be taken when developing a model for the clutter, namely either a parametric or non-parametric approach. The former makes assumptions about the data fitting a particular PDF, while the latter makes no assumptions as to what PDF best describes the clutter [13].

Since parametric approach assumes a particular distribution and then estimates the parameters for the PDF, it becomes nonadaptive when dealing with clutter from a variety of sources such as foliage, ocean, or snow, since those clutter returns might better fit a different PDF model.

The non-parametric approach requires the estimation of a particular PDF, as well as the parameters of interest. Again, if we assume the radar first observes a scene of interest then we can use the response vector from Eq. 2.3 to determine the underlying PDF and its parameters. Both parametric and non-parametric approaches are used within the scope of this thesis to gather detection results.

### 2.2.1 PDF Estimation

Assuming that the distribution of the clutter in which a target resides is unknown, then estimation techniques must be employed to find a suitable model. Listed below are two common methods used in this regard. The discussion below focuses on the technique, implementation and the strengths as well as the weaknesses.

**Histogram PDF Estimation**

A basic and simple method to implement, this approach relies on using a histogram to try and fit a model to the data. Stated earlier, the radar would send out transmitted signals to be used as training pulses. The responses from the received signal are stored and used in a histogram plot. The spacing between bins in the histogram is based upon Freeman-Diaconis rule (FD) in Eq. 2.9, where $IQR$ is the interquartile range.

$$FD = 2(IQR) \times \text{length(data)}^{-\frac{1}{3}}. \quad (2.9)$$

Using Eq. 2.9, the data can be plotted and different PDFs can be fitted to the data. Once the PDF’s are fitted, other measures can be used to evaluate the model; such methods include
Minimum Mean Square Error (MMSE) or Least Squares (LS). The following illustrates this concept with data fit with Normal, Log-Normal, and Weibull distributions.

![Histogram of response received from radar](image)

Figure 2.2: Histogram of response received from radar

![Histogram with fitted PDF’s](image)

Figure 2.3: Histogram with fitted PDF’s

Once a type of model has been decided, the parameters of its PDF can be estimated using the histogram. A problem with this approach is the determination of the appropriate spacing and number of bins used to construct the histogram. Having a small number of bins will make the data blocky, where too many bins results in loss of information. These disadvantages are due to the discrete nature of the histogram.
Kernel Density Estimation

The other method discussed in this research relies on a kernel for the estimation and produces a smooth estimate of the PDF for the data under consideration. A popular choice for a kernel is the Gaussian Kernel, the estimation process is defined in Eq. 2.10.

\[
G_k = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right).
\]  

(2.10)

Where \( n \) is the number of data points and \( h \) is the bandwidth that acts as a free parameter the user can choose, \( X_i \) are independent and identically distributed (i.i.d.) data, and \( K \) is the kernel being used to estimate the data. Depending on the suspected underlying PDF the choice of \( h \) can depend upon rules developed for a specific PDF. The fit of a kernel estimate can be evaluated using MMSE or LS. Figure 2.4 gives an example of kernel estimation for an estimation of a Gaussian distribution.

![Kernel Estimation of PDF](image)

Figure 2.4: Kernel Density Estimation of Gaussian Distribution

The method provides a smooth estimate of the PDF. A disadvantage of kernel estimation is that it depends on the choice of the bandwidth parameter. Too small a value for the bandwidth results in under smoothing while too large a value results in over smoothing.

Having discussed two methods for non parametric estimation, the next step involves estimating the parameters to be used with the PDF model and is discussed in the next section.
2.2.2 Parameter Estimation

Two groups exist for statistical inference, the frequentest approach and the Bayesian approach. The frequentest approach has the parameters remaining deterministic while the Bayesian approach as the parameters being non deterministic.

**Maximum Likelihood Estimators**

Parameters of a PDF include the mean or variance and these parameters can be estimated from the data retrieved from the radar. A common approach to parameter estimation is the use of an MLE. An example of MLE follows in which the PDF under consideration is log-normal. The parameters, $\sigma$ and $\mu$, are estimated by making use of the Eq. 2.11 and 2.12 where $n$ is the number of data points and $i$ is the current data point in the vector from Eq. 2.3.

\[
\hat{\mu} = \frac{1}{n} \sum_{i} \ln x_i, \quad (2.11)
\]
\[
\hat{\sigma} = \frac{1}{n} \sum_{i} (\ln x_i - \hat{\mu})^2. \quad (2.12)
\]

**Bayesian Estimation**

The use of Bayesian estimation examines the parameters of the proposed PDF as non-deterministic, meaning the parameters are considered to be a random process. The process uses Bayes Theorem which is stated in Eq. 2.13, where $P(x)$ is the a priori distribution and $P(x \mid y)$ is the a posterior distribution:

\[
P(x \mid y) = \frac{P(y \mid x)P(x)}{P(y)}. \quad (2.13)
\]

Treating the parameters as random processes allows for the consideration that the parameters can fluctuate with respect to time and space.

Provided that we have a model for the PDF along with the estimated parameters, the next step is to determine how good a fit is the chosen mode. We use the observed data to do this evaluation. Common algorithms include LS and statistical tests such as Anderson-Darling.
2.2.3 Goodness Of Fit Tests

A goodness of fit test will provide the user with information regarding how well the chosen model fits the observed data. The section below briefly examines two common approaches, one dealing with the estimated and observed data while the other relies on a statistical hypothesis based approach.

