I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Randy S. Depoy ENTITLED UHF-SAR and LIDAR Complementary Sensor Fusion for Unexploded Buried Munitions Detection BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Engineering.

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Depoy, Randy S. M.S.Egr., Department of Electrical Engineering, Wright State University, 2012. UHF-SAR and LIDAR Complementary Sensor Fusion for Buried Unexploded Munitions Detection.

Given the UHF bands properties of foliage and ground penetration, a UHF-SAR image contains both above- and below-surface scatterers. The problem of detecting sub-surface objects is problematic due to the presence of above-surface scatterers in the detection images. In case of a single-pass anomaly image or a two-pass change image, the resulting anomalies or changes are due to scatterers above and below the surface, where the above surface anomalies/changes act as confusers. LIDAR digital elevation models (DEM) provide georegistered information about the above-surface objects present in the UHF-SAR scene. Detection of the above-surface objects in the LIDAR domain is used to rule out above-surface false-alarms in the UHF-SAR domain detection images. A complementary sensor fusion algorithm is implemented which exploits the limited ground penetrating capabilities of UHF-SAR and the false-alarm removal using LIDAR. For unitemporal and multitemporal UHF-SAR collections (both containing multiple-passes and multiple-polarizations) anomaly detection and change detection are implemented, respectively. In this thesis, various pixel-based and feature-based change detection algorithms are implemented to study the effectiveness of multitemporal change detection algorithms. In addition, incorporation of UHF-SAR multiple-passes and multiple-polarizations further improves detection results. The algorithms are tested using data collected under JIEDDOs Halite-1 program, which provides both UHF-SAR and LIDAR DEM.
ACKNOWLEDGEMENTS

Special thanks to Dr. Kevin Priddy from AFRL for granting the permission necessary to perform academic research on the JIEDDO funded HALITE-1 data collection. In addition, thanks to Richard Van Hook from AFRL for expediting the public release process thereby guaranteeing my timely graduation. A very special thanks to friends, faculty, and instructors at Wright State University for offering guidance and support during this research. Thanks to my family, especially my mother and four year old son, for the support and patience during this effort.
## Contents

1 Introduction  

2 Dataset Description  
   2.1 Introduction  
   2.2 Target Description  
   2.3 UHF-SAR Dataset  
   2.4 LIDAR Dataset  

3 LIDAR DEM Processing Techniques  
   3.1 Introduction  
   3.2 Anomaly Detection Thresholding (AD)  
   3.3 Relative-Flatness Elevation Ratio (RFER)  
   3.4 DEM Elevation Differencing (DED)  
   3.5 Performance Conclusions  

4 Anomaly Detection using Multiple Passes and Multiple Polarizations  
   4.1 Introduction  
   4.2 Single-Pass Single-Polarization  
   4.3 Extension to Multiple-Pass Multiple-Polarization  

5 Change Detection Algorithms  
   5.1 Introduction  
   5.2 Pixel-Based Change Detection  
   5.3 Feature-Based Change Detection  
      5.3.1 Texture-Based Change Detection  
      5.3.2 Statistical-Based Change Detection  
      5.3.3 Geometrical Change Detection  
   5.4 Performance Conclusions  
   5.5 Multiple Polarization and Multiple-Pass Change Detection  

6 Complementary Sensor Fusion Algorithms  
   6.1 Introduction  
   6.2 Single-Collection Day- Anomaly Detection in UHF-SAR Domain  

v
6.3 Multiple-Collection Days - Change Detection in UHF-SAR Domain . . . 79
6.4 Conclusions and Suggestions for Future Work . . . . . . . . . . . . . 91

A Table of all 17 Targets: HH073 UHF-SAR images from Baker East 94
B NCFD Change Detection Method 104
C IILR Change Detection Method 114
D Texture Difference Change Detection Method 124
E Power-to-Mean Change Detection Method 134

Bibliography 144
List of Figures

2.1 Table provided in the data description elaborating on the data collection dates (not dependent on target placement dates) and the flight conditions. ................................................. 8
2.2 Tables provided in the data description showing all the truth locations and placement dates for each SAR scene. .......................................................... 9
2.3 Images illustrating the four orthogonal flight paths for UHF strip map SAR collection, as well as, the two strips of land the SAR images are back projected to. ......................................................... 11
2.4 Table provided in the data description summarizing the parameters of the custom UHF-SAR. Figure from [14]. .......................................................... 12
2.5 Images of the Baker East SAR scene for day one (reference image) and day three (mission image) cropped around target 12. ................................. 13
2.6 Images of the Baker East SAR scene for day one (reference image) and day three (mission image) cropped around target 12. ................................. 13
2.7 Full UHF-SAR images formed through back projection of the HH polarization from collection heading 073 (Baker East). ......................................................... 14
2.8 Full UHF-SAR images formed through back projection of the HH polarization from collection heading 163 (Baker East). ......................................................... 15
2.9 UHF-SAR images day one and day three cropped about target 3 for HH polarizations considering both collection headings 073 and 163 (Baker East). ......................................................... 16
2.10 Table provided in the data description summarizing the parameters of the LIDAR sensor. Figure from [1]. .......................................................... 17
2.11 Full LIDAR surface DEM of Baker East illustrate the gradual increase in elevation. .......................................................... 18
2.12 LIDAR surface DEM zoomed in on target 12, showing the elevations about the road region in the SAR scene from the third day of data collection. ......................................................... 19
2.13 LIDAR ground DEM zoomed in on target 12, showing the elevations about the road region in the SAR scene from the third day of data collection. ......................................................... 20
3.1 Resulting single-parameter CFAR processed LIDAR image. ................................. 24
3.2 CFAR LIDAR processing on (Left Image) surface DEM and (Right Image) ground DEM. Window sizes: inner 8x8, guard 12x12, outer 18x18. ......................................................... 25
3.3 The resulting CFAR LIDAR image after thresholding zoomed around target 12. Window sizes: inner 8x8, guard 12x12, outer 18x18. 26
3.4 Window placement in the LIDAR DEM for RFER processing. 27
3.5 Full LIDAR surface DEM of Baker East after RFER processing, the global variation in elevation is mitigated and global thresholding is applicable. 28
3.6 RFER processing of LIDAR surface DEM zoomed in on the same area about target 12, illustrating the preservation of relative peaks and troughs. 29
3.7 Surface DEM RFER thresholded at $T = 1$, eliminating a majority of above surface false-alarms outside of the road-region. 30
3.8 Zoomed in region about target 12, showing the effectiveness of the surface DEM RFER LIDAR processing technique at removing above-surface false-alarms. 31
3.9 Resulting RFER elevation image for the surface-ground combination. 32
3.10 Zoomed in region about target 12, where one image is thresholded at $T = 1$ and the other has an optimized threshold. 33
3.11 LIDAR DED processing images showing the full resulting image. 34
3.12 LIDAR DED processing images zoomed in around target 12. 35
3.13 LIDAR DED processing image thresholded and zoomed in around target 12. 36
4.1 Example areas for CFAR anomaly detection. Illustrating inner, guard, and outer as red, green, and blue rectangles respectively. 40
5.1 Top Left: HH polarization collection pass 073 reference SAR image. Top Right: HH polarization collection pass 073 mission SAR image. Bottom Left: Resulting CFD image. Bottom Right: Resulting NCFD image. 49
5.2 Top Left: HH polarization collection pass 073 reference SAR image. Top Right: HH polarization collection pass 073 mission SAR image. Bottom Left: Resulting NCCCD image. Bottom Right: Resulting CCCD image. 51
5.3 Top Left: HH polarization collection pass 073 reference SAR image. Top Right: HH polarization collection pass 073 mission SAR image. Bottom Left: Resulting CMLE image. Bottom Right: Resulting NCMLE image. 52
5.4 Intensity Image Likelihood Ratio (IILR) change statistic for the collection heading 073 and polarization HH. 54
5.5 Resulting change image from the gradient differencing change detection algorithm. 56
5.6 Kurtosis difference image for collection heading 073 polarization HH. 59
5.7 Skewness difference image for collection heading 073 polarization HH. 60
5.8 Power-to-Mean difference image for collection heading 073 polarization HH. 60
5.9 Top Image: Normal Kullback-Leibler Divergence for collection heading 073 polarization HH. Bottom Image: Rayleigh Kullback-Leibler Divergence for collection heading 073 polarization HH. 62
5.10 Resulting change image for Hu’s first-invariant moment. 64
5.11 ROC plot comparing the performances of the various pixel-based change detection algorithms. 65
5.12 ROC plot comparing the performances of the various statistical feature-based change detection algorithms. ......................................................... 66
5.13 ROC plot comparing the performances of the various feature-based change detection algorithms. .............................................................. 67
5.14 ROC plot comparing the performances of the best pixel-based and feature-based change detection algorithms. ......................................................... 68
6.2 Left Image: Multiple-Polarizations fixed collection heading 073. Right Image: Multiple-Passes fixed polarization HH. ......................................................... 74
6.4 ROC plot comparing the performance gains from implementing complementary sensor fusion on single-pass single-polarization anomaly detection. ................................................................. 76
6.5 ROC plot comparing the performance gains from using multiple-passes multiple-polarizations versus single-pass single-polarization. ...................... 77
6.6 ROC plot comparing the performance gains from using all collection headings and polarizations. ................................................................. 78
6.7 Resulting NCFD multiple-pass and multiple-polarization change detection images. ......................................................................................... 81
6.8 Resulting IILR multiple-pass and multiple-polarization change detection images. ......................................................................................... 83
6.9 Resulting texture differencing multiple-pass and multiple-polarization change detection images. ................................................................. 85
6.10 Resulting power-to-mean multiple-pass and multiple-polarization change detection images. ................................................................. 87
6.11 Showing ROC curves for NCFD change detection image. ...................... 88
6.12 Showing ROC curves for the IILR change detection image. ...................... 89
6.13 Showing ROC curves for Texture Differencing change detection image. ..... 89
6.14 Showing ROC curves for the Power-to-Mean change detection image. .... 90
# List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>AD</td>
<td>Anomaly Detection</td>
</tr>
<tr>
<td>CCCD</td>
<td>Coherent Correlation Change Detection</td>
</tr>
<tr>
<td>CD</td>
<td>Change Detection</td>
</tr>
<tr>
<td>CFAR</td>
<td>Constant False-Alarm Rate</td>
</tr>
<tr>
<td>CFD</td>
<td>Coherent Frame Differencing</td>
</tr>
<tr>
<td>CMLE</td>
<td>Coherent Maximum-Likelihood Estimation</td>
</tr>
<tr>
<td>DED</td>
<td>DEM Elevation Differencing</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>EO</td>
<td>Electro-Optic</td>
</tr>
<tr>
<td>GLCM</td>
<td>Gray Level Co-occurrence Matrix</td>
</tr>
<tr>
<td>HH</td>
<td>Horizontal Horizontal</td>
</tr>
<tr>
<td>HME</td>
<td>Home Made Explosive</td>
</tr>
<tr>
<td>IED</td>
<td>Improvised Explosive Device</td>
</tr>
<tr>
<td>IILR</td>
<td>Intensity Image Likelihood-Ratio</td>
</tr>
<tr>
<td>JIEDDO</td>
<td>Joint Improvised Explosive Device Defeat Organization</td>
</tr>
<tr>
<td>KLD</td>
<td>Kullback-Leibler Divergence</td>
</tr>
<tr>
<td>LIDAR</td>
<td>Light/Laser Detection And Ranging</td>
</tr>
<tr>
<td>MLE</td>
<td>Maximum-Likelihood Estimation</td>
</tr>
<tr>
<td>NCCCD</td>
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<tr>
<td>NCFD</td>
<td>Non-Coherent Frame Differencing</td>
</tr>
<tr>
<td>NCMLE</td>
<td>Non-Coherent Maximum-Likelihood Estimation</td>
</tr>
<tr>
<td>PD</td>
<td>Probability of Detection</td>
</tr>
<tr>
<td>PFA</td>
<td>Probability of False-Alarm</td>
</tr>
<tr>
<td>RFER</td>
<td>Relative Flatness Elevation Ratio</td>
</tr>
<tr>
<td>ROC</td>
<td>Receiver Operating Characteristic</td>
</tr>
<tr>
<td>SAR</td>
<td>Synthetic Aperture RADAR</td>
</tr>
<tr>
<td>UHF</td>
<td>Ultra High Frequency</td>
</tr>
<tr>
<td>VOIED</td>
<td>Victim Operated IED</td>
</tr>
<tr>
<td>VV</td>
<td>Vertical Vertical</td>
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Introduction
Increasing efforts to detect and safely remove unexploded buried munitions in many war-stricken regions of the world is essential for protecting and saving the lives of troops and civilians. A complementary sensor fusion algorithm is developed for unexploded buried munitions detection. A complementary sensor fusion algorithm enhances the knowledge about a given scene using multiple sensors [5]. UHF-SAR images and LIDAR elevation data are combined and the complementary information from each sensor is exploited to form the sensor fusion algorithm. UHF band has foliage and limited ground penetrating capability [3]; therefore imaging spatially represents scatterers above and below the surface in the scene. On the other hand, LIDAR digital elevation models (DEM) only contain above-surface objects in the scene. The combination of UHF-SAR and LIDAR DEM yield more knowledge about the scene than each sensor by itself.

The complementary fusion is evaluated using simultaneous UHF-SAR and LIDAR collections from an aerial surveillance platform [1]. The algorithms exploit the limited ground penetration capabilities of SAR collected from the UHF bands for detection of above- and below-surface objects. However, the UHF-SAR detection is unable to discern above-surface objects from below-surface objects, hence the complementary fusion with LIDAR digital elevation models (DEM). Detection of the above-surface objects is performed in the LIDAR domain, where abundant elevation data is processed then thresholded to discern above-surface objects from the ground plane.