Least Squares

LS is a common method for curve fitting. Let us denote an observed data set \( y \) and an estimated data set (based upon the observed data) as \( z \) and define both as follows:

\[
y = [y(0), y(1), y(2),...y(n)] \tag{2.14}
\]

then

\[
z = [z(0), z(1), z(2),...z(n)] \tag{2.15}
\]

We then use the LS method on the above vectors by subtracting data points to compute the residuals, which we define as \( r \), between the observed and estimated data sets. The residuals are then squared and summed together where the best fit minimizes the resulting value, i.e.,

\[
LS = Min \sum_{i}^{n} [y_{i} - x_{i}]^{2} . \tag{2.16}
\]

Anderson-Darling

This type of test is performed on a observed data set, to tell whether a sample of data is unlikely to be a member of the assumed distribution [14]. The two competing hypothesis for the test are as follows:

\[
H_{0} : \text{Data follows a specific distribution} \tag{2.17}
\]

\[
H_{1} : \text{Data does not follow specific distribution} . \tag{2.18}
\]

The test statistic that is used is only known for a small collection of PDFs, such as normal, log-normal, Weibull, and Log-Logistic. The test is defined as follows:
\[ A^2 = -N - \frac{1}{n} \sum_{i=1}^{n} (2i - 1) \ln W_i + \ln 1 - W_{n-i+1} \]. \hspace{1cm} (2.19)

The parameter, \( n \), used in the test statistic is the sample population and \( W \) is the cumulative distribution function of the distribution under consideration. After the test statistic is computed, it is then compared to a significant value \( \alpha \) and, if the test statistic is greater than the critical value, it will reject the null hypothesis.

### 2.3 Template Matching Review

Template matching is the process of taking an image of an object for which we are searching and looking for that object within another image. Let us denote a template \( T \) and the desired image as \( I \); then, we proceed by taking the template and overlay it on top of every point within \( I \). At every position a value is computed based upon a predefined algorithm and the end results is a matrix of values that can then be used to tell whether the object resides in the searched image.

The method used within this thesis is called Normalized Cross Correlation (NCC). The template is convolved with the image to produce a new image where each location in the new image is filled with a value between 0 and 1. The closer to 1 a value is then the more likely that the algorithm has found the object. The normalized cross correlation is computed in the spatial domain and the formula is defined as follows.

\[
\gamma(u, v) = \frac{\sum_{x,y} [f(x, y) - \bar{f}_{u,v}] [t(x - u, y - v) - \bar{t}]}{\sqrt{\sum_{x,y} [f(x, y) - \bar{f}_{u,v}]^2 \sum_{x,y} [t(x - u, y - v) - \bar{t}]^2}}. \hspace{1cm} (2.20)
\]

Here, \( f \) is the image under consideration, \( t \) is the template, \( x \) and \( y \) correspond to the spatial domain, and \( u, v \) are the current positions in the \( x \) and \( y \) directions. The resulting image, \( \gamma \), will contain the normalized coefficients within the image. More information on template matching is found in the literature [15].

### 2.4 Vector Field Operations Review

This section gives a brief review of the gradient and divergence operations being performed on a vector field. The two operations in question allow us to transform between scalar and vector fields. A scalar field has a numeric value at every position within the field, while a vector field gives a magnitude and direction at any given point.
2.4.1 Gradient

The gradient operation takes a scalar field and transforms it into a vector field. Let us denote a two-dimensional (2D) scalar field, \( S(x, y) \), where \( S \) is given in Eq. 2.21 this is known as Himmelblau’s Function:

**Example 2**

\[
S = (x^2 + y - 11)^2 + (x + y^2 - 7)^2.
\] (2.21)

Then, the gradient operation on a scalar is given in Eq. 2.22.

\[
\nabla \vec{F} = \left( \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right)
\] (2.22)

will generate a vector field \( \vec{F} \) where \( \vec{F} \) now contains vector components that show how the scalar field changes with respect to direction or steepness. (See Fig. 2.5 for a graphical version of the process).

![Function S](image1)

![Gradient of S](image2)

(a) Function S  (b) Gradient of S

Figure 2.5: The Himmelblau function and the resulting gradient vector field

2.4.2 Divergence

The divergence operation is performed on a vector field and will return a scalar field as shown in Eq. 2.23.

\[
\nabla \cdot \vec{F} = \left( \frac{\partial f}{\partial x} + \frac{\partial f}{\partial y} \right)
\] (2.23)
The divergence will measure the compressibility at every point within the image. The compressibility tells us if the vectors point towards or away from a particular position within the image. Higher values act as sources, while lower values are considered sinks. (See Fig. 2.6 a graphical version of the process)

![Divergence of Vector Field F](image)

Figure 2.6: Divergence of the Himmelblau function
Chapter 3

Synthetic Aperture Radar Reconstruction

This chapter details the process of reconstructing a generic Stripmap (See Fig. 3.1) SAR image to be used in the simulation of clutter environments. The reconstruction of a target scene is based upon the efficient Range-Doppler (RD) approach being adopted in [16]. The chapter overviews the transmit signal, received signal, and clutter models along with the parameters and assumptions of the target scenario.

Figure 3.1: Stripmap SAR geometry
3.1 SAR Image Formation

The RD algorithm is a commonly used set of approaches that is efficient for processing SAR data. The RD algorithm offers processing of range and cross-range separately. Our implementation follows the block diagram structure of Fig. 3.2 along with additional steps for producing an image for a simulated clutter environment.

\[ S(t) = \begin{cases} A \cos(\omega t), & 0 \leq t \leq T \\ 0, & \text{otherwise} \end{cases} \] (3.1)

The flow chart is covered in the proceeding sections and examines the reconstruction, and modeling of SAR images to be used for clutter environments.

3.1.1 Signal Models

The targets within the scene are point targets which radiate the transmitted pulse back toward the receiver. Modeling the transmitted signal and received signal from a target’s echo are detailed in this section. The transmitted signal sent by the radar is a Radio Frequency (RF) pulse described as follows, where \( A \) is the signal amplitude and \( T \) is the pulse duration:

\[ S(t) = \begin{cases} A \cos(\omega t), & 0 \leq t \leq T \\ 0, & \text{otherwise} \end{cases} \] (3.1)

The proposed radar concept will make use of OFDM (See Fig. 3.3 as a way of providing image reconstruction using various signal bandwidths. OFDM is a technique used to send out multiple signals simultaneously. The above signal model allows for the simplification of an OFDM implementation. The orthogonal property allows for efficient use of the bandwidth.

Let us consider a baseband OFDM signal using \( N \) sub-bands centered at \( kf_1 \) sub-carrier frequencies \((k=1, 2N)\), where \( f_1 = F_s/(2N) \) and \( F_s \) is the sampling frequency of a Digital-to-Analog (D/A) converter in an OFDM radar transmitter. The signal will have a discrete spectrum with \( 2N+1 \) samples. The resultant time-domain vector will have the same number of points.
Let our baseband SAR signal be such an UWB OFDM pulse. Let $\tilde{s}$ and $\tilde{S}$ be the vectors representing the original UWB OFDM signal with $2N+1$ samples in time and in frequency domains, respectively. Then, $\tilde{S}$ can be written as

$$\tilde{S} = [0 \ S(1) \ S(2) \ldots S(N) \ S(N) \ S(N-1) \ldots S(1)] , \quad (3.2)$$

where $S(k)$ are real-valued samples of the one-sided spectrum $X$:

$$S(k) = \sum_{n=1}^{2N+1} s(n) \cdot e^{-j2\pi kn \frac{k}{2N+1}} , \quad k = 1 \ldots N , \quad (3.3)$$

where $s(n)$ are samples of the time-domain vector $\tilde{s}$.

Therefore, after the operation of Inverse Discrete Fourier Transform (IDFT) is applied to the vector $\tilde{S}$ and passing the result through a D/A converter, we will obtain a linear combination of RF pulses centered at $kf_1$. Thus, we can approach the problem of SAR signal processing by considering a number of sub-bands each containing an RF pulse spectrum at different center frequencies [17].

![Figure 3.3: OFDM signal model implementation](image)

Now let us consider the modeling of the received signal as returned from the point targets. The received signal returned from the observed scene is given as follows, where the parameters are defined in the supplied table.
The terms summarized in Table 3.1 provide the parameters with which we are concerned when modeling responses from targets. The complete response is given in Eq. 3.4:

\[
S_r(t) = \sum_{k=0}^{M} P_{ant}(r_k, \theta_k) \cdot A e^{j\omega(t - \frac{2r_k}{c + v_{ant}})} \cdot e^{j\Phi_k} \cdot \sigma_k(\theta) + \sigma_c + N .
\] (3.4)

One component that needs further elaboration is the power received by the radar, which is based upon the dipole antenna. The received power depends upon the magnetic and electric fields, where the power is defined in Eq. 3.5.

\[
P = \frac{1}{2} * \text{Re} [\vec{E} \times \vec{H}] .
\] (3.5)

where \(\vec{E}\) and \(\vec{H}\) are the electric and magnetic fields, respectively, given by.

\[
\vec{H} = j \frac{I_0 e^{-j\beta r}}{2\pi r} \left( \frac{\cos(\beta L \cos \theta) - \cos(\beta L)}{\sin(\theta)} \right),
\] (3.6)

and

\[
\vec{E} = \eta \vec{a}_p H_\theta .
\] (3.7)

Where \(I_0\) is the current, \(L\) is the length of the antenna, \(\beta\) is the propagation constant, and \(\eta\) is the impedance of the medium. Therefore, using the definitions presented above, we observe that the power returned to the receiver depends upon the distance and angle of observation the radar is to the target. The remaining reconstruction terms in Table 3.1 and their importance in modeling are each explained in the following reconstruction sections.
3.1.2 Range Reconstruction

The process of reconstructing a target scene in the range or fast time direction starts with the received signals from the targets located within the scene. The received signal from the targets depends on the angle and range of the radar in relation to its targets. This will be followed by performing range compression by making use of a matched filter operation to complete the range reconstruction.

Let \( N \) be the number of positions in which our radar will transmit pulses toward the ground. The positions along the range direction will consist of a vector with \( Q \) number of points as seen in Fig. 3.4. The vectors will be filled with the return power from the targets. The values of \( r_k \) and \( \theta_k \) can be determined from the following relationships in Eq. 3.8 and 3.9 between the current radar range position \( X_c \) and targets position \( X_k, Y_k \), where \( X_k \) is the range position and \( Y_k \) is the cross range position.

\[
\begin{align*}
    r_k &= \sqrt{(X_k - X_c)^2 + Y_k^2} \\
    \theta_k &= \arccos\left(\frac{r_k^2 + X_c^2 - R_k^2}{2r_kX_c}\right).
\end{align*}
\]

The position of each target’s signal within each vector is based upon the sampling frequency, \( F_s \), and the range from the target, \( r_k \), where \( k \) is the current position of the radar from the \( k^{th} \) target.

\[
    \text{ResponsePosition} = \frac{2r_kF_s}{C}.
\]

Using Eq. 3.10 we can fill each vector with each target’s received signal response from Eq. 3.4. Another important parameter in range reconstruction is the range resolution, \( \Delta r \) which relates to the radar’s ability to resolve nearby targets. The range resolution is stated as follows:
\[ \Delta r = \frac{c}{2\beta}, \quad (3.11) \]

where \( c \) is the speed of light and \( \beta \) is the bandwidth. Using the above information, we can store vectors at each position of the radar for each individual point target located within the scene. The return signal responses for each target are summed together at each position. Once the vector generation is complete, we then take each vector and add Additive White Gaussian Noise (AWGN) and then perform match filtering of our original transmit signal with the received signal. Matched filtering is used as the range compression which increases Signal-to-Noise (S/N) level. The matched filtering greatly improves the response (See Fig. 3.5).

![Figure 3.5: Matched Filtering Process of return signal from a point target](image)

The results from the range reconstruction process are displayed in Fig 3.6 for single and multiple point targets.