In the UHF-SAR domain anomaly detection and change detection is implemented on unitemporal and multitemporal data collections, respectively. Each temporal collection contains multiple-passes and multiple-polarizations, which are exploited to add information about the area-of-interest. For the unitemporal collection, where all unexploded buried munitions are buried on the day of collection, single-parameter CFAR anomaly detection is used [18]. The resulting anomaly image contains detections of both above- and below-surface objects. In order to reduce the number of above-surface false-alarms, the LIDAR detection image is used to remove the detected above-surface objects, thereby isolating the
below surface objects, corresponding to the unexploded buried munitions.

For multitemporal collections it is assumed that at least one temporal collection contains no targets; whereas the other temporal collections contain at least one target. For multitemporal collections change detection methodologies are used to detect the unexploded buried munitions. Change detection is a well studied method of target detection, where no a priori information is available on the target, rather a priori information is provided on the background. Background information is provided with the initial temporal instance of collection, since zero targets are present in the scene. The other temporal instances contain changes in the background or the appearance of targets within the background. Images containing only background are referred to as reference images; whereas images containing both background and target are referred to as mission images.

A survey of change detection methodologies is presented in [19], where different methodologies are discussed which provide change images. A resulting change image preserves the reference and mission images coordinate system; however only the changes are present. The stationary background contained in both reference and mission images is suppressed to some degree. The performance of the change detection method depends on the change preservation and background suppression capability of each algorithm. Several change methods discussed in [19] are implemented in this thesis, including are frame differencing (referred to as simple differencing in [19]) and likelihood ratio tests. These methods are categorized as pixel-based change detection methods.

A majority of pixel-based change detection methods derived for SAR imagery start from a likelihood ratio test. Forming a likelihood ratio test requires knowledge of the statistics of the imagery used. In [17] [16] [27] [4] [24], the assumption is reference and mission SAR images are complex Gaussian in nature. Based on this assumption, either a correlation statistic or a maximum-likelihood statistic is derived providing an estimate of the coherence between reference and mission SAR images. In [29], the statistics of the intensity SAR image are assumed to obey a Gamma distribution, where the intensity image is analogous to
the power image (or amplitude image squared). The derivation of the likelihood ratio test
under the Gamma distribution yields an intensity image likelihood-ratio change statistic.
Each aforementioned pixel-based change method is implemented using sliding window
statistical measures in both reference and mission SAR images. Therefore, each pixel-
based change method is a sample-based change statistic, either sample-coherence estimate
or sample likelihood-ratio test.

In addition to pixel-based change detection methods, various feature-based change de-
tection methods are implemented to enhance multitemporal detection performance. Feature
extraction in SAR imagery is categorized into three different groups, texture features, sta-
tistical features, and geometric features. Texture-based change detection algorithms have
been developed for SAR imagery focusing on remote-sensing problems in [7] [22] [23].
Each method focuses on populating a gray-level co-occurrence matrix (GLCM) then cal-
culate parameters of the image from the GLCM matrix in order to find changes between
the reference and mission SAR images. Another approach is to take the texture difference
between reference and mission images, as presented in [13]. This approach convolves, both
reference and mission images, with x- and y-gradient operators (derived x- and y-gradient
matrices, specifically Sobel operator), computes the resulting gradient magnitude of each
image followed by a pixel-based change detection. Texture differencing, as presented in
[13], is applied to EO images; however in this thesis it is adapted and applied to SAR
imagery.

Statistical features of a SAR image are explored in [20] in addition to other various
gray-level populated matrices. Several statistical features discussed are kurtosis, skewness,
power-to-mean, homogeneity, and contrast. Each statistical feature is computed from local
statistics in the reference and mission SAR images. Local statistics are sample statistics
from a windowing process across the reference and mission SAR images. Therefore, if the
window is centered over background in both reference and mission SAR images the sample
statistics are assumed to vary little; whereas if the window is centered over background in
the reference SAR image and a target in the mission SAR image the sample statistics will exhibit larger variation. Extracting the statistical features from the SAR images is meant to enhance the presence of the target relative to stationary background. In addition to statistical feature extraction, this thesis effort pursues geometric feature extraction using an invariant geometric moment analogous to a pixel-based moment of inertia [8].

In order to further improve detection performance an extension of the proposed complementary sensor fusion algorithm is developed which exploits the multiple-passes and multiple-polarizations acquired during the reference and mission data collections. Each temporal collection contains four different collection headings (referred to as passes) and two polarizations (HH and VV). The extension is derived starting with single-parameter CFAR under an assumption of a homogeneous background. Furthermore, the measurements are taken from multiple SAR images (formed through backprojecting complex phase-histories from various collection headings and polarizations), yielding the extended multiple-pass multiple-polarization single-parameter CFAR.

This M.S. Thesis is organized as follows: Chapter 2 introduces the data collection, target description, and individual datasets collected under the JIEDDOs Halite-1 program [1]. LIDAR processing and above-surface object detection is presented in Chapter 3. Chapter 4 introduces the complementary sensor fusion algorithm and derives the extension from single-pass single-polarization to multiple-pass multiple-polarization for unitemporal anomaly detection in the UHF-SAR domain. Chapter 5 introduces various change detection methods implemented for multitemporal detection in the UHF-SAR domain and provides a comprehensive comparison of detection performances. Finally, Chapter 6 presents results for unitemporal and multitemporal detection in the UHF-SAR domain with false-alarm removal using the complementary sensor fusion algorithm as well as the extension to multiple-passes and multiple-polarizations.
Publications following from this Thesis work:

Dataset Description
2.1 Introduction

The multisensor data in this thesis was collected under JIEDDO’s Halite-1 project and the data description given in this chapter largely follows the description supplied with the data [1]. The dataset provided includes UHF-SAR images and LIDAR elevation maps for three different collection days. Over the three days seventeen targets (unexploded buried munitions) are emplaced in the scene. The first day’s data collect captured SAR data and LIDAR elevations of the undisturbed scene with no targets emplaced. The second day’s collection contains a fraction of the total amount of targets. On the third day, the captured UHF-SAR data and LIDAR elevation measurements contain all the targets that were emplaced in the collection scenes. A description of the flight conditions on each of the three collection days is provided in figure 2.1. All seventeen targets are assumed to be buried below the surface in a realistic manner. In this context realistic manner allows for possible visible (to the human eye) detection. The truth locations and placement of each of the seventeen targets are shown in figure 2.2, coordinate frame is UTM zone 11 with elevation referenced to the WGS-84 ellipsoid [1]. In addition, the code-name for the buried munitions is provided; however, the specific type of munitions used is unknown.

<table>
<thead>
<tr>
<th>Date</th>
<th>Flight Time</th>
<th>Conditions</th>
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<tbody>
<tr>
<td>Mon, Aug 3</td>
<td>18:00–18:40</td>
<td>Heavy turbulence</td>
</tr>
<tr>
<td>Fri, Aug 7</td>
<td>06:55–07:30</td>
<td>mostly smooth</td>
</tr>
<tr>
<td>Fri, Aug 14</td>
<td>05:50–06:35</td>
<td>smooth air</td>
</tr>
</tbody>
</table>

Figure 2.1: Table provided in the data description elaborating on the data collection dates (not dependent on target placement dates) and the flight conditions.

Initially this chapter introduces a more thorough target description with what information is provided from the JIEDDO Halite-1 data collection. Then the UHF-SAR dataset is introduced, along with the imagery of the aforementioned target regions in the mission UHF-SAR image where the targets are visibly discernible. The chapter is concluded with an inspection of the LIDAR elevation data.
### Table 1: Baker East targets

<table>
<thead>
<tr>
<th>PLACEMENT DATE</th>
<th>POINT</th>
<th>NORTHING</th>
<th>EASTING</th>
<th>ELEV</th>
<th>NAME</th>
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<tr>
<td>4-Aug</td>
<td>H_B_E_080409_001</td>
<td>3960155.86</td>
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<td>3961401.28</td>
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<td>3961159.40</td>
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<td>Mango</td>
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</table>

### Table 2: Baker West targets

<table>
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<tr>
<th>PLACEMENT DATE</th>
<th>POINT</th>
<th>NORTHING</th>
<th>EASTING</th>
<th>ELEV</th>
<th>NAME</th>
</tr>
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<tbody>
<tr>
<td>4-Aug</td>
<td>H_B_E_080409_001</td>
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<td>425376.24</td>
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<td>424942.73</td>
<td>687.46</td>
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<td>6-Aug</td>
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<td>425469.38</td>
<td>677.05</td>
<td>Mango</td>
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<tr>
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</tr>
<tr>
<td>7-Aug</td>
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<td>425162.43</td>
<td>682.72</td>
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</tr>
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<td>Banana</td>
</tr>
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<td>9-Aug</td>
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<td>3961518.88</td>
<td>424899.40</td>
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</tr>
<tr>
<td>11-Aug</td>
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<td>3961149.84</td>
<td>425100.85</td>
<td>685.49</td>
<td>Coconut</td>
</tr>
<tr>
<td>11-Aug</td>
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<td>425071.11</td>
<td>686.55</td>
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</tr>
<tr>
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<td>3961329.45</td>
<td>425049.17</td>
<td>685.96</td>
<td>Mango</td>
</tr>
</tbody>
</table>

Figure 2.2: Tables provided in the data description showing all the truth locations and placement dates for each SAR scene.
2.2 Target Description

Emplacement of the unexploded buried munitions in the test lanes is done in a realistic manner. Noting that in this context realistic manner of emplacement of buried explosives is such that visual detection is possible. JIEDDO Halite-1 collected realistic data on the emplacement of simulated victim operated IED for two test lanes. Each test lane is actively sensed using UHF-SAR from multiple flight headings transmitting and receiving in HH and VV and a commercial LIDAR sensor. Truth locations for each emplaced explosive are provided and listed in figure 2.2. The emplaced munitions are not specifically known; however it is known they closely simulated a standard victim operated IED (VOIED). According to the data description [1], there are ten different types of targets code named as listed in figure 2.2 simulating an IED main charge (landmine, munitions, or homemade explosives (HME)) on the order of 60 and 155 mm artillery shells. Each main charge is buried in the roadbed, as is expected for an VOIED. The triggering mechanism for VOIED is also buried in the roadbed and along the side of the roadbed. Furthermore, sections of wire extending perpendicular to the road are emplaced as a triggering device. In addition to simulated VOIED, the collection team included duds (false-positives). The dud is generated by digging a hole in the roadbed which is refilled in a realistic manner.

In total, 34 different targets are emplaced in two test strips, 17 in each. Footprints, vehicle tracks, etc exist in the scene making for realistic target detection problem, but are not used in this effort. In the context of this thesis, the words target, IED, and VOIED all represent the unexploded buried munitions to be detected.
2.3 UHF-SAR Dataset

Initially, the two test strips are actively sensed using a UHF RADAR sensor collecting strip map SAR. As shown in figure 2.3 the UHF-SAR data is collected from four orthogonal flight headings, such that the center of the collection geometry box is always illuminated. From the collected UHF-SAR complex phase-history, back projected SAR images are generated for two strips of land. The two strips of land are referred to as Baker East and Baker West, as shown in figure 2.3. Considering the two strips of land, the four collection headings (also referred to as passes in this thesis), and polarizations HH and VV collected in each pass; there are a total of sixteen UHF-SAR images collected on each day.

Figure 2.3: Images illustrating the four orthogonal flight paths for UHF strip map SAR collection, as well as, the two strips of land the SAR images are back projected to.

The UHF-SAR sensor description provided in the data description [1] is shown in figure 2.4. The key specification for the UHF-SAR data are the spatial resolution (0.5 meters x 0.7 meters) and the frequency range in P-band (220 440 MHz). Several desirable features of operating in UHF band are foliage penetration and the limited ground-penetration capabilities. The actual ground-penetrating depths are not provided; however it is fair to assume that the unexploded buried munitions are buried at realistic depths to be effective as victim operated explosives. Studies into UHF-SAR as a tool for effective ground surveillance are provided in [3]. The paper discusses the ability to achieve fine spatial resolution granted
long integration times are allowable; as well as noticeable ground penetration capabilities and potential corresponding phase distortions.

<table>
<thead>
<tr>
<th>Sensor Type</th>
<th>Custom UHF SAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial Resolution</td>
<td>0.5 x 0.7 m</td>
</tr>
<tr>
<td>Frequency Range</td>
<td>220 – 440 MHz (P-band)</td>
</tr>
<tr>
<td>Wavelength</td>
<td>0.7 – 1.4 m</td>
</tr>
<tr>
<td>Pulse Duration</td>
<td>10 μs</td>
</tr>
<tr>
<td>Positional Accuracy</td>
<td>Better than 1 m</td>
</tr>
<tr>
<td>Altitude</td>
<td>5,000 ft AGL</td>
</tr>
<tr>
<td>Velocity</td>
<td>~190 kt</td>
</tr>
<tr>
<td>Swath Width</td>
<td>4 km @ 5,000 ft AGL</td>
</tr>
</tbody>
</table>

Figure 2.4: Table provided in the data description summarizing the parameters of the custom UHF-SAR. Figure from [14].

Henceforth, the UHF-SAR is assumed to provide backscatters above and below surface, where the targets are unexploded buried munitions. The SAR images alone contain large numbers of above surface scatterers corresponding to the natural features of the region. The two back projected SAR strips of land are centered about roads, which have above surface features similar to arid (desert-like) landscapes. Figure 2.5 shows two UHF-SAR images where target-12 was emplaced in Baker East for day-1 and day-3. These SAR images were formed using complex phase-history from collection heading 073 and HH polarization. The red circle marks the supplied truth location for the given target and the blue circle around the truth location is the defined radius of detection (used later for detection performance evaluation through ROC plots). It is evident from figure 2.5 that there is no scatterer present within the radius of detection in the reference UHF-SAR image, however the mission UHF-SAR image contains a strong scatterer response close to the supplied truth location within the radius of detection. Based on visual inspection, it can be concluded that the scatterer in the mission image of figure 2.5 corresponds to the 12th target emplaced in the Baker East strip because of its proximity to the provided truth location. However, the algorithms developed in this thesis do not make use of the supplied truth locations in
making automated detection decisions.