### 3.1.3 Cross-Range Reconstruction

Cross range reconstruction or slow time resolution is accomplished through the phase history of each of the targets. The phase history is a record of the phase delay as a function of the \( x \)-axis position of the radar antenna. The assumption of having complete knowledge of the phase history in our signal model is not a characteristic of a true OFDM multicarrier signal. OFDM requires a different approach to estimate the phase history; such an approach is presented and described in the literature [17]. The assumption within this paper simplifies the reconstruction of a SAR image in the cross range.

Since this is a computer based simulation, the phase history at each position can be calculated by the use of \( r_k \), where the phase history is given by:
\[ \text{Phase History} = e^{-j\omega_0 \frac{2\sqrt{(X_k - X_c)^2 + Y_k^2}}{C}} n \rightarrow e^{-j\omega_0 \frac{2r_k}{C}}. \]  

The complete phase history of each target is calculated using the above equation at each range position. A random phase term \( \phi_k \) will be added to the phase history of each target with a range between \( 0 - 2\pi \). The random phase term provides a realistic effect in the received signal model. After the phase history is generated for each target, it will then be cross correlated with a reference phase. The reference phase will be a vector of a phase history of a reference target located at the center of the image.

The reference phase and true phase of each target have a strong correlation when they are cross correlated at the correct target location. Doing this for every point target in the scene will create the cross-range image of the target scene. The cross range image reconstruction shown in Fig. 3.7 for single and multiple point targets.

### 3.1.4 Reconstructed Image

The cross range reconstruction can now be combined with the range reconstructed image to produce the target reconstructed image. The reconstructed image is produced though point by point multiplication of the range reconstruction and cross range reconstruction. The final image is presented in Fig. 3.8 for single and multiple point targets without clutter.

Since, the use of OFDM requires that the bandwidth be split between multiple sub carriers, the splitting of the bandwidth results in the range resolution of the SAR reconstructed image to be reduced. The relation the bandwidth has on the resolution is shown in 3.13.
\[ \Delta r = \frac{C}{2\beta}. \]  

(3.13)

The images in Fig. 3.9 show an example that demonstrates the affect of bandwidth on the reconstructed images.
3.2 Environment and System Models

The completion of the SAR reconstruction leads directly into the modeling of the clutter, target and the environment itself. The following goes through the set-up and assumptions of a target simulated in a target environment.

3.2.1 Clutter Model

The reconstruction process described in the previous section will now be applied to the reconstruction of the target scene with frequency-dependent clutter. The clutter that will be added to each image will be modeled from an empirical vegetation model [3]. This model of the vegetation clutter uses the Normalized Radar Cross-Section (NRCS), $\sigma_c(f)$, as follows:

$$\sigma_c(f) = D + 10\alpha\log(f) + 8.6\beta f^\alpha - M\theta ,$$

(3.14)

where $f$ is the radar operating frequency in GHz, $\theta$ is the grazing angle in degrees, and the coefficients $D,M, \alpha$ and $\beta$ are given in the Table 3.2.

The model in Eq. 3.14 gives the backscatter coefficient or NRCS in dBs. The backscatter is a dimensionless quantity that is normalized to the area of the clutter contribution. Therefore, to acquire the Radar Cross-Section (RCS) of the clutter, the backscatter coefficient is multiplied by the illuminated area, i.e,

$$\sigma_{r_{cs}} = \sigma_0 A_c ,$$

(3.15)

Figure 3.9: SAR Reconstruction with different bandwidths
where $A_c$ is the illuminated area; for Stripmap SAR, the area in the along-track dimension continues to grow as long as the radar platform continues to collect data; therefore, we concern ourselves with the swath length.

$$A_c = R \csc(\psi) \theta_B ,$$

(3.16)

where $R$ is the range, $\psi$ is the grazing angle, and $\theta_B$ is radar beam width. The values were chosen to represent typical parameters of a SAR system. Note: a typical foliage clutter model is shown in Fig. 3.10.

If the normalized RCS model above will allow for the modeling of the clutter and signal propagation occurs in a forest environment, for example, then we can use a frequency-dependent RCS model based upon a log-normal, or a log-logistic distribution to model the entire propagation channel for UWB signals [18].
3.3 Target Scenario

This section details the target under observation as well as the parameters and assumptions of the target within the scene.

3.3.1 Scenario Assumptions

The following are assumptions used in the work of this thesis and provide the set-up for the study of target detection within clutter environments. We assume:

- the target is stationary
- one type of clutter exists within the environment
- the number of targets within a given scene are sparse
- target is modeled from collection of point targets

3.3.2 Target Scene Parameters

A target scene image produced by SAR reconstruction can have other elements that distort and hide objects of interest. Elements not wanted in a image are called clutter. Clutter can be buildings, trees, or atmospheric effects all of which can differ depending on the environment in which the radar is currently being used. We focus on foliage as the clutter encountered in our scenarios. The results of this analysis will be presented later as means of showing the potential of the research. The main area of the research is the identification of targets hidden in low Signal-to-Clutter Ratio (SCR), either man made or natural.

Another topic of interest will be the target that is trying to be located. The target concept is a collection of extended point targets that resembles the pattern of a tank. The picture in Fig. 3.11 shows the target description.
Figure 3.11: Tank Target

The target is approximately 10 meters in length and is surrounded by an area of foliage and vegetation 200m x 200m. The next chapter will detail the methods researched to provide an automatic target detection algorithm to be used to compare performance of a full bandwidth SAR image and when the bandwidth is broken into smaller subsections.
Chapter 4

Detection Algorithms

4.1 Overview

This chapter details the implementation of different ATD’s formulated for the detection of targets. Detection is defined, as it pertains to our research, as correctly identifying images that contain a target of interest. The following sub-sections detail each method researched as well as the implementation. While the methods discussed in this chapter were not implemented in the final algorithm design, they inform the reader with information on a variety of ways to approach a detection problem.

The design of the detectors include statistical analysis, template matching, and image processing; each area is further elaborated upon in the following sections and the reasons for not pursuing a solution based on the described approach is discussed as well.