Figure 2.5: Images of the Baker East SAR scene for day one (reference image) and day three (mission image) cropped around target 12.

For collection heading 253 HH polarization, the back projected UHF-SAR image is shown in figure 2.6. Once again the image is cropped about the 12th target to better visualize changes around the provided truth location. The same above-surface features are present in both UHF-SAR images and the target is present in similar locations for both mission UHF-SAR images, which reinforces the visual classification. For the 17 targets emplaced only 15 targets can be visually detected for Baker East, and these are studied further throughout the investigation.

Figure 2.6: Images of the Baker East SAR scene for day one (reference image) and day three (mission image) cropped around target 12.
The two collection headings considered thus far (073 and 253) are collected such that the down-range is approximately parallel to the roads centered in the two strips, whereas the cross-range is approximately orthogonal to the roads. For the remaining two orthogonal collection headings the down-range is approximately orthogonal to the roads and the cross-range is approximately parallel with the roads. The collection headings 073 and 253 yield UHF-SAR images with less obscuration due to road-side bank presence than the collection headings 343 and 163 and this effect is visually apparent in figure 2.7 and figure 2.8.

Figure 2.7: Full UHF-SAR images formed through back projection of the HH polarization from collection heading 073 (Baker East).
Figure 2.8: Full UHF-SAR images formed through back projection of the HH polarization from collection heading 163 (Baker East).

The prominent road-side banks are detrimental to detection of blob-like targets in the UHF-SAR images if the targets response is occluded by the bank’s response. This is better visualized in figure 2.9 where the UHF-SAR image is zoomed on target 3. Referring to figure 2.9, for collection heading 073 the target can be seen visually with apparent no occlusion; however the image corresponding to collection heading 163 provides no obvious target response.
Figure 2.9: UHF-SAR images day one and day three cropped about target 3 for HH polarizations considering both collection headings 073 and 163 (Baker East).

After studying the provided back projected UHF-SAR images from various collection headings and polarizations, it is clear that UHF-SAR is capable of providing a response for the buried targets at certain headings. It should be noted that this visual analysis has no effect on the complete complementary sensor fusion algorithm considered in this work. Target truth locations are not used during the UHF-SAR detection or LIDAR detection process, but used only for detection performance evaluation. Unlike the visual analysis presented here, the detection in the UHF-SAR domain is applied to the entire backprojected UHF-SAR image, and not on cropped sub-images. A more complete set of mission and reference SAR images is provided in appendix A for all 17 targets emplaced in Baker East.
2.4 LIDAR Dataset

The second piece of the complementary sensor dataset is the LIDAR digital elevation models (DEM) for the two target strips of land (Baker East and Baker West). Specifications for the LIDAR sensor are given in figure 2.10, which is available commercially through the Optech.

<table>
<thead>
<tr>
<th>Sensor Type</th>
<th>Optech ALTM 3100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial Resolution</td>
<td>0.3 m</td>
</tr>
<tr>
<td>Wavelength</td>
<td>1064 nm</td>
</tr>
<tr>
<td>Positional Accuracy</td>
<td>Better than 1 m</td>
</tr>
<tr>
<td>Altitude</td>
<td>1,000 &amp; 1,700 m AGL</td>
</tr>
<tr>
<td>Velocity</td>
<td>~110 kt</td>
</tr>
<tr>
<td>Swath Width</td>
<td>300 m</td>
</tr>
</tbody>
</table>

Figure 2.10: Table provided in the data description summarizing the parameters of the LIDAR sensor. Figure from [1].

LIDAR data collection is performed aerially, such that the platform navigates a race-track loop up Baker East and then down Baker West. The race-track flight pattern is repeated multiple times until the collection ends. The criteria for ending the collection was based on time-of-flight and not the amount of raw data collected, because the collection teams were constrained to a specific amount of time for collection. The raw elevation data is geo-referenced; therefore Baker East elevations are separated from the Baker West elevations. Geo-referencing the raw data allows for the generation of digital elevation models (DEM) for each test lane. A surface DEM and ground DEM are generated from the raw point-cloud data.

The surface DEM is generated using all allowable raw elevation point-clouds geo-referenced to the Baker East and Baker West regions. Surface digital elevation model provides a terrain plus above-surface object elevation map of the scene. Therefore, any above-surface objects present in the test lanes are represented in the surface DEM. The
surface DEM for Baker East is shown in figure 2.11; where the coordinate system is in Latitude vs Longitude, and the elevation referenced to the WGS-84 ellipsoid. There is an inherent increase in elevation for the Baker East test lane, as seen in the full surface DEM. All LIDAR processing and detection is performed on the full LIDAR DEM; however for visualization purposes smaller subsets of the LIDAR DEM are discussed next.

Figure 2.11: Full LIDAR surface DEM of Baker East illustrate the gradual increase in elevation.

A smaller subset of the surface DEM for Baker East centered about the 12th target is shown in figure 2.12 (same target area as for the aforementioned UHF-SAR images). The vegetation and hills in the scene can be seen around the road region. The truth location for target 12 is plotted along with the radius of detection illustrating an approximate roadbed placement of the unexploded buried munitions. Inspecting the region immediately surrounding the truth location, there is an absence of any identifying features correspond-
ing to target placement; alluding to the realistic manner of unexploded buried munitions placement.

Figure 2.12: LIDAR surface DEM zoomed in on target 12, showing the elevations about the road region in the SAR scene from the third day of data collection.

Unlike the surface digital elevation model, the ground digital elevation model takes the lowest allowable raw elevations providing an elevation map of only the terrain. Therefore, the ground DEM should theoretically not include elevations from vegetation in the scene, rather only elevations corresponding to hills, rocks, etc should be present [26]. The ground DEM for the same region about target-12 is shown in figure 2.13. As expected, the local peaks in the ground DEM are lower in height than the local peaks in the surface DEM.

At the local level, there is plentiful elevation data exploitable for complementary sensor fusion. It is desirable to formulate an effective elevation threshold which separates the relatively flate road-region from above-surface features present in the scenes. The thresholding must be applied to the entire LIDAR DEM. A global thresholding scheme where
a single threshold is used to classify areas as above-surface objects seems appropriate but has certain drawbacks. The global thresholding scheme is complicated due to the inherent but realistic uneven terrain elevation in the region of the two test strips of interest that can be visualized in figure 2.11, where the entire surface DEM is shown for the Baker East strip. In Chapter 3, various LIDAR processing techniques are demonstrated. Each LIDAR processing technique is implemented to remove the gradual but even increase in elevation while preserving local peaks.
LIDAR DEM Processing Techniques
3.1 Introduction

As previously presented the LIDAR dataset provides two digital elevation models (DEM) formed from the raw elevation points. Also established is the gradual increase in elevation in the resulting LIDAR DEM (shown in figure 2.11). Furthermore, the objective of the complementary sensor fusion algorithm is to remove above-surface false-alarms in UHF-SAR detection images using LIDAR elevation data. Detecting above-surface objects using the LIDAR DEM is achieved by thresholding the elevation data, such that all elevations above the given threshold correspond to an above-surface object and all elevations below the threshold correspond to ground plane elevations. With the gradual increase in elevation in the terrain of interest a global LIDAR thresholding scheme is not appropriate.

Therefore, prior to thresholding the LIDAR DEM must be processed to remove the effect of the gradual increase in elevation while preserving local elevation peaks. This problem is approached through a localized windowing operation, denoted as $\mathcal{H}\{L^{s,g}\}$, applied to the LIDAR DEM prior to thresholding. The variable $L^{s,g}$ denotes dependence on the surface and ground DEMs, since both can be used in the processing techniques discussed in a later section. Table 3.1 shows the three processing techniques where, RFER is a Relative-Flatness Elevation Ratio measure of the LIDAR DEM, DED is a DEM Elevation Differencing measure of the LIDAR DEM, and CFAR is a single-parameter anomaly detection measure of the LIDAR DEM where the anomalies correspond to above-surface objects.

<table>
<thead>
<tr>
<th>Name</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>AD</td>
<td>$\mathcal{H}_{AD}{L^{s,g}} = \frac{\text{mean}{L^{s,g}}}{\text{mean}{L^{s,g}}}$</td>
</tr>
<tr>
<td>RFER</td>
<td>$\mathcal{H}_{R}{L^{s,g}} = \frac{\text{max}{L^{s,g}}}{\text{mean}{L^{s,g}}}$</td>
</tr>
<tr>
<td>DED</td>
<td>$\mathcal{H}_{D}{L^{s,g}} = \text{max}{L^{s,g}} - \text{mean}{L^{s,g}}$</td>
</tr>
</tbody>
</table>

Table 3.1: Various LIDAR DEM filtering techniques implemented prior to detecting above-surface objects.
Each of the LIDAR filtering techniques operates on the entire full-resolution LIDAR DEMs in an attempt to identify the local peaks or elevated regions while removing the gradual increase in elevation. The detection of above-surface objects in the filtered LIDAR DEM ($H \{ L^{s,g} \}$) is obtained through thresholding operation as shown in equation 3.1.

$$D = \mathcal{I} \{ H \{ L^{s,g} \} \} \geq T$$  \hspace{1cm} (3.1)

The $\mathcal{I} \{}$ operator represents the interpolation process from geo-referenced LIDAR domain to geo-referenced UHF-SAR domain. The interpolation step is performed for two reasons. Firstly, the LIDAR DEMs are at much higher resolution than the SAR imagery and secondly, LIDAR DEM information is needed at the precise geolocations where the SAR pixel samples are collected. The resulting detection image $D$ contains the detected above-surface objects in the UHF-SAR domain. The denotation of $L^{s,g}$ is meant to illustrate that different possible combinations of surface DEM and ground DEM may be utilized in the filtering operation. The different possible combinations of $\{s, g\}$ are surface-surface, surface-ground, and ground-ground. $T$ is the threshold selected empirically to detect the above-surface objects.

Equation 3.1 essentially encapsulates the proposed complementary SAR-LIDAR fusion concept that this work is based upon. Three operations are being performed in 3.1. The filtering operation ($H$) emphasizes the local peaks in the LIDAR DEMS. Next, the interpolation operation ($\mathcal{I}$) determines the relative LIDAR elevations at the precise locations where the UHF-SAR data is sampled. The thresholding operation ($T$) is performed on the filtered and interpolated LIDAR data but it generates the precise SAR locations where an above-ground object may exist causing false alarms in the SAR domain.

This chapter is organized such that single-parameter CFAR is implemented first to detect above-surface objects. However, anomaly detection is insufficient at preserving the local peaks, therefore two additional processing techniques are implemented to better preserve local peaks. Both RFER and DED are implemented to better preserve the local peaks.
3.2 Anomaly Detection Thresholding (AD)

The processing operator for a single-parameter CFAR is shown in equation 3.2, where the mean functions are implemented using a three window filter. The three window filter consists of an inner window \( I_{i,j} \), guard window \( G_{i,j} \), and outer window \( O_{i,j} \); where the equivalent mathematical representation is given in equation 3.2.

\[
H_{AD}(n,m) = H_{AD}\{E_{g}\} = \frac{1}{N_i} \sum_{i=0}^{N_i} \sum_{j=0}^{N_i} I_{i,j} - \frac{1}{N_g} \sum_{i=0}^{N_g} \sum_{j=0}^{N_g} G_{i,j}
\]

The summations represent two-dimensional averages of each of the three windows centered around pixel \( n, m \) in the LIDAR DEM. The inner, guard, and outer windows are of dimension \( N_i, N_g, \) and \( N_o \); respectively. Implementing the single-parameter anomaly detection on the LIDAR DEM preserves the location of the anomalies, which correspond to above-surface objects in the LIDAR DEM, in the resulting processed LIDAR image. The resulting processed LIDAR image is shown in figure 3.1, where it is immediately obvious that the global variation in elevation is mitigated. Detection would be implemented on the full processed LIDAR image, such that a single threshold \( T \) is selected to separate above-surface anomalies from the ground plane. As in previous analysis, next the resulting processed image is cropped about target 12 to offer visual evaluation.

![Figure 3.1: Resulting single-parameter CFAR processed LIDAR image.](image-url)
Selection of the window sizes is a factor in the effectiveness of the anomaly detection processing technique. The inner window should approximately match the size of the expected target. However, the guard window must be sufficiently large to provide separation between inner and outer statistics and the outer window must provide sufficient background statistics [15]. If the inner window size is not on the order of the expected target size then the resulting anomaly image is susceptible to slight variations in the terrain. Figure 3.2 shows the resulting anomaly image.

![Figure 3.2: CFAR LIDAR processing on (Left Image) surface DEM and (Right Image) ground DEM. Window sizes: inner 8x8, guard 12x12, outer 18x18.](image)

The resulting CFAR processed LIDAR images preserve the local peaks as anomalies, which are then thresholded at $T$ to detect the above-surface objects. Elaborating further on the above-surface object detection image, the anomalies which satisfy the threshold $T$ correspond to above-surface objects. Therefore, the anomalies that fail to satisfy the threshold correspond to the ground plane or some acceptable elevation. Furthermore, the complementary sensor fusion algorithm uses the LIDAR detection image to remove false-alarms from the UHF-SAR domain detection. In order to detect regions where positive-detection of buried objects in UHF-SAR domain is possible, the complement of the resulting LIDAR
detection image $D$ is used as a mask. The resulting CFAR processed LIDAR detection image zoomed in about target 12 is shown in figure 3.3, such that regions that are white correspond to positive-detection in the UHF-SAR domain and regions that are black correspond to potential false-detection in the UHF-SAR domain. A false-detection in the UHF-SAR domain corresponds to detection of an above-surface object by the SAR detection algorithms.

![Figure 3.3: The resulting CFAR LIDAR image after thresholding zoomed around target 12. Window sizes: inner 8x8, guard 12x12, outer 18x18.](image)

The relatively poor performance of CFAR may be attributed to the averaging operation in the numerator of equation 3.2 that tends to smooth out the peaks. In order to preserve the peaks in the LIDAR data, two other LIDAR processing techniques are considered next.
3.3 Relative-Flatness Elevation Ratio (RFER)

The relative-flatness elevation ratio (RFER) LIDAR DEM filtering is used to allow thresholding detections of above-surface objects in the LIDAR domain. Consider the LIDAR DEM as $L^{s,g}$, where $s$ and $g$ denotes surface and ground DEM, respectively. RFER is implemented using a two window filter; where each window is denoted as $A_1$ and $A_2$. Each window is centered around pixel $(m, n)$ in the respective LIDAR DEM and $A_2$ must be greater than $A_1$ in order to sufficiently preserve peaks from the LIDAR DEM. Therefore, the larger window $A_2$ contains the smaller window $A_1$, as shown in figure 3.4.

\[
H_R(n, m) = H_R \{L^{s,g}\} = \frac{\max_{i,j \in A_1} \{L_{i,j}\}}{\frac{1}{N^2} \sum_{i,j \in A_2} L_{i,j}}; \quad (3.3)
\]

where $A_1$ and $A_2$ are $M \times M$ and $N \times N$ subsets of the LIDAR DEM, respectively. $M = 7$ and $N = 41$ pixels were used in our experiments and the resulting processing effects on the LIDAR surface DEM are shown in figure 3.5, where the global variation in elevation is eliminated while preserving the original peaks and troughs of the original surface DEM.

![Figure 3.4: Window placement in the LIDAR DEM for RFER processing.](image-url)
Figure 3.5: Full LIDAR surface DEM of Baker East after RFER processing, the global variation in elevation is mitigated and global thresholding is applicable.

Figure 3.6 shows the same relative peaks located around target 12, therefore showing that elevation information is not degraded through processing the surface DEM. A threshold can be intuitively determined through relatively simple reasoning. The RFER resulting elevation map is a ratio of a maximum value for a subset \( A_1 \) to the mean value of a larger subset \( A_2 \) of the LIDAR DEM. Therefore, if the area \( A_1 \) is centered about a peak (corresponding to pixel \((m, n)\)), the maximum value from the corresponding subset will be greater than the mean value of a larger area \( A_2 \) centered around the same peak. This will yield a ratio greater than one for that specific pixel location \((m, n)\). Similarly, the opposite situation occurs when the area \( A_1 \) is centered around flat ground or a trough yielding a value less than one. This follows from the maximum value of \( A_1 \) being less than that of the larger area \( A_2 \) which may contains peaks, thereby increasing the mean value. However, the latter is only true if the larger area \( A_2 \) contains peaks. following the aforementioned scenarios, the natural choice for a threshold is one \((T = 1\) referring to equation 3.1). Even though, intuitively it follows that \( T = 1 \) is a reasonable choice for a threshold, in practice this value should be determined by an analyst implementing the algorithm based on the
nature of the terrain.

Figure 3.6: RFER processing of LIDAR surface DEM zoomed in on the same area about target 12, illustrating the preservation of relative peaks and troughs.

Evaluating equation 3.1 with \( T = 1 \), the resulting above-surface object detection image is shown in figure 3.7. The resulting detection image is better viewed, not in terms of how many above-surface detections, but rather in terms of the amount of above-surface false-alarms that are removed. Therefore, in figure 3.7 the above-surface detections are shown as black pixels, whereas the lower elevation pixels are shown as white pixels. In other words, from the detections in the LIDAR domain (shown as black pixels) represent the potential regions of above-surface false-alarms in the UHF-SAR domain; whereas the white pixels represent potential detection regions in UHF-SAR domain. It is important to note that road regions are vulnerable for VOIED emplacements and the RFER thresholding effectively separates the relatively flat road region as seen by the narrow white strip in the Baker East test lane.
Figure 3.7: Surface DEM RFER thresholded at $T = 1$, eliminating a majority of above surface false-alarms outside of the road-region.

To better visualize the effectiveness of the RFER thresholding, the resulting detection image is cropped about target 12 (refer to figure 3.8). The plotted blue line represents the radius of detection about the truth location. Significant above-surface regions are detected using the RFER thresholding around the truth location for target 12. Any UHF-SAR detection in black above-surface region will be declared as false-alarms. Essentially the entire off-road region is considered an above-surface false-alarm with a threshold of $T = 1$. Therefore, for applications involving detection of unexploded munitions buried on roadways the threshold selection of $T = 1$ is sufficient. It may be noted here that because
RFER is defined as a ratio it is unit less.

![RFER DEM Thresholded](image)

Figure 3.8: Zoomed in region about target 12, showing the effectiveness of the surface DEM RFER LIDAR processing technique at removing above-surface false-alarms.

The original combination of taking the LIDAR DEM subsets $A_1$ and $A_2$ from the surface DEM is effective at removing significant above-surface false-alarms. In order to improve above-surface object detection even further, the definitions of both surface and ground digital elevation models are considered. The surface DEM is generated by considering all points collected from the raw LIDAR data, and the resulting DEM effectively maps the elevations of the terrain and above-surface objects in the scene to a geo-referenced grid. The ground DEM is generated using the lowest valid raw elevation points collected and maps the terrain to a geo-referenced grid. Implementing both surface and ground DEM in the RFER filtering process is considered next, where the max-filter is implemented on the surface DEM and the mean-filter is implemented on the ground DEM. Organizing the RFER in this order will yield maximum elevation values for above-surface objects normalized by the surrounding ground elevations, which serves to provide information about absolute height of the above-surface objects. The resulting RFER elevation image is shown.
in figure 3.9, where the larger elevations correspond to above-surface objects in the scene relative to the ground elevation.

Figure 3.9: Resulting RFER elevation image for the surface-ground combination.

Considering the detection process of thresholding the resulting RFER elevation map, the intuitively derived threshold of $T = 1$ is no longer optimal based on observation. In figure 3.10 both detection images are shown with threshold $T = 1$ and an empirically obtained optimum threshold of $T = 1.00012$. Once again, for this thesis the unexploded buried munitions are assumed to exist in the road-region of the scene of interest, therefore the definition of optimal threshold is sought to match the criteria of maximizing road-region and minimize off-road region based on visual inspection. However, the detection process can be adapted by varying the threshold to consider more off-road regions as potential detection-regions, as needed.
Figure 3.10: Zoomed in region about target 12, where one image is thresholded at $T = 1$ and the other has an optimized threshold.
3.4 DEM Elevation Differencing (DED)

The final LIDAR processing technique considered in this thesis effort is the DEM elevation differencing (DED). The differencing is constructed by taking the maximum of a subset of the LIDAR DEM and subtracting the mean of a larger subset of the same (or different) LIDAR DEM. Therefore, DED processing is performed using a two window filter similar to RFER. The resulting LIDAR DED image is shown in figure 3.11 where the subsets are taken from surface DEM and ground DEM. DED effectively removes the global variations in elevation, while providing a residual measure of the above-surface objects in meters.

![LiDAR DED Processing - Maximum Surface subtract Mean Ground](image)

Figure 3.11: LiDAR DED processing images showing the full resulting image.

This is represented mathematically as a windowing function centered around pixel \( n, m \) in the LIDAR DEM. Implementation of the DED using this methodology is similar to the ratio methodology used in RFER, however unlike the ratio differencing yields a residual elevation measure relative to the mean of the ground DEM. Processing the LIDAR DEM using DED instead of RFER offers actual elevation information which could be useful to an algorithm user, i.e., the residual elevation data in meters relative to the average ground
elevation. The mathematical representation of DED is as follows,

\[ H_D(n, m) = \mathcal{H}_D \{ \mathcal{L}^s,g \} = \max_{i,j \in A_1} \{ L_{i,j} \} - \frac{1}{N^2} \sum_{i,j \in A_2} L_{i,j}; \]  

(3.4)

where \( A_1 \) and \( A_2 \) are \( M \times M \) and \( N \times N \) (where \( M = 7 \) and \( N = 41 \) pixels) subsets of the LIDAR surface DEM and LIDAR ground DEM, respectively. The resulting DED processed image is shown in figure 3.12 zoomed to the truth location for target 12. Both an above-surface look at the resulting image and a down-road look at the resulting image are provided. The surrounding above-surface objects elevations are provided in meters in the z-axis.

![Figure 3.12: LIDAR DED processing images zoomed in around target 12.](image)

The resulting UHF-SAR domain, above-surface object detection image is shown in figure 3.13. A threshold of \( T = 0.05\text{m} \) (found empirically) is used to separate out the road-region in the scene of interest. A large number of above-surface objects are mitigated while the road-region remains intact, demonstrating the effectiveness of the DED processing in the complementary sensor fusion algorithm.
3.5 Performance Conclusions

Each localized LIDAR processing technique effectively removes the gradual increase in elevation which prevented above-surface object detection using a global elevation threshold. The single-parameter CFAR processing technique preserved local peaks as corresponding anomalies; however, the local peaks are not preserved in magnitude due to averaging. To overcome the problem of averaging, two other processing techniques, namely RFER and DED, are implemented to provide a residual measure of a maximum to a mean ground area. The RFER processing technique is effective at preserving local peaks, using an intuitive threshold of $T = 1$. Furthermore, DED processing offers more insight into the preserved peaks, specifically the magnitude associated in meters. However, DED requires visual optimization of the threshold, as does anomaly detection processing. Therefore, RFER is implemented in all further simulations with a threshold set at $T = 1$. 

Figure 3.13: LIDAR DED processing image thresholded and zoomed in around target 12.
Anomaly Detection using Multiple Passes and Multiple Polarizations
4.1 Introduction

In the previous chapters LIDAR processing and above-surface object detection methods were established. However, it should be emphasized that in the LIDAR domain unexploded buried munitions detection is not possible. The LIDAR wavelengths illuminating the scene do not have foliage or ground penetration capabilities. Hence, detection of unexploded buried munitions must be performed in the UHF-SAR domain, where UHF-SAR images contain above- and below-surface scatterers. The UHF-SAR collection by JIEDDO contains three separate temporal instances each containing multiple-passes and multiple-polarizations, where a temporal instance designates the collection day. In order to make use of the full collection the UHF-SAR domain the detection problem is extended to incorporate the multiple-passes and multiple-polarizations. Previous work on extension to multiple-polarization and multiple-passes can be found in [16] [17]; however this extension is limited to a single change detection algorithm (correlation and maximum-likelihood based estimation of coherence). For this thesis effort a more general extension to multiple-passes and multiple-polarization is adopted allowing for a variety of change detection algorithms. The extension is based on a single-parameter CFAR anomaly detection in the UHF-SAR domain.

4.2 Single-Pass Single-Polarization

Focusing now on the UHF-SAR domain detection problem of detecting unexploded buried munitions, as opposed to above-surface object detection, the single-parameter CFAR detector is introduced. Anomaly detection was implemented in the LIDAR domain in order to detect above-surface objects in the scene. However, in the UHF-SAR domain any departure from the homogeneous background is designated as anomalies. However, since UHF-SAR has limited ground penetration capability, the anomalies may include both above- and
below-surface objects, not just the above-surface objects. From [18], the two-parameter CFAR is derived as

$$\frac{1}{N_i^2} \sum I_{i,j} - \frac{1}{N_o^2} \sum O_{i,j}^* \over \sqrt{\frac{1}{N_o^2} - 1 \sum (O_{i,j}^* - \frac{1}{N_o^2} \sum O_{i,j}^*)^2} > t; \quad (4.1)$$

where $I_{i,j}$ and $O_{i,j}^*$ are the target and background areas centered around pixel $i, j$ as mentioned in [18]. The sample-variance is denoted using an operator, acting on the background area, as follows

$$\sqrt{\text{Var} \{O_{i,j}^*\} = \sqrt{\frac{1}{N_o^2} - 1 \sum (O_{i,j}^* - \frac{1}{N_o^2} \sum O_{i,j}^*)^2}; \quad (4.2)$$

However, under an assumption of a homogeneous background the variance reduces to a constant. Assuming that $\sqrt{\text{Var} \{O_{i,j}^*\} = c$ and rearranging the CFAR equation to

$$\frac{1}{N_i^2} \sum I_{i,j} - \frac{1}{N_o^2} \sum O_{i,j}^* = \frac{t}{c} > t; \quad (4.3)$$

a modified threshold can be established as $t^* = ct - 1$. The original threshold $t$ is defined by assuming a Swerling model used to determine an RCS for a given target, therefore a priori information is assumed on the target statistics. The resulting single-parameter CFAR is shown in equation 4.4 ignoring the new thresholding variable $t^*$, since an anomaly image is desired as opposed to an anomaly detection image where the detection criteria is constrained to a specific target type. Henceforth, any reference to CFAR is meant to yield an anomaly image, not a thresholded anomaly detection image. Therefore, anomaly magnitudes in the UHF-SAR domain using cell-averaging CFAR, as opposed to a detection mask in the UHF-SAR domain resulting from the thresholding, is desired.

$$\text{CFAR} = \frac{1}{N_i^2} \sum I_{i,j} - \frac{1}{N_o^2} \sum O_{i,j}^* = \frac{\text{AverageInnerPixels}}{\text{AverageOuterPixels}}; \quad (4.4)$$
The outer pixels are defined as $O_{i,j} = O_{i,j} - G_{i,j}$ each window is centered around pixel $i, j$. Representing the anomaly image as a three window filter with an inner, guard, and outer filtering window, the resulting mathematical representation is as follows

$$CFAR = \frac{\frac{1}{N^2_i} \sum_{i=0}^{N_i} \sum_{j=0}^{N_j} I_{i,j}}{\frac{1}{N^2_o} \sum_{i=0}^{N_i} \sum_{j=0}^{N_j} O_{i,j} - \frac{1}{N^2_g} \sum_{i=0}^{N_i} \sum_{j=0}^{N_j} G_{i,j}}; \quad (4.5)$$

where the inner and outer area of pixels is separated by a guard area of pixels. This is illustrated in figure 4.1, where inner, guard, and outer areas are labeled as $I_{i,j}$, $G_{i,j}$, and $O_{i,j}$, respectively.

Figure 4.1: Example areas for CFAR anomaly detection. Illustrating inner, guard, and outer as red, green, and blue rectangles respectively.