4.2 Statistical Detection

Statistical analysis was the first area researched when formulating a detection algorithm. The area was a focus early on in the algorithm design due to a large amount of research available within the area. The statistical analysis of clutter is an important part in the development of a detection algorithm. The radar system transmits training pulses and stores the responses; the data retrieved from the training pulses would then be used to model the PDF of the clutter, and based upon the resulting PDF, a detection strategy would be implemented.

After empirical modeling of the background clutter is performed via training pulses, the model’s parameters are found through estimation of the stored data. The design of the detector is implemented by employing the theorem for hypothesis testing as discussed in Chapter 2. The range cells within the formed SAR image will then be put through the detector to decide if the current location corresponds to a target or a background class.

The detectors implemented here are designed around the GLRT and LRT as discussed
in Chapter 2. A general block diagram of the detection implementation is shown in Fig. 4.1.

![Flow Diagram of Statistical Detection](image)

Figure 4.1: Flow Diagram of Statistical Detection

The proceeding section will look at the implementation of two detectors in which the clutter follows two different PDF’s. The design and derivation of these detectors follows from previous work [11].

## 4.3 Detectors

The design and implementation of the two detectors are to be used in environments in which the background is log-normal or Weibull distributed. The derivation of the two detectors is based upon an unknown amplitude level within the scene. The goal of the detectors is two separate pixels into two different classes. The current pixel will belong to either the background class or target class.

### 4.3.1 Log-Normal Clutter Detector

The log-normal distribution probability density function is defined in Eq. 4.1, where $\mu$ is the mean and $\sigma$ is the variance:

$$F_{ln}(x) = \frac{1}{x\sqrt{2\pi\sigma^2}} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}}. \quad (4.1)$$

A property of the log-normal distribution used in the derivation of the detector is described in Eq. 4.2.

$$if \ X \sim Log \sim N(\mu, \sigma^2), \ then \ ln(X) \sim N(\mu, \sigma^2). \quad (4.2)$$

The above property states that the natural logarithm of a variable that is log-normal distributed results in a variable that is distributed normally. Therefore, applying the natural logarithm will result in the background clutter being normally distributed and a detector based upon unknown amplitude can then be realized using the GLRT as shown in 4.3.

$$\frac{\rho(x; A, H_1)}{\rho(x; H_0)} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2} \sum_{n=0}^{N} (x[n]-A)^2} > \gamma. \quad (4.3)$$
The test statistic that will then be implemented is

\[ T(x) = \frac{1}{N} \sum_{n=0}^{N-1} > \frac{\sigma^2}{N} \ln \gamma + \frac{A}{2} = \gamma'. \quad (4.4) \]

The threshold \( \gamma' \) can be found from the probability of false alarm, defined in Eq. 4.5:

\[ \gamma' = \sqrt{\frac{\sigma^2}{N} Q^{-1}(P_{FA})}. \quad (4.5) \]

Therefore, for a given false alarm rate, an appropriate threshold can be determined to classify the pixels under test. Table 4.1 lists false alarm values versus thresholds for a \( \sigma \) value of .33 and \( N = 5 \).

<table>
<thead>
<tr>
<th>Threshold Value</th>
<th>False Alarm Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 10^{-3} )</td>
<td>1.02</td>
</tr>
<tr>
<td>( 10^{-4} )</td>
<td>1.25</td>
</tr>
<tr>
<td>( 10^{-5} )</td>
<td>1.41</td>
</tr>
<tr>
<td>( 10^{-6} )</td>
<td>1.62</td>
</tr>
<tr>
<td>( 10^{-7} )</td>
<td>1.71</td>
</tr>
</tbody>
</table>

Table 4.1: Log-normal PFA vs Threshold

4.3.2 Weibull Clutter Detector

Another distribution is commonly used to describe foliage backscatter is the Weibull Distribution. Its PDF is defined in Eq. 4.6 for values of \( x \geq 0 \) with shape parameter \( k \) and scale parameter \( \lambda \) as

\[ Weibull = \frac{k}{\lambda} \left( \frac{x}{\lambda} \right)^{k-1} e^{-\frac{x}{\lambda}}. \quad (4.6) \]

The implemented GLRT assumes the amplitude is unknown, which results in the following test statistic, shown in Eq. 4.7.

\[ \frac{\rho(x; A, H_1)}{\rho(x; H_0)} = \frac{k}{\lambda} \left( \frac{x-A}{\lambda} \right)^{k-1} e^{-\frac{x-A}{\lambda}} > \gamma. \quad (4.7) \]
The simplification of the detector stops with the test statistic being the mean of the subgroup of pixels under test, namely,

\[ T(x) = \frac{1}{N} \sum_{n=0}^{N-1} X(n) . \] (4.8)

4.4 Statistical Detection Results

The results shown in Figs. 4.2 and 4.3 are target detection results from images at low levels of clutter that is log-normal distributed, as well as when the bandwidth is segmented from 3 GHz to 750 MHz.

![Detection Results for Bandwidth of 3 GHz in Log-Normal Clutter](image)

(a) Original Image  
(b) Detection Result PFA = 10\(^{-3}\)  
(c) Detection Result PFA = 10\(^{-5}\)  
(d) Detection Result PFA = 10\(^{-7}\)

Figure 4.2: Detection Results for Bandwidth of 3 GHz in Log-Normal Clutter
Figure 4.3: Detection Results for Bandwidth of 750 MHz in Log-Normal Clutter
Simulations for a Weibull detector was not performed as we focused on clutter returns from foliage being log-normal distributed. The following summarizes the results of the implemented statistical detector.

### 4.4.1 Summary of Statistical Statistical Detection

The use of statistics to describe clutter within an image is a common and well researched approach as discussed in Chapter 2. However, a disadvantage arises when the situation cannot be characterized by the assumed PDF. A variety of detectors would need to be implemented for different scenarios. This causes the detectors to become non adaptive and is one of the weaknesses of this approach. An advantage is if we were to deploy our system in a particular environment, then a specific detector could be designed and implemented.