The sizes of each area of pixels must be selected to gather sufficient information about
the imaged scene [15]. The outer window must contain enough pixels to provide a sufficient representation of the background statistics, whereas the inner window must be on the order of the target size to provide sufficient statistics on the target. The guard band ensures separation between inner and outer statistics, or rather separation between target and background clutter. All of which is illustrated in figure 4.1, where the inner window is selected to match the expected size of the scene’s targets (3x3). The guard band is sufficiently large (7x7) to provide barrier between the target and clutter and the outer window is sufficiently large (9x9) to provide a statistic of the background clutter.

The resulting single-parameter CFAR is implemented on single-pass single-polarization mission UHF-SAR images. In figure 4.1, the windows centered around pixel $i, j$ are plotted over the UHF-SAR image backprojected to Baker East from the collection heading 073 collection in HH polarization. However, an anomaly image may also be computed using the 8 different single-pass single-polarization UHF-SAR mission images that were collected on the same day. Specifically, there exists 4 separate collection headings and 2 separate polarizations of UHF-SAR data and therefore 8 possible single-pass single-polarization anomaly images can be formed. Extending to multiple-passes and multiple-polarizations allows for exploitation of different combinations of collection headings (passes) and polarizations.

### 4.3 Extension to Multiple-Pass Multiple-Polarization

The extension from single-pass single-polarization to multiple-pass multiple-polarization follows from the derivations in [16][17][18]. In [16][17] specifically, an extension of the correlation and maximum-likelihood estimation of coherence from single-polarization to multiple-polarization is derived. The derivation assumes the data is $K$ dimensional complex Gaussian, hence there is a measurement vector $K \times 1$ consisting of a pixel from $K$ differently polarized complex SAR images. Extending this measurement vector from a single-pixel to $N$ pixels contained in each complex SAR image yields a $KN \times 1$ measure-
ment vector. The measurement vector is formed by concatenating $K$ complex SAR images reshaped into vectors $N \times 1$. Furthermore, the derivation follows by substituting the concatenated measurement vector in for a single measurement vector. From this properties of i.i.d. complex Gaussian are exploited to arrive at the sample correlation and sample maximum-likelihood equations.

Similarly, the extension of single-pass single-polarization cell-averaging CFAR to multiple-pass multiple-polarization cell-averaging CFAR is performed. Initially the assumption is made that the complex UHF-SAR images backprojected from $P$ different passes and $M$ different polarizations are i.i.d. complex Gaussian. Each UHF-SAR image is assumed to have a homogeneous background, yielding a constant background variance. The noisy measurement vector consisting of concatenated UHF-SAR images is denoted as

$$\bar{Z} = [\bar{X}_1^T, \ldots, \bar{X}_K^T]^T; \quad (4.6)$$

where each $\bar{X}_i$ are vectorized complex UHF-SAR images.

Starting the CFAR derivation similar to [18] by forming a binary hypothesis test; such that the Null hypothesis is true when a target is present (denoted as $H_0$). The resulting hypothesis likelihood ratio is as follows

$$\frac{p(\bar{Z}|H_0)}{p(\bar{Z}|H_1)} > \frac{p(H_0)}{p(H_1)}; \quad (4.7)$$

where adopting Neymann-Pearson criteria yields $\frac{p(H_0)}{p(H_1)} = t$. Yielding a similar result to equation 4.1, which is the two-parameter CFAR for single-pass single-polarization. However, instead of the noisy measurement vector consisting of a single UHF-SAR image it consists of multiple UHF-SAR images. Therefore, the designated target area and background areas formulated exist in all $K$ UHF-SAR images. The resulting single-parameter CFAR is as follows
\[ CFAR = \frac{\sum_{k=1}^{K} \left( \frac{1}{N_i^2} \sum I_{i,j}^{(k)} \right)}{\sum_{k=1}^{K} \left( \frac{1}{N_o^2} \sum O_{i,j}^{* (k)} \right)} \quad \text{(4.8)} \]

where \( I_{i,j}^{(k)} \) and \( O_{i,j}^{* (k)} \) are the inner and outer areas of the \( k^{th} \) UHF-SAR image centered around pixel \( i, j \). In other words, \( I_{i,j}^{(k)} \) and \( O_{i,j}^{* (k)} \) are subsets of the \( k^{th} \) noisy measurement \( \bar{X}_k \). The relationship with the three window filter, given a inner, guard, and outer filter window centered about pixel \( i, j \), is denoted as \( O_{i,j}^{* (k)} = O_{i,j}^{(k)} - G_{i,j}^{(k)} \). The guard window is implemented to separate target statistics from background statistics throughout all \( K \) UHF-SAR images used. Since the dataset is geo-registered, pixel \( i, j \) in the \( k^{th} \) UHF-SAR image at the same geological location as pixel \( i, j \) in the \( l^{th} \) UHF-SAR image; where \( k, l \in [1, \ldots, K] \). Therefore, \( k^{th} \) and \( l^{th} \) UHF-SAR images exist in the set of all UHF-SAR images considered in the summation. It should be mentioned that at the initial stage of this effort subpixel registration between different mission and reference passes were studied and there was no obvious indication of misregistration.

The multiple-pass implementation of the single-parameter CFAR for the single day of collected data is shown in equation 4.9, where \( P \) is the number of passes considered. Therefore, the set of UHF-SAR images contains up to all of the UHF-SAR images back-projected from different collection headings fixing the polarization. The number of passes can consist of up to four passes \((P = 4)\) for this dataset, where \( p = 1, \ldots, P \) corresponding to collection headings 073 to 343 in equation 4.10.

\[ CFAR = \frac{\sum_{p=1}^{P} \left( \frac{1}{N_i^2} \sum I_{i,j}^{(p)} \right)}{\sum_{p=1}^{P} \left( \frac{1}{N_o^2} \sum O_{i,j}^{* (p)} \right)} \quad \text{(4.9)} \]

\[ = \frac{\left( \frac{1}{N_i^2} \sum I_{i,j}^{(073)} + \frac{1}{N_i^2} \sum I_{i,j}^{(163)} + \frac{1}{N_i^2} \sum I_{i,j}^{(253)} + \frac{1}{N_i^2} \sum I_{i,j}^{(343)} \right)}{\left( \frac{1}{N_o^2} \sum O_{i,j}^{* (073)} + \frac{1}{N_o^2} \sum O_{i,j}^{* (163)} + \frac{1}{N_o^2} \sum O_{i,j}^{* (253)} + \frac{1}{N_o^2} \sum O_{i,j}^{* (343)} \right)} \quad \text{(4.10)} \]
Inner and outer subsets of the UHF-SAR images are a fixed size for all collection headings considered in the outer summation. The resulting CFAR effectively extended to multiple-pass UHF-SAR data. The total number of passes ($P$) does not have to consider all four of the collection heading as shown here. Rather a more advantageous selection of collection headings is recommended to provide improved anomaly images, as opposed to diminished anomaly images through sub-optimal combinations. Obscuration of targets in passes 163 and 343 suggest that these passes yield diminished multiple-pass anomaly images, however passes 073 and 253 can be combined to improve the anomaly image.

Extending to multiple-polarizations follows similarly to extending to multiple-passes; however instead of considering the $p = 1, \ldots, P$ passes in the outer summation, the $m = 1, \ldots, M$ available polarizations are considered. For this dataset two polarizations ($M = 2$) are available, both HH and VV, which is shown in equation 4.11.

\[
CFAR = \frac{\sum_{m=1}^{M} \left( \frac{1}{N^2_i} \sum_{i,j} I^{(m)}_{i,j} \right)}{\sum_{m=1}^{M} \left( \frac{1}{N^2_o} \sum_{i,j} O^{(m)}_{i,j} \right)}
= \frac{\left( \frac{1}{N^2_i} \sum_{i,j} I^{(HH)}_{i,j} + \frac{1}{N^2_i} \sum_{i,j} I^{(VV)}_{i,j} \right)}{\left( \frac{1}{N^2_o} \sum_{i,j} O^{(HH)}_{i,j} + \frac{1}{N^2_o} \sum_{i,j} O^{(VV)}_{i,j} \right)}
\tag{4.11}
\]

The resulting extension of the single-parameter CFAR that include both multiple-passes and multiple-polarization is shown in equation 4.12. Combination of multiple-passes with multiple-polarizations is not limited to $p = 1, \ldots, P$ and $m = 1, \ldots, M$, such that all collection headings and polarizations are considered.

\[
CFAR = \frac{\sum_{m=1}^{M} \left( \sum_{p=1}^{P} \left( \frac{1}{N^2_i} \sum_{i,j} I^{(p,m)}_{i,j} \right) \right)}{\sum_{m=1}^{M} \left( \sum_{p=1}^{P} \left( \frac{1}{N^2_o} \sum_{i,j} O^{(p,m)}_{i,j} \right) \right)}
\tag{4.12}
\]
It should be noted that equations 4.10 and 4.11 are both special cases of equation 4.12. For the multiple-pass equation presented in equation 4.10, starting with equation 4.12 and setting $M = 1$ which is equivalent to fixing the polarization, the equation reduces to the combination of $1, \ldots, P$ collection headings. Conversely, starting with equation 4.12 and setting $P = 1$ which is equivalent to fixing the collection heading, the equation reduces to a combination of $1, \ldots, M$ polarizations for a fixed collection heading. Pursuing this reasoning even further, fixing both the polarization $M = 1$ and the collection heading $P = 1$, equation 4.12 reduces back to the aforementioned single-pass single-polarization CFAR equation (equation 4.4).

Implementing single-parameter CFAR anomaly image algorithm provides a method for imaging anomalies in the UHF-SAR domain. Anomalies correspond to above- and below-surface scatterers, since UHF-SAR images image above- and below-surface objects. However, the single-parameter CFAR is unable to discern between the above-surface scatterers and the unexploded buried munitions. In this context any above-surface scatterers are considered false-alarms or false-detections by an observer or an algorithm. Incorporating LIDAR above-surface object detection effectively removes the above-surface false-alarms in the anomaly image. This is addressed in chapter 6 where complementary sensor fusion with LIDAR is introduced. Attempting to improve the UHF-SAR domain detection problem even further (without introducing LIDAR), SAR change detection methodologies are introduced in the next chapter. Anomaly detection is well suited for unitemporal collections (in this context a single-days collection); whereas change detection requires multitemporal collections (in this context multiple-days of collections). Utilization of the a priori information on the background is expected to increase the performance of a multitemporal detection methodology over a unitemporal detection methodology considered in this chapter.
Change Detection Algorithms
5.1 Introduction

The provided dataset contains a vast amount of UHF-SAR images that can be exploited to improve the performance of the complementary sensor fusion algorithm, prior to introduction of LIDAR false-alarm removal. Exploitation of the single-polarization and single-pass change data acquired over multiple collection days is considered in this chapter, which leads naturally towards change detection. The day-1 collection contains zero targets and primarily provides a priori reference information about the stationary background; whereas the day-3 collection contains the stationary background and all seventeen targets. Therefore the change detection algorithms presented in this chapter are performed using day-1 and day-3 data. Change detection using all three days (day-1, day-2, and day-3) are not considered. All the change detection results presented here are in the UHF-SAR domain and do not combine with the LIDAR above-surface object detection presented in chapter 3. The LIDAR complementary fusion is incorporated in chapter 6, where the overall fusion algorithm are presented. This chapter focuses on comparing the performances of the different change detection algorithms to improve UHF-SAR domain detection problem. The SAR change detection methodologies considered are categorized into pixel-based and feature-based algorithms and the goal is to identify the best performing UHF-SAR domain change detection algorithm that enhance the residual information from day-1 to day-3 UHF-SAR images.

5.2 Pixel-Based Change Detection

The first set of change detection algorithms considered in this study are the pixel-based algorithms which exploit pixel-by-pixel changes between the two images. In addition, statistically derived coherence between pixel windows of two images also fall into this category. Pixel-based change detection algorithms are well developed and studied, where
references to the fundamental theoretical backgrounds is easily obtained in the technical literature ([17] [16] [27] [4] [24]). The pixel-based change detection algorithms considered in this study are: coherent frame differencing (CFD), non-coherent frame differencing (NCFD), coherent cross-correlation change detection (CCCD), non-coherent cross-correlation change detection (NCCCD), coherence maximum-likelihood estimator (CMLE), and non-coherent coherence maximum-likelihood estimator (NCMLE). With the addition of a statistically derived options, the intensity image likelihood ratio (IILR) method developed in [29] is also included in this category. This list is not exhaustive as there exist other methodologies for pixel-based change detection in the literature.

**Frame Differencing**

The truly pixel-by-pixel change detection algorithms are the coherent and non-coherent frame differencing. The remaining four change detection algorithms are statistical window-based change algorithms meant to estimate the coherence, $\gamma$, between the two UHF-SAR images. Mathematically representing the UHF-SAR images, the reference image is referred to as $I^{(R)}$ and the mission image is referred to as $I^{(M)}$. Where the first day of collection contains only information about the scene devoid of any targets and contains a priori information on the background and clutter; whereas the third day of collection contains information of both background and the buried targets. The mathematical definition of the frame differencing algorithms is as follows

$$FD = |\Gamma^{(R)} - \Gamma^{(M)}|$$  \hspace{1cm} (5.1)

where $\Gamma^{(i)}$ is defined as follows

$$\Gamma^{(i)} = \begin{cases} 
I^{(i)} & : Coherent \\
|I^{(i)}| & : Non-Coherent
\end{cases}$$  \hspace{1cm} (5.2)
such that coherent processing exploits both real and imaginary parts of the complex SAR image. However, non-coherent processing exploits the magnitude or absolute value of the complex SAR image. This notation is adopted to avoid replicated equations, but it should be obvious that coherent versus non-coherent is merely a function of the representative images being of either the complex SAR images or the absolute value or magnitudes of the SAR images.

Performing both CFD and NCFD on the HH polarization from collection heading 073 the results are shown in figure 5.3. The target truth is marked by the red circle plotted at the provided truth location for target 12 and the blue circle plotted around the truth location is the radius of detection.

Figure 5.1: Top Left: HH polarization collection pass 073 reference SAR image. Top Right: HH polarization collection pass 073 mission SAR image. Bottom Left: Resulting CFD image. Bottom Right: Resulting NCFD image.
The resulting change images show a strong response from the target scatterers that appear only in the mission image. The strong target response is accompanied by several residual responses due fluctuations in the stationary background response, hindering detection performance. The residual of the stationary objects should theoretically be removed from the pixel-by-pixel differencing; however SAR imagery is susceptible to fluctuations in responses due to slight variations in collection geometry. Additional resulting change images of NCFD zoomed on all the other targets is included in Appendix B.

**Coherence Estimation: Correlation and Maximum-Likelihood**

Coherence estimation change detection algorithms CCCD and NCCCD are mathematically represented as

$$
\gamma_{\text{Corr}} = \left| \sum_{A_{i,j}} \Gamma^{(R)} \cdot \Gamma^{(M)} \right| \sqrt{\left( \sum_{A_{i,j}} \Gamma^{(R)} \cdot \Gamma^{(R)} \right) \left( \sum_{A_{i,j}} \Gamma^{(M)} \cdot \Gamma^{(M)} \right)}
$$

(5.3)

where $A_{i,j}$ is the selected window centered around pixel $i, j$ and $\Gamma^{(i)}$ is the variable used to designate coherent versus non-coherent processing ($\Gamma^{(i)}*$ denotes the complex conjugate of the UHF-SAR image hence is only valid for coherent processing). For the correlation estimation of the coherence between images, only the magnitude is considered. However, for coherent processing $\Gamma^{(i)} = I^{(i)}$, the result may be complex valued with a phase $\phi$. The phase information is not exploitable for single-pass single-antenna collections. Generally the phase between two collection antennas (channels) is exploited in interferometric processing. The resulting correlation change detection image is provided in figure 5.2, where the coherent and non-coherent are plotted side-by-side for comparison.

The resulting non-coherent correlation outputs a strong response for the target with additional clutter inside the radius of detection. Considering the coherent correlation, there is not a strong response from the target inside the radius of detection, the returns visually
Figure 5.2: Top Left: HH polarization collection pass 073 reference SAR image. Top Right: HH polarization collection pass 073 mission SAR image. Bottom Left: Resulting NCCCD image. Bottom Right: Resulting CCD image.

appear as clutter-like false-alarms. The reason for the coherent correlation to underperform the non-coherent correlation is not well understood and may well be an inherent feature of the UHF-SAR returns for targets buried underground. Phase distortions introduced to UHF-SAR images due to ground penetration is noted in [3]. Therefore, phase distortions from ground penetrating aerial SAR could have influenced the coherence estimates when coherently processed, contributing to the visual false-alarms.
The final set of coherence estimation change detectors is the coherence maximum-likelihood estimation, mathematically derived as

\[
\gamma_{mle} = \frac{2 \sum_{A_{i,j}} \Gamma^R \ast \Gamma^M}{\sum_{A_{i,j}} \Gamma^R \ast \Gamma^R + \sum_{A_{i,j}} \Gamma^M \ast \Gamma^M},
\]

starting from a likelihood ratio test. Once again, \(A_{i,j}\) is the selected window centered around pixel \(i, j\) and \(\Gamma^{(i)}\) is the variable used to designate coherent versus non-coherent processing. The sample cross-covariance and auto-covariance follow from MLE estimates of each respective unknown covariance [17]. The resulting change images from the coherence MLE change detector are shown in figure 5.3.

Figure 5.3: Top Left: HH polarization collection pass 073 reference SAR image. Top Right: HH polarization collection pass 073 mission SAR image. Bottom Left: Resulting Cmle image. Bottom Right: Resulting NCMLE image.

The coherent and non-coherent maximum-likelihood estimation of the coherence yield relatively strong responses from the target. However, the coherent MLE appears to introduce similar false-alarms within the radius of detection as in the case of the coherent
correlation discussed earlier. Interestingly enough, this seems to be an issue with coherent implementations of the pixel-based estimations of coherence.

**Intensity Image Likelihood Ratio**

The intensity images are defined as \( |I^{(R)}|^2 \) and \( |I^{(M)}|^2 \) for both reference and mission complex SAR images. In [29], the statistics of the SAR intensity images obey a Gamma distribution, from which a likelihood ratio change statistic is derived. The resulting change statistic is shown in the following equation (original derivation is found in [28])

\[
LR = \frac{\sum_{A_{i,j}} |I^{(R)}|^2}{\sum_{A_{i,j}} |I^{(M)}|^2} + \frac{\sum_{A_{i,j}} |I^{(M)}|^2}{\sum_{A_{i,j}} |I^{(R)}|^2},
\]

where the local statistics are computed from the subset \( A_{i,j} \) centered around the pixel \( i, j \) in the UHF-SAR intensity image. The resulting likelihood ratio change image is shown in figure 5.4. It can be seen that stationary objects present in both reference and mission images are almost completely mitigated. Instead of residual responses from fluctuations in object responses between temporal instances, a clutter-like background is observed in the IILR resulting change image. The targets response is clearly visible and the response is located in the area centered about the truth location for target 12. Therefore, the IILR change detection method appears to be very effective for blob-like target detection among other stationary blob-like object responses in the scene. Before the complementary sensor fusion algorithm is applied to remove above-surface false-alarms via LIDAR thresholding; these results demonstrate that the IILR change detection method by itself has the capacity to remove significant above-surface false-alarms. Additional resulting change images from the IILR zoomed about all the individual targets are given in Appendix C.
5.3 Feature-Based Change Detection

Change detection methodologies are not limited to pixel-based or statistical window-based changes between two multitemporal images. Exploitation of features extracted from SAR images is another change detection methodology used to determine changes between multitemporal images [2][6][20][22][23][25]. In case of the supplied UHF-SAR images, the target responses are inherently blob-like due to the relative size of the buried munitions and the resolution of the UHF-SAR image (Please refer to Appendix A where UHF-SAR images are presented showing the region around the truth locations for all targets). From the assumption of a blob-like targets, the feature-based change detection algorithms were considered to be appropriate. A texture-based change detection algorithm, adapted from [13], is implemented in this thesis work which takes the difference in gradient magnitudes between the reference and mission images. Furthermore, statistical features are used to perform change detection implementing the windowing filters, changes in the UHF-SAR images directly change the statistical distributions from the windowed subset. In addition, information theoretic methodologies are implemented (Kullback-Leibler divergence)
based on the inherent statistics of the UHF-SAR images, such that deviations in the inherent statistics constitute change in the UHF-SAR images. Finally geometric moments are implemented as a geometric feature-based change detection method, exploiting the blob-like nature of the unexploded buried munitions.

5.3.1 Texture-Based Change Detection

In [13], a texture-based change detection algorithm (texture differencing) is fused with a pixel based change detection algorithm (frame differencing). Adapting the texture differencing change detection algorithm in [13], a slightly different change detection algorithm is used to exploit the texture features of the UHF-SAR images. The texture differencing change detection algorithm takes the gradient magnitude of the reference and mission UHF-SAR images and subtracts them. For the blob-like object responses in the UHF-SAR image the gradient magnitude helps to amplify the instantaneous changes in texture. Therefore, the gradient from background clutter to object response in the UHF-SAR image should be significant, as clutter is assumed to be spatially homogeneous. From this, the difference between the reference and mission images is expected to have pronounced residuals due to the target whereas the residual of all stationary objects should tend to zero.
Figure 5.5: Resulting change image from the gradient differencing change detection algorithm.

The resulting change image from the gradient change detection algorithm is shown in figure 5.5, where the implemented gradient change detection algorithm is defined as follows,

$$\Delta G = \sqrt{(G_x^{(R)})^2 + (G_y^{(R)})^2} - \sqrt{(G_x^{(M)})^2 + (G_y^{(M)})^2}$$  \hspace{2cm} (5.6)

where the $x$ and $y$ gradient images are defined as,

$$G_x^{(i)} = \Delta_x * |I^{(i)}|;$$  \hspace{2cm} (5.7)

and

$$G_y^{(i)} = \Delta_y * |I^{(i)}|;$$  \hspace{2cm} (5.8)

where $I^{(i)}$ is either the mission or reference complex-SAR image. The $\Delta_x$ and $\Delta_y$ are gradient matrices, which are commonly referred to as operators. For the implementation of
this change detection algorithm any of the popular gradient operator can be used, including Sobel, Scharr, Prewitt, etc. For this thesis effort the Sobel operator has been implemented, as it was the operator used in [13]. As shown mathematically, the gradient matrix both $x$ and $y$ are convolved with the reference and mission UHF-SAR magnitude images to acquire the gradient images in each Cartesian dimension $G_x^{(i)}$ and $G_y^{(i)}$. The magnitude of the $x$ and $y$ gradient images are used to find the gradient magnitude for reference and mission UHF-SAR amplitude images. In [13] a maximum-likelihood change statistic is used to find changes between the reference and mission gradient magnitudes. However, in this thesis subtracting the two gradient magnitudes is shown to be sufficient, hence the adopted texture-based change detection method is based on texture differencing.

5.3.2 Statistical-Based Change Detection

Inherent statistical properties of SAR images is a well understood and is exploited to form several statistical-based change detection methodologies [9][10][20][21]. Representing SAR images as complex random variables several governing distributions are well accepted. The real and complex parts of a complex SAR image are normally distributed. Furthermore, the magnitude (voltage) of a complex SAR image obeys a Rayleigh distribution; whereas the intensity (power) of a complex SAR image obeys a Gamma distribution [18]. Considering again windowing subsets of the complex SAR image, which provide sample statistics of the complex SAR image about the $(n, m)$ pixel, such that any change occurring within the subset of the complex SAR image will influence a statistical change in the sample statistics from reference to mission images. Thus, statistical filtering employing the window-based sample operations are used to enhance the statistics of a SAR image prior to performing change detection.

Approaching the statistical-based change detection problem differently, information theoretic measures of divergence between two statistical distributions using the Kullback-Leibler divergence change detection method has been developed. In [9], several parame-
ters of a SAR image are estimated to form the governing statistical distribution using the Pearson system [11]. For this implementation, an estimated distribution is used for both reference and mission images to find the Kullback-Leibler divergence using a sliding window. Another implementation of the Kullback-Leibler divergence [21] exploits the inherent statistics of the SAR image (complex SAR, magnitude SAR, and intensity SAR). Closed form Kullback-Leibler divergence are implemented based on the governing distribution of the SAR image. In this thesis both normal distribution (applied to the complex SAR image) and the Rayleigh distribution (applied to the amplitude SAR image) have been considered.

**Statistical Filtering**

Initially statistical filtering techniques are used to formulate different change detection algorithms. The general equation in terms of operators is shown in equation 5.9, where the $C$ operator represents a pixel-based change detection algorithm and the $S$ operator represents statistical filtering. The statistical filtering is implemented using sliding window $A_{n,m}$ centered about pixel $n,m$. Sample statistics are computed using the UHF-SAR image pixels that are located in the window $A_{n,m}$.

$$S_{CD} = C\{S\{I^{(R)}, I^{(M)}\}\}$$  \hspace{1cm} (5.9)

Selection of statistical filters is based on computing sample statistics for a given subset of the UHF-SAR image. This thesis utilizes several standard statistical features such as Kurtosis, Skewness, and the Power-to-Mean ratio which are defined in the following equations,

$$Kurtosis = \frac{E[(|I^{(i)}| - \mu^{(i)})^4]}{(\sigma^{(i)})^4},$$  \hspace{1cm} (5.10)

$$Skewness = \frac{E[(|I^{(i)}| - \mu^{(i)})^3]}{(\sigma^{(i)})^3},$$  \hspace{1cm} (5.11)
\[
Power - to - Mean = \frac{E[(|I^{(i)}| - \mu^{(i)})^2]}{E[|I^{(i)}|]} = \frac{(\sigma^{(i)})^2}{\mu^{(i)}}, \tag{5.12}
\]

where the \(E[\cdot] \) is the expectation operator. In this context the expectation operates on the UHF-SAR image pixels in the window \(A_{n,m} \). Also relevant, \(\mu^{(i)} \) and \((\sigma^{(i)})^2 \) are the sample-mean and -variance of the window \(A_{n,m} \). Each statistical feature is computed using the amplitudes of the reference and mission UHF-SAR images, denoted as \(|I^{(i)}| \) where the superscript \((i) \) denotes reference or mission. Extracting Kurtosis, Skewness, and Power-to-Mean statistical features will illustrate the effectiveness of each to enhance the targets presence prior to pixel-based change detection. Figure 5.6 and figure 5.7 show resulting change images using Kurtosis and Skewness statistical filters as \(S \) and frame differencing as \(C \). Compared to the performance of previous change detection methodologies, both Kurtosis and Skewness fail to show the desired change at the target location. In addition, clutter statistics are amplified to undesirable levels and show up as residual.