Additionally, the identification and separation of pixels from the background does not imply that the marked locations are targets; they could be reflections from roads, trees, buildings, etc. We believe that an additional step is needed to determine potential targets within a scene. The next section discusses such a method that could possible help identify targets within an image.

### 4.5 Template Matching Detection

After processing an image through our statistical detector we still cannot be for certain that the pixels marked are in fact targets. The marked pixels distinguish themselves from the background. To try and further identify targets, an extension was implemented in the form of template matching. The groundwork of template matching was laid out in Chapter 2. The goal is to identify areas that contain a potential match once the images have gone through our statistical detector.

![Template matching procedure](image)

Figure 4.4: Template matching procedure
The generation of the template to be used for the identification of targets was a problem that arose during the implementation. Should the template be generated using a synthetic based on SAR simulations, or one realized through real images of objects. During our initial design, we proposed a synthetic template based off the full bandwidth of the SAR reconstruction as shown in Fig. 4.5.

![Figure 4.5: Synthetic Template](image)

Figures 4.6 illustrated a result based on the above template, which was used on the full bandwidth of 3 GHz and a sub-image of 750 MHz. The detection threshold for the template matching was 70%.

![Figure 4.6: Template Matching Result](image)

### 4.5.1 Summary of Template Matching Approach

Ultimately the incorporation of template matching has two main flaws in the approach. The first is the generation of the template to be used to search for a target. Knowledge of the target signature would be needed in order to generate a reasonable template. Secondly the
process is neither rotation or scale invariant. The target could differ in size and orientation within the image and the need for multiple templates would be required in order to correctly locate potential targets.

The use of multiple templates has further implications in that the performance of the detection algorithm would slow down with increasing templates. Lastly, a appropriate matching level is not an easily determined variable and would most likely vary depending on clutter type and current situation. Knowing these problems, further research and analysis was discontinued in favor of alternative approaches.

4.6 Image Processing Detection

A final alternative approach for target detection that we examined at involved the use of image processing techniques. We wanted to apply operations that would segment the images from a similar distributed background. The operations investigated are morphological operations and would alter the images to allow for segmentation. (more information can be found in the literature [19]. These operations can be used on digital, binary, and gray scale images to analyze geometrical structures within the image. The following are the different types of morphological operations.

**Dilation**- This adds pixels to the objects; in other words it makes the object thicker.

**Erosion**- This removes pixels from the objects, making them thinner.

**Opening**- This is erosion followed by dilation. This can be implemented using morphological or via image reconstruction. The latter retains the shape of the objects better than the former.

**Closing**- This is dilation followed by erosion. This can also be implemented via morphological operations or image reconstruction.

A disadvantage is that these operations may require large amounts of computational time, depending on the size of the image and, thus, could lead to a inefficient algorithm for real time purposes. A demonstration of these operations are shown in Fig. 4.7

4.6.1 Morphological Detection Summary

The use of image processing techniques did show potential in segmenting objects from a homogeneous background; however, the approach was not further developed due to the following reasons. The first drawback of the approach is due to the fact that we are altering the images without seeing them. Since this is a Automatic Target Detection (ATD) algorithm, we are not interested in making the images easier to comprehend for human consumption, rather we are looking at making the computer better able to process the images. Secondly The operations can be computationally expensive for a real time approach and may not be feasible. Lastly, the individual operations depend upon a structuring element such as circles,
disks, and other polygons to segment the images. The geometric shapes themselves can change size which connects to the first reason of not seeing the effects the operations have on the images. Given the above reasons, a algorithm relying on image processing approaches was not pursued.

Figure 4.7: Morphological Segmentation Result
Chapter 5

Novel Automatic Target Detection Algorithm

Our past target detection algorithms focused on finding a target via statistical measures, template matching, and image processing techniques; however, the past algorithms all had disadvantages that made those implementations not worth pursuing. Instead, we chose to focus on a different approach and develop an algorithm that would possibly alleviate the flaws in the previous ATD developments.

We have based our new algorithm upon image field analysis. Specifically, we are interested in viewing a reconstructed scene as two distinct types of fields, scalar and vector fields with respect to two dimensions. The former provides amplitude information, while the latter provides magnitude and direction at a given position in 2D dimensional space. The definitions of these fields along with their mathematical operations serve as the foundation of the proposed algorithm.

The block diagram in Fig. 5.1 provides an overview of the operations being performed on the reconstructed target scene. The following sections will discuss the implementation of each operation as well as any assumptions and reasoning that each segment entails. The use of vector fields and scalar fields lends itself as a novel ATD approach. The groundwork laid out in this chapter provides the reader with the formulations and background material for the successful detection of targets or anomalies within an image.

![Figure 5.1: Flow Diagram of ATD process](image)

Figure 5.1: Flow Diagram of ATD process
5.1 Imaged Based Field Analysis

The derivation of our ATD is as follows: we first denote a SAR reconstructed scene with a system bandwidth of $\beta$ as $I(x, y)$. The position in the image for a given $x$ and $y$ value returns the amplitude corresponding to the range and cross range position. The values that are contained within the image matrix make up a scalar field (See Fig. 5.2), where every position returns the corresponding amplitude.

![Figure 5.2: Scalar Field](image1)

**Block Processing**

The above scalar field is filtered via block processing, in which we segment the image into discrete blocks of a set size along the range and cross-range direction as shown in Fig. 5.3.

![Figure 5.3: Block processed image](image2)
The size of the blocks has to be taken into consideration with the size of targets being located. A new image will be formed where each block in the new image contains the largest amplitude value from the original target scene. Let us denote the new image described in Eq. 5.1

\[ F(x, y) = \text{Block Processed } I(x, y). \]  

(5.1)

Figures 5.4(a-d) show the results of applying block processing on a reconstructed image of bandwidth 3GHz. We compare with and without block processing.