![Kurtosis Differencing Image - Target 12](image)

**Figure 5.6:** Kurtosis difference image for collection heading 073 polarization HH.
The resulting change image associated with extracting the statistical feature Power-to-Mean ($S$) followed by frame differencing ($C$) is shown in figure 5.8. In this case, the target’s response is significantly increased and residual statistical clutter is mitigated, relative to both Kurtosis and Skewness resulting images. In conclusion, all three statistical feature extraction approaches followed by frame differencing failed to improve change detection results especially when compared to some of the other change detection methods attempted.
Kullback-Leibler Divergence

Implementing the Kullback-Leibler Divergence for SAR image change detection follows from the derivations in [21]. For this particular study the Kullback-Leibler Divergence for both Normally and Rayleigh-Distributions are implemented. The derived mathematical representations for the two cases are shown in the following equations [21],

\[
KL_N(I^{(M)}|I^{(R)}) = \frac{1}{2} \left( \log\left(\frac{(\sigma^{(R)})^2}{(\sigma^{(M)})^2}\right) - 1 \right) + \frac{(\mu^{(R)})^2 + (\mu^{(M)})^2 + (\sigma^{(R)})^2 - 2\mu^{(R)}\mu^{(M)}}{2(\sigma^{(R)})^2}
\]

and

\[
KL_R(I^{(M)}|I^{(R)}) = \frac{(b^{(M)})^2}{(b^{(R)})^2} - 2\log(b^{(R)}) + 2\log(b^{(M)}) - 1;
\]

where \(\mu^{(i)}\) and \((\sigma^{(i)})^2\) are the mean and variance of the Gaussian distribution and \(b^{(i)}\) is the single non-negative parameter of the Rayleigh distribution. The mean of a Rayleigh distribution is related to the parameter \(b\) through the following equation, \(\mu = b\sqrt{\frac{\pi}{2}}\). The resulting Kullback-Leibler change detection images are shown in figure 5.9. The Kullback-Leibler Divergence derived for a Normal distribution is applied to the complex SAR images \((I^{(R)}\) and \(I^{(M)}\)); whereas the Kullback-Leibler Divergence derived for a Rayleigh distribution is applied to the amplitudes of the complex SAR images \((|I^{(R)}|\) and \(|I^{(M)}|\).

5.3.3 Geometrical Change Detection

Considering features, other than those already discussed (texture and statistical), such as geometrical features is problematic for SAR imagery. The standard geometrical features derived and developed for optical imagery do not apply to SAR images, due to fluctuations in a SAR templates with respect to aspects angles, etc. However, with small (blob-like) targets in relatively low-resolution SAR imagery, several geometric measures can still pro-
vide features. The main geometric feature implemented in this study is the first of the complete set of Hu’s invariant moments [8]. Considering equation 5.9, where the $C$ operator represents pixel-based change detection and the $S$ now represents geometric windowing function. In this implementation, the $S$ operator is Hu’s first-invariant geometric moment. Hu’s first invariant moment is analogous to a moment of inertia, which will vary based on the blob-like shape of the target response and the resulting SAR amplitude values for the target response. The stronger the target response, the larger the moment of inertia. The mathematical description of the first invariant moment is shown in equation 5.15; which is
calculated using the Cartesian moments defined in equation 5.16.

\[
\phi_1 = \eta_{20} + \eta_{02}
\]  

(5.15)

where

\[
\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{(\frac{p+q}{2})} + 1}, \quad \mu_{00} = m_{00}
\]

\[
\mu_{20} = m_{20} - \mu_{00}x^2, \quad \bar{x} = \frac{m_{10}}{m_{00}}
\]

\[
\mu_{02} = m_{02} - \mu_{00}y^2, \quad \bar{y} = \frac{m_{01}}{m_{00}}
\]

These are calculated from Cartesian moments defined as

\[
m_{pq} = \sum_{x}^{N} \sum_{y}^{M} x^p y^q |I(x, y)| = \sum_{x}^{N} \sum_{y}^{M} \Phi(x, y) |I(x, y)|;
\]  

(5.16)

such that \( |I(x, y)| \) is the amplitude SAR image and \( \Phi = \tilde{n}^p (\tilde{m}^q)^T \) is a basis function computed for a window sized \((N \times M)\); where \( \tilde{n} = [1, \ldots, N]^T \) and \( \tilde{m} = [1, \ldots, M]^T \). The Cartesian moments are calculated for sliding windows; therefore the moment of inertia is relative to the center pixel in the window. The exponents \( p \) and \( q \) are representative of the order of the Cartesian moment in \( x \) and \( y \) dimensions, respectively. Setting \( C \) as the maximum-likelihood change statistic, the first-invariant moment change image is shown in figure 5.10. The target’s response is visible near the truth location; however this methodology fails to suppress the off-road background responses which occur in both reference and mission SAR images. In addition, clutter variations of the background seem to be amplified by using this invariant moment, as opposed to being suppressed.
5.4 Performance Conclusions

In this section the performance gains associated with various change detection methodologies are studied for the provided UHF-SAR dataset. The performance of change detection algorithms for SAR images is primarily dependent on the nature of the targets and the clutter background. For the current application of detecting unexploded buried munitions, the targets cover small areas of the SAR images and in many cases the targets closely resemble the above-surface objects in the UHF-SAR scene. Therefore the change detection algorithm must be able to detect the changes caused by the targets while mitigating effects of the clutter and stationary above-surface objects present in the SAR scene. Of the various change detection algorithms a majority effectively removed stationary background while providing a residual response for the targets. Based on visual inspection the following change detection methodologies appear to offer reasonable results: IILR, NCFD, CFD, NCMLE, Texture Differencing, Power-to-Mean, and both Kullback-Leibler divergences. Attempting to extract the statistical features of Kurtosis and Skewness did not help change detection. Likewise, for geometric feature extraction analogous to moment of inertia failed to offer any performance gains.
In addition to visually comparing the effectiveness of the various change detection methods, ROC plots are generated to compare the detection performance of each method. The first ROC plot, shown in figure 5.11, shows the results for pixel-based change detection methods. At this point in the study no above-surface false-alarm removal via fusion with LIDAR dataset, nor multiple-passes and multiple-polarizations have been exploited. It is immediately clear from figure 5.11 that IILR is the best performing change detection method for strictly UHF-SAR domain detection. In addition, NCFD and CFD outperform the other pixel-based change detection algorithms followed by NCMLE.

Figure 5.11: ROC plot comparing the performances of the various pixel-based change detection algorithms.

Therefore, based on the ROC plots, for detecting unexploded buried munitions using multitemporal UHF-SAR collections IILR, NCFD, CFD, and NCMLE are the superior change detection methodologies. IILR yielded positive-detections for all 17 targets in Baker East (using HH polarization 073 collection heading) at approximately $10^3$ false-alarms per square-kilometer; whereas NCFD and CFD yield positive-detection for all 17 targets at approximately $20^3$ to $40^3$ false-alarms per square-kilometer.

For the feature-based change detection algorithms ROC plot is shown in figure 5.12. Power-to-Mean and both Kullback-Leibler divergence (Normally distributed and Rayleigh
distributed) perform the best out of the various statistical feature-based change detection algorithms. The Power-to-Mean, statistical filtering followed by differencing, removed the above-surface false-alarms in both reference and mission images; however the filtering process amplified several regions of clutter which inhibits performance. Both Kullback-Leibler divergence information theoretic measures perform similarly and the ROC curves essentially overlap for these two cases. The remaining statistical change detectors suffer from lack of clutter suppression and stationary background suppression using reference and mission images.

![ROC plot comparing the performances of the various statistical feature-based change detection algorithms.](image)

Figure 5.12: ROC plot comparing the performances of the various statistical feature-based change detection algorithms.

The results for the remaining feature-based change detection methodologies are shown in figure 5.13, along with IILR for a glimpse at relative performance. As visually determined, the geometric features analogous to moment of inertia exhibits poor performance. However, texture differencing performs just as well as NCFD and CFD, and in fact, for these two cases the ROC curves are slightly shifted to the left. Therefore, extracting texture features prior to frame differencing enhances performance slightly. Furthermore, extracting texture features followed by CMLE pixel-based change detection performs worse than frame differencing result.
Figure 5.13: ROC plot comparing the performances of the various feature-based change detection algorithms.

Superimposed ROC plots of the top performing among the pixel-based and feature-based change detection methods are shown in figure 5.14 for comparison. It is immediately obvious that a majority of the pixel-based and feature-based change detection methods implemented have very similar detection performance, with the exception of IILR. For the single-pass single-polarization UHF-SAR only case studied in this chapter, IILR offers the best overall unexploded buried munitions detection performance relative to all the other change detection methodologies implemented in this thesis effort.
5.5 Multiple Polarization and Multiple-Pass Change Detection

It should be noted here that analogous to Chapter 4, change detection utilizing multiple passes and multiple polarizations have also been conducted in this thesis. The details of these results are given in Section 6.3, where the performance has been compared with the detection performance after fusion with above-surface elevation information provided by LIDAR DEMs for false alarm removal.
Complementary Sensor Fusion

Algorithms
6.1 Introduction

Thus far this thesis effort introduced various individual parts of the complementary sensor fusion algorithm. It is important to note that the provided JIEDDO Halite-1 dataset include multiple UHF-SAR images from multiple collection headings and multiple-polarizations furnishing information on above and below surface objects. Each UHF-SAR image is sufficiently registered to one another and is geo-referenced. The LIDAR dataset contains two digital elevation models (DEM) from each day (temporal instance) of collection. Unlike the UHF-SAR images, the LIDAR DEM only contain above-surface objects. Each LIDAR DEM is geo-referenced making interpolation and geo-registration between LIDAR and UHF-SAR domains feasible.

LIDAR and UHF-SAR are two complementary sensors yielding two complementary datasets tending naturally to complementary sensor fusion to isolate the unexploded buried munitions. For this thesis effort the complementary sensor fusion algorithm is based on two different detection problems; LIDAR domain detection and UHF-SAR domain detection.

LIDAR domain detection was discussed in Chapter 3 and it consists of LIDAR processing technique followed by thresholding. Processing the LIDAR DEM is required initially to remove the gradual incline in terrain elevation which prohibited global elevation thresholding. The different local thresholding techniques are cell-averaging CFAR based anomaly detection (AD), RFER thresholding, and DED thresholding of the LIDAR DEMs. Each technique effectively removed the global variation in elevation while preserving the local elevation peaks. All the LIDAR processing techniques except RFER required empirical threshold selection. Therefore RFER has been in the following detection experiments with the intuitive choice of RFER threshold of $T = 1$.

UHF-SAR domain detection is partitioned into two separate categories: anomaly detection (AD) and change detection (CD) depending on whether targets need to be detected using data collected on a single or multiple days, respectively. In the case of AD, a cell-averaging CFAR statistic is implemented to form an anomaly image in the UHF-SAR do-
main. The anomalies correspond to both above- and below-surface objects in the scene. Anomaly detection does not use any a priori information about targets (through Swerling models) or the background. Unlike anomaly detection, change detection exploits a priori information provided on the background void of targets when detecting changes in an image containing both background and targets. Simply comparing the two in terms of the information provided to the detectors, where more information can only help a detector, change detection should outperform anomaly detection. However, some applications (unitemporal UHF-SAR and LIDAR data collections) are constrained to anomaly detection. In addition, the UHF-SAR data collection contains multiple-passes and multiple-polarizations which are combined to improve detection performance even further.

Furthermore, the UHF-SAR detection problem has limitations with its ability to distinguish above-surface objects from below-surface objects. In order to solve this problem the complementary information in the two sensor modalities are exploited to isolate the unexploded buried munitions. The resulting detection image (mask) of valid LIDAR elevations is interpolated to the UHF-SAR domain to remove the above-surface false-alarms from both anomaly detection images and change detection images. The UHF-CFAR domain anomaly image obtained from cell-averaging CFAR statistic contains anomalies corresponding to above- and below-surface objects. Furthermore, when evaluated using ROC curves the above-surface anomalies which are counted as false-detections can be mitigated using the LIDAR elevation mask. Likewise, the change detection algorithm may not suppress all stationary background/clutter objects; therefore the change image contains residuals corresponding to above- and below-surface objects. The LIDAR elevation mask is used to rule out the above-ground objects and isolate the unexploded buried munitions. Exploiting multiple-passes and multiple-polarizations helps to improve the complementary sensor fusion algorithms ability to detect the unexploded buried munitions.

This chapter is organized to analyze the two different subsets of UHF-SAR detection, first anomaly detection followed by change detection. The presentation focuses on target
used as a typical case, as in previous chapters. The results for targets other than target 12 are given in the appendices. Multiple-passes and multiple-polarizations in UHF-SAR domain are implemented for both anomaly detection and change detection. Each UHF-SAR detection algorithm is evaluated using ROC curves. It is important to note that these experimental studies keep the LIDAR domain detection fixed, where RFER processing is used followed by thresholding at $T = 1$, while varying the UHF-SAR domain detection algorithm.
6.2 Single-Collection Day- Anomaly Detection in UHF-SAR Domain

Initializing the simulations for the complementary sensor fusion algorithms, anomaly detection using the single collection day (mission SAR images collected on day-3). The resulting anomaly images for target 12 are shown in figure 6.1. In the sub plotted figure both reference and mission images are provided, however only the mission UHF-SAR image is used in this case. Both targets and false-alarms are present in the resulting anomaly detection image, corresponding to below- and above-surface objects, respectively.


Distinguishing the targets from false-alarms is difficult, either visually or using a computer algorithm if the truth locations are not given. Incorporating information from the LIDAR above-surface detection mask effectively isolates the anomalies in the UHF-SAR domain at allowable elevation heights in the LIDAR domain and the result is shown in the lower
right subplot image. It can be observed that the anomaly corresponding to target 12 in the UHF-SAR domain is isolated using the complementary sensor fusion with LIDAR. All the off-road above-surface false-alarms are mitigated, drastically reducing the false-alarms of cell-averaging anomaly detection using single-pass single-polarization data.

The extension to multiple-passes and multiple-polarizations is shown in figure 6.2. Incorporating additional passes and polarizations effectively averages out background clutter contained in both anomaly detection images. With the reduction in clutter the random fluctuations will no longer be classified as above-surface false-alarms, instead they average out to a semi-constant background level. In addition, the target and above-surface object response are amplified with the mitigation of clutter improving the resulting anomaly image quality.

![Figure 6.2: Left Image: Multiple-Polarizations fixed collection heading 073. Right Image: Multiple-Passes fixed polarization HH.](image)

Improving the anomaly image even further, the four SAR images from collection headings 073 and 253 both HH and VV polarizations are used to form a multiple-pass multiple-polarization anomaly detection image. The resulting image is shown in figure 6.3. The responses from the target and the off-road above-surface objects in the scene remain prominent, while a majority of the background clutter is removed. Once again, clutter is mitigated while the anomalies around target 12 are amplified. Both reference and mission UHF-SAR images are provided so that anomalies can be visually matched with objects.
imaged in the UHF-SAR scene. Applying the above-surface false-alarm removal using the complementary sensor fusion algorithm a single anomaly is isolated. Based on the provided truth location, this anomaly corresponds to target 12 as can be confirmed visually.