![Reconstructed SAR scene: Scalar Field](a) Original Image

![Block Processed image](b) Block Processed Image

![Original Image Height Map](c) Original Image Height Map

![Block Processed Height Map](d) Block Processed Height Map

Figure 5.4: Comparison of applying block processing

The block processed images now contain refined areas of the target scene. Next we analyze the block processed image for targets by viewing the scene as a vector field.
5.1.1 Vector Field Analysis

Applying vector field analysis allows us to transform the scalar field into giving us a direction and magnitude at every position \( x \) and \( y \) within the target scene. The transformation and analysis of the vector field is accomplished via two vector calculus operations: the gradient and the divergence. The definition and implementation of each operation is discussed in the following sections.

5.1.2 Gradient

The gradient operation upon the block processed image in Eq. 5.1 is indicated in Eq. 5.2 follows where \( \partial F/\partial x \) and \( \partial F/\partial y \) are the partial derivatives in the range and cross range direction:

\[
V(x, y) = \nabla F(x, y) = \left( \frac{\partial F}{\partial x}, \frac{\partial F}{\partial y} \right). \tag{5.2}
\]

The gradient allows us to see the variations at any given position within the image by representing each position in the form of vector components. The vector field represents potential targets or objects as comprised of vectors. An object within the scene that has a higher backscattering return than the surrounding clutter will appear brighter causing the vectors to be oriented towards the area of greatest change. Figure 5.5 shows the vector fields formed from a reconstructed scene at various levels of SCR.

5.1.3 Divergence

After the generation of the vector field, \( V(x, y) \), processing the vector field for targets is the next step. Identifying the locations of potential targets is accomplished by locating areas that contain high compressibility; in other words, locating areas that contain vectors oriented in the direction of a common region. Finding these areas requires the implementation of another vector calculus operation, the divergence. The divergence of a vector field will find sources, which are positive in amplitude, as well as sinks, which are negative in amplitude. The divergence is used on the vector field formed in Eq. 5.2 and is performed on the vector field \( V(x, y) \) through the divergence operation described in Eq. 5.3.

\[
\nabla \cdot \vec{D} = \left( \frac{\partial V}{\partial x} + \frac{\partial V}{\partial y} \right). \tag{5.3}
\]

The divergence operation is shown in Fig. 5.6 for different SCR levels for a full bandwidth reconstructed image.
Figure 5.5: Vector Field Generation from the Result of Gradient Operation
Figure 5.6: Scalar field generation from divergence operation
5.1.4 Gradient Spread

After the identification of an area or areas of potential targets, we first mark the location of interest by storing the row and column of the corresponding position. Before processing the stored location we revert back to the original vector field, $V(x, y)$, which is used to form the gradient magnitude image. The gradient magnitude is defined in Eq. 5.4, where $V_x$ and $V_y$ represent the $x$ and $y$ components of the vector field.

$$\|\nabla V\| = \sqrt{V_x^2 + V_y^2} \quad (5.4)$$

The gradient magnitude values in Eq. 5.4 is used in deciding if a potential target is within a given scene. We use the marked locations of the row and column as the starting location, which is called the Pixel Under Test (PUT). We proceed by collecting all the neighbors within a desired radius in terms of pixels from the PUT. The pixels are collected in order from a radius of one, to the maximum search radius of $n$. The values are stored in order in a new vector defined in Eq. 5.5, where $P_i$ is the neighbors collected at radius $i$ from the location of interest:

$$P = [P_1, P_2, P_3, \ldots P_n] \quad (5.5)$$

The resulting vector in Eq. 5.5 is then normalized in order to account for clutter and target amplitudes. We refer to Eq. 5.5 as the gradient spread as the vector contains values from the gradient magnitude. After the normalization a linear fit is applied to the vector, where the slope of the trend is then used to decide whether a target is present by comparing the result to a threshold value denoted by $\gamma$.

The presence of a target will result in the magnitude vectors surrounding the location of interest to decrease, as the search radius is increased. When no target is present, the result remains relatively trend-less. Figure 5.7 show the magnitude values around a known target location with a pixel radius of 5.

5.1.5 Algorithm Parameters

The algorithm has several parameters that can be changed in order to modify performance and sensitivity. The list of those parameters that are modifiable are as follows.

- **Block Size** - The size of the discrete blocks to use on a reconstructed scene
- **Threshold** - The value in which a target is declared present
- **PUT vector** - The number of elements to collect around the pixel under test

The choice of block size, threshold, and pixel radius depend upon target size, the resolution in range and cross range, and other factors such as other potential objects within the scene.
Figure 5.7: Linear Fit with target embedded in clutter
5.1.6 Summary of Image Based Target Detection

In conclusion, the algorithm presented above demonstrates a novel approach to target detection. The algorithm addresses some of the flaws of the previous developed algorithms such as the following. Representing the target scene in the form of vectors means the statistical nature of the background is no longer a part of the equation unlike in statistical detectors. Secondly, another benefit of vector representation is that the sizes and shapes of targets are less of a concern. The algorithm focuses on areas that have a negative divergence instead of the physical structure of the target.

As far as disadvantages, the operations used within the algorithm such as the gradient and divergence may require more processing time than other methods; however, still believed that the algorithm would be suitable for real-time detection. Next, the demonstration of detection using the above algorithm coupled with the multispectral radar concept is presented for various parameters and bandwidths.
Chapter 6

Results and Conclusions

The results of our target detection are based upon the frequency model described in Chapter 3 as well as the ATD discussed in Chapter 5. This section presents probability of detection graphs for SAR reconstructed scenarios using the full bandwidth of 3 GHz and for sub-images, where the bandwidth is divided into 750 MHz and 375 MHz. The probability of detection was determined to fluctuate with the threshold and is shown for full and divided bandwidths. The probability of false alarm also depends upon the threshold and is shown in the proceeding graphs.