The performance gains from implementing the complementary sensor fusion are illustrated in the ROC plot shown in figure 6.4. Implementing complementary sensor fusion reduces false-alarms per square-kilometer by an order-of-magnitude, which helps improve the overall performance of the algorithm. The detection performance comparison of the single-pass single-polarization case versus the multiple-passes multiple-polarization case
is shown in the ROC plot in figure 6.5. The aforementioned gain in performance due to complementary sensor fusion is evident. The ROC curve for multiple-passes tends to follow the best performing single-pass single-polarization case.

Figure 6.4: ROC plot comparing the performance gains from implementing complementary sensor fusion on single-pass single-polarization anomaly detection.
Figure 6.5: ROC plot comparing the performance gains from using multiple-passes multiple-polarizations versus single-pass single-polarization.
Figure 6.6 compares performance for multiple-passes versus multiple-polarizations versus multiple-pass and multiple-polarization, the ROC plots. Even though the image quality visually improves exhibiting reduction of background clutter the detection performance does not improve much beyond the best single-pass single-polarization anomaly detection performance. However, an order of magnitude consistent performance gains associated with the complementary sensor fusion in all cases is highly desirable for removing above-surface false-alarms.

Figure 6.6: ROC plot comparing the performance gains from using all collection headings and polarizations.
6.3 Multiple-Collection Days - Change Detection in UHF-SAR Domain

This section presents results on implementing the complementary sensor fusion algorithm for multiple days of collection data. This implementation is dependent on obtaining a collection with apriori information on the scene without targets, such that change detection can be performed. The various change detection methodologies implemented were covered in chapter 5. Table 6.1 gives the complete list of CD algorithms considered in this thesis. In the table, the change detection algorithms are grouped into two subsets, pixel-based and feature-based. The main difference between pixel-based and feature-based is the feature-exploiting image filtering that is implemented for the feature-based change detection algorithms.

<table>
<thead>
<tr>
<th>Pixel Based</th>
<th>Feature Based</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCFD</td>
<td>Texture Difference</td>
</tr>
<tr>
<td>CFD</td>
<td>Kurtosis</td>
</tr>
<tr>
<td>NCCCD</td>
<td>Skewness</td>
</tr>
<tr>
<td>CCCD</td>
<td>Power-to-Mean</td>
</tr>
<tr>
<td>NCMLE</td>
<td>Kullback-Leibler Divergence</td>
</tr>
<tr>
<td>CMLE</td>
<td>Invariant Moment</td>
</tr>
<tr>
<td>IILR</td>
<td></td>
</tr>
</tbody>
</table>

Table 6.1: Various Change Detection methodologies grouped into pixel-based and feature-based subsets. The boxed change detection methods are studied further in this section.
As described in Chapter 5, the best performing change detection methods are NCFD, IILR, Texture Differencing, and Power-to-Mean. For NCFD single-pass single-polarization change detection, a majority of the stationary false-alarms in the off-road region are suppressed through the pixel-by-pixel differencing. However background clutter variations were still present. Visually, the differences between coherent or non-coherent differencing is negligible, which was supported by the resulting ROC curves. Incorporating multiple-passes and multiple-polarizations for NCFD and CFD improve the results through enhancing the targets response and mitigating background clutter. In figure 6.7, the resulting multiple-pass and multiple-polarization change detection images are shown in the left column. Utilization of both multiple-passes and multiple-polarizations is expected to aid and enhance suppression of clutter and residual stationary false-alarms. However, several stationary scatterers are still present in the change images, which get removed by the complementary sensor fusion algorithm, as shown in the right column of figure 6.7.
Figure 6.7: Resulting NCFD multiple-pass and multiple-polarization change detection images.
The best performing change detection algorithm is the intensity image likelihood-ratio (IILR), which removes significant stationary false-alarms present in the SAR scene. The resulting multiple-pass and multiple-polarization change images using IILR are shown in the left column of figure 6.8, whereas the right column shows the corresponding results after sensor fusion algorithm is applied to the change image. The resulting change image visually appears to have removed stationary false-alarms coinciding with the above-surface false-alarms the complementary sensor fusion algorithm removes in the case of other algorithms.
Figure 6.8: Resulting IILR multiple-pass and multiple-polarization change detection images.
Considering next the texture differencing change detection algorithm, which performed frame differencing on the resulting gradient images, the effects of multiple-passes and multiple-polarizations are similar to those of NCFD. In figure 6.9 the resulting multiple-pass and multiple-polarization change images are shown in the left column. The right column of figure 6.9 shows the corresponding results after sensor fusion algorithm is applied to the change image.
Figure 6.9: Resulting texture differencing multiple-pass and multiple-polarization change detection images.
The final change detection algorithm presented in this section is the power-to-mean differencing algorithm. The resulting multiple-passes and multiple-polarization change images are shown in the left column of figure 6.10, whereas the right column shows the corresponding results after sensor fusion algorithm is applied to the change image. In the resulting change images the same stationary scatterers present in NCFD and texture differencing are present, however in the multiple-passes image the stationary scatterers are slightly attenuated. At the same time, the entire noise floor (background clutter) is being amplified.
Figure 6.10: Resulting power-to-mean multiple-pass and multiple-polarization change detection images.
The resulting ROC plots for the four change detection algorithms are shown in figure 6.11 through figure 6.14. The ROC plots provided compare the individual single-pass single-polarization change images with the combined multiple-pass single-polarizations change image, for each of the four change detection methods. The reduction in false-alarms from the complementary sensor fusion is immediately apparent. All of the considered change detection algorithms show a performance improvement from the complementary sensor fusion; however multiple-passes as well as multiple-polarizations do not consistently share the same trend.

Figure 6.11: Showing ROC curves for NCFD change detection image.
Figure 6.12: Showing ROC curves for the IILR change detection image.

Figure 6.13: Showing ROC curves for Texture Differencing change detection image.
Figure 6.14: Showing ROC curves for the Power-to-Mean change detection image.
6.4 Conclusions and Suggestions for Future Work

Anomaly detection and change detection UHF-SAR domain detection algorithms are effective tools for detecting unexploded buried munitions; however limitations exist with respect to distinguishing between above-surface and below-surface targets which inhibit detection performance. Specifically, UHF-SAR band radars yield images with both above- and below-surface objects that appear largely similar to the detection algorithms. Therefore detection algorithms applied to the UHF-SAR images are incapable of distinguishing between above-surface and below-surface objects causing considerable false alarms. The introduction of the LIDAR DEM offers additional complementary elevation information about the scene. Hence, the idea of complementary sensor fusion leads to above-surface false-alarm removal using the LIDAR above-surface object detection for improved detection performance in the UHF-SAR domain.

Incorporating multiple-pass and multiple-polarization combination further improves detection performance through clutter reduction and anomaly/change amplification. Strictly UHF-SAR domain detection of the unexploded buried munitions using anomaly detection on single day’s data is not sufficient, due to numerous above-surface false-alarms from above-surface objects imaged in the UHF-SAR scene. Change detection, on the other hand, exploits a priori information about the background and therefore mitigates stationary background between reference and mission images. However, due to sensitivity of SAR imaging to slight changes in collection geometry, change detection does not completely suppress all of the stationary background. In the study of UHF-SAR change detection, IILR was found to be the best performing methodology since it suppressed a majority of stationary background leaving only the buried targets (represented as change between the reference and mission UHF-SAR images).

Being provided with terrain elevation information from additional sensors, specifically the LIDAR sensor in this study, it is shown that significant above-surface false-alarms encountered as anomalies in anomaly images or residual in change images corresponding to
above-surface objects, can be removed. The effectiveness of LIDAR false-alarm removal is apparent in all ROC plots (except IILR, refer to figures 6.11 through 6.14). The best performance encountered during the thesis effort is obtained using NCFD multiple-pass change detection methodology, where HH polarization for collection headings 073 and 253 are combined using the multiple-pass cell-averaging CFAR statistic. The ROC curve shows that all 17 targets are detected with only 10 false-alarms per square-kilometer.

Contributions from this thesis effort include extension of the single-pass single-polarization complementary sensor fusion algorithm to multiple-passes and multiple-polarizations. In addition, a thorough survey of change detection methodologies ranging from standard pixel-based (NCFD, CFD, NCCCD, CCCD, NCMLE, and CMLE) to relatively new pixel-based (IILR) algorithms. Furthermore, feature-based change detection methodologies are explored including texture differencing, that exploits texture features, statistical feature extraction (Kurtosis, Skewness, and Power-to-Mean) based change methods, as well as geometric feature extraction using moment of inertia. Therefore, the study included a thorough examination of a variety of UHF-SAR domain detection algorithms. The additional performance improvement from the complementary sensor fusion is unattainable given only UHF sensors. Overall, the best buried target detection results were obtained for change detection by exploiting multiple-pass and multiple-polarization UHF-SAR data in conjunction with LIDAR elevation. For the best case, positive detection of 17 blob-like unexploded buried targets was achieved over a large stretch of land yielding only 10 false-alarms per square-kilometer.

Recommendations on the future expansion of this solution to the unexploded buried munitions detection problem are as follows: In [3] the authors mention phase distortions arising from the scattering of objects below the surface when imaged with UHF ground penetrating RADAR. One recommendation for future work is the exploration of phase-based buried object detection in UHF-SAR images. In essence, can the phase information from a single-pass single-polarization UHF-SAR image allow for buried object detection
by exploiting the anticipated phase distortions.

Other avenues for future work exist in the UHF-SAR domain, specifically, improving the UHF-SAR domain detection problem to better isolate the unexploded buried munitions. Future work could include: Implementing additional information theoretic change detection techniques such as applying the Kullback-Leibler Divergence to the UHF-SAR intensity images. The underlying clutter statistics for a SAR intensity image obey the Gamma distribution, there exists a derived closed form Kullback-Leibler Divergence between two Gamma distributions parameterized by the shape \( k \) and scale \( \theta \) in [21] which can be applied to the intensity UHF-SAR images. Estimation of the shape and scale can be performed through sample mean and variance of the intensity UHF-SAR images along with the known relationships between mean, variance, shape, and scale. Furthermore, UHF-SAR domain anomaly detection should be expanded to improve performance past that of single-parameter cell-averaging CFAR. Implementing the two-parameter (mean and variance) CFAR, along with Swerling models, to improve unexploded buried munitions detection for a single days collection. In addition, various other anomaly detectors should be implemented, such as the standard RX anomaly detection. RX anomaly detection uses Mahalanobis distance, therefore it assumes Gaussian data, and can be applied to the real and imaginary parts of the UHF-SAR images [12].

Future work should be done on the methods used for combining multiple passes and multiple polarizations. Specifically, work should be done to develop information theoretic combination techniques or applying a whitening filter to the UHF-SAR images prior to combination using single-parameter cell-averaging CFAR statistic. Improving the combining strategies could yield a better use of the multiple passes and multiple polarizations provided with the data; which will improve the unexploded buried munitions detection.
Table of all 17 Targets: HH073

UHF-SAR images from Baker East
Figure A.1: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 1. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure A.2: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 2. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure A.3: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 3. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure A.4: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 4. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure A.5: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 5. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure A.6: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 6. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure A.7: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 7. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure A.8: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 8. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure A.9: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 9. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure A.10: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 10. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure A.11: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 11. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure A.12: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 12. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure A.13: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 13. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure A.14: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 14. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure A.15: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 15. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure A.16: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 16. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure A.17: Reference and Mission UHF-SAR images collected using HH polarization 073 heading and backprojected to Baker East. Zoomed about target 17. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
NCFD Change Detection Method
Figure B.1: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 1. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure B.2: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 2. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure B.3: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 3. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure B.4: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 4. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure B.5: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 5. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure B.6: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 6. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure B.7: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 7. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure B.8: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 8. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure B.9: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 9. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure B.10: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 10. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure B.11: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 11. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure B.12: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 12. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure B.13: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 13. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure B.14: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 14. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure B.15: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 15. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure B.16: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 16. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure B.17: NCFD multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 17. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
IILR Change Detection Method
Figure C.1: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 1. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure C.2: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 2. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure C.3: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 3. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure C.4: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 4. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure C.5: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 5. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure C.6: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 6. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure C.7: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 7. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure C.8: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 8. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure C.9: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 9. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure C.10: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 10. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure C.11: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 11. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure C.12: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 12. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure C.13: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 13. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure C.14: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 14. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure C.15: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 15. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure C.16: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 16. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure C.17: IILR multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 17. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Texture Difference Change Detection

Method
Figure D.1: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 1. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure D.2: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 2. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure D.3: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 3. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure D.4: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 4. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure D.5: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 5. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure D.6: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 6. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure D.7: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 7. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure D.8: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 8. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure D.9: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 9. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure D.10: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 10. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure D.11: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 11. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure D.12: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 12. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure D.13: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 13. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure D.14: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 14. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure D.15: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 15. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure D.16: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 16. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure D.17: Texture Differencing multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 17. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Power-to-Mean Change Detection

Method
Figure E.1: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 1. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure E.2: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 2. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure E.3: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 3. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure E.4: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 4. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure E.5: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 5. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure E.6: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 6. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure E.7: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 7. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure E.8: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 8. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure E.9: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 9. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure E.10: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 10. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure E.11: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 11. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure E.12: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 12. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure E.13: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 13. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure E.14: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 14. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure E.15: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 15. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Figure E.16: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 16. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.

Figure E.17: Power-to-Mean multiple-polarization change image using HH and VV polarization collection heading 073 Baker East. Zoomed about target 17. The red circle corresponds to the provided truth location and the blue circle corresponds to radius of detection used in ROC plots.
Bibliography