Two scenarios were used to evaluate the detection probabilities. The first is when the parameters of the underlying clutter PDF were known and secondly when the parameters of the PDF had to be estimated. The estimation case employed MLE to measure the parameters. The clutter was first added in the first scenario and then the images were processed through the ATD; in the case of the unknown clutter, known clutter was added to the images, which were then sampled to estimate the parameters for the clutter returns. The following figures present our findings from our simulation by varying bandwidth, threshold, and block size.
6.1 Known Parameters Probability of Detection

6.1.1 3 GHz Bandwidth Detection

![3GHz Detection Graph](image)

Figure 6.1: Detection Results 3GHz

6.1.2 1.5 GHz Bandwidth Detection

![1.5GHz Detection Graph](image)

Figure 6.2: Detection Results 1.5 GHz
6.1.3 750 MHz Bandwidth Detection

A set threshold of $10^{-3}$ was used for each figure regardless of bandwidth. Observing the full bandwidth of 3 GHz in Fig. 6.1, we can see that the detection rate starts to fall around 14 dB and declines until 3 dB. Dividing the bandwidth into two images of 1.5 GHz results in a substantial increase in detection for each sub band as shown in Fig. 6.2. Comparing Figs. 6.1 and 6.2 to the results when using four sub carriers of 750 MHz shown in Fig. 6.3, we can see the detection increases for the various sub-bands with the first sub-band offering detection as low as -12 dB. While the splitting of the bandwidth does increase detection, the change from two to four images offers a much lower increase than a 3 GHz bandwidth to a 1.5 GHz bandwidth.
6.2 Unknown Parameters Probability of Detection

6.2.1 3 GHz Bandwidth Detection

![Graph showing estimated parameter detection results for 3 GHz bandwidth]

Figure 6.4: Estimated Parameter Detection Results 3GHz

6.2.2 1.5 GHz Bandwidth Detection

![Graph showing estimated parameter detection results for 1.5 GHz bandwidth]

Figure 6.5: Estimated Parameter Detection Results 1.5 GHz
6.2.3 750 MHz Bandwidth Detection

Figure 6.6: Estimated Parameter Detection Results 750MHz

Observing the results for Figs. 6.4, 6.5 and 6.6 for unknown parameters shows similar results to Figs. 6.1, 6.2 and 6.3 with the detection degrading by 0.5 - 1 dB. The next set of results looks at how the threshold affects the probability of detection and the probability of false alarm.
6.3 Probability of false alarm graphs

6.3.1 False Alarm vs. Threshold

![Graph of Probability of False Alarm vs. Threshold](image1)

Figure 6.7: Probability of false alarm vs. varying threshold

6.3.2 Detection vs. Threshold

![Graph of Detection vs. Threshold](image2)

Figure 6.8: Detection vs. varying threshold

Analyzing the probability of false alarm graphs we see that the threshold is the main parameter that controls the false alarm rate. The threshold for the bandwidth (between four
sub carriers) can be slightly higher than the full bandwidth in order to lower the number of false alarms. The same conclusion can be drawn from Fig. 6.8 in which we compare the detection rate versus the threshold. Not only do we gain the ability to detect the presence of target on lower levels of clutter, but we can increase the threshold while still maintaining acceptable levels of detection and false alarms.

6.4 Conclusions

This thesis presented a novel radar concept in which OFDM is used to obtain multiple images of a target scene in the form of sub carriers. The images obtained can then be analyzed separately to check for targets. Another objective of the thesis was the development of an ATD that could be used in the images to locate potential targets. The radar and the ATD results were presented in the previous figures.

While the conclusions drawn from our results seem to support the concept of a multi-spectral radar as well as the developed ATD, we still have to be mindful that this is a simulation and results will differ from a real world application. Nonetheless, the results are promising and provide incentive for further research. The following chapter will look ahead at the next set of problems and suggestions that need future study.
Chapter 7

Future Work

The research and work presented in this thesis demonstrates the novelty of a OFDM multi-spectral radar for remote sensing applications and the developed ATD provides a framework to detect whether or not an image contains a target. However, additional work and research still must be performed in improving the ATD as well as the multi-spectral radar as a viable concept. The following are the most important factors that need to be addressed.

Using a simulation based approach, we showed how we can correctly detect a target within clutter by employing a image based ATD. Further improvements were made by using the OFDM radar concept in which the radar bandwidth was divided in order to acquire multiple images. The next logical step would be to replace the simulated data with real data sets. The transition from simulation to real data would allow for the evaluation of detection performance of the ATD and multi-spectral radar.

We should acquire data either from preexisting collections or by taking the idea one step further and building a physical prototype that would then be used to collect the data. The evaluation metrics obtained from a physical system would further validate the claim and provide more credibility to the research. The building and testing of such a system would most likely warrant a stand alone thesis.

Secondly, further research into the ATD and additional improvements is needed. Such factors include investigating an appropriate block size for targets, and appropriate thresholds. Currently, an additional idea exists in which, after the samples are collected around a potential target location, a window with a width of \( p \) pixels slides over the samples and multiple slopes are calculated. A slope that exceeds the threshold value would cause the ATD to then declare a target present.

Furthermore, the ATD only looked at the most likely location for a target; instead multiple locations could be marked and processed due to the fact that clutter could form structural or geometrical shapes that resemble targets and give false alarms. Analyzing or reducing such factors would greatly enhance the robustness of the ATD.

While the research focused on the detection performance of the ATD, we also intend to investigate the performance as compared to other detection algorithms. Common approaches use
statistical analysis, segmentation, and discriminators. Not only would detection performance be investigated but false alarms, as well as speed. How fast the algorithm can process an image would be valuable information, as it would determine the suitability of using the ATD in real time scenarios. A factor that also would likely increase the processing would be the fact that multiple images would be obtained from the OFDM radar. The resulting images would be of lower resolution and contain less range and cross-range cells. The processing would stop once a target has been detected in one of the images.

In summary, much work and research is still needed to fully determine the usability, limitations, and functionality of the proposed radar and ATD. The work presented in this thesis lays the groundwork for further investigation.
Bibliography


