



**EXPERIMENTAL VALIDATION OF A
HETEROGENEOUS RADAR CLUTTER
STATISTICAL ESTIMATION METHOD**

THESIS

Elliot R. Erstein, Captain, USAF
AFIT-ENG-MS-17-M-026

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Captain, USAF

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Abstract

Radar clutter models are important for improving radar target detection when clutter is present. A new method for estimating single clutter type, homogeneous, radar clutter statistics through measurement of a multiple type, heterogeneous clutter was developed in 2015 by researchers at the Air Force Institute of Technology. The estimation method is greatly valued in the clutter research and modeling world for reducing clutter campaign measurement time and cost. This thesis looks at validation steps for the MH Algorithm through the use of simulations and experimental radar clutter measurements.

The simulations and experimental radar clutter measurements focus on a simplified two clutter type scenario using metallic grass and rock clutter types. The clutter measurements are split into homogeneous and heterogeneous scenarios to test the estimation method's accuracy and validity through the analysis of a selected goodness of fit technique.

The results show that for the key estimation method assumption, using a linear mixing model, is validated through experimental radar clutter measurement analysis. However, the accuracy of the estimation method requires further validation due to experimental measurement inconsistencies and constraints.

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EXPERIMENTAL VALIDATION OF A HETEROGENEOUS RADAR CLUTTER STATISTICAL ESTIMATION METHOD

I. Introduction

Target detection for a radar system relies on the ability of the system to properly differentiate a target from its background environment. In a real world application for a United States Air Force (USAF) airborne platform proper detection can be the difference between life and death. This thesis focuses on validating an estimation method that characterizes clutter statistics using an iterative Metropolis Hastings (MH) approach to identify underlying clutter probability density functions (PDFs) and parameters. To validate the MH Algorithm an experimental set of clutter scene measurements are captured, computed using the MH Algorithm and results are analyzed to measure the goodness of fit.

1.1 Problem Statement

The MH Algorithm was developed in 2015 by Scott Gabert [1] and was tested by running simulated as well as measured bistatic radar data. The simulations proved successful; however, the measured data proved to be incomplete in nature as no comparison to the true clutter type could be accurately made [1]. To validate the MH Algorithm, a series of experimental clutter measurements are taken which are used to validate the key assumption of the MH Algorithm and the accuracy of the results. The key assumption is that clutter linearly mixes in accordance with their physical proportions when combined in a coarse resolution clutter cell. A set of homogeneous, uniform and single type, clutter measurements and a set of heterogeneous, spatially

varied and two type, clutter measurements are taken. With these two data sets the linear mixing assumption and the accuracy of the estimation results are assessed.

1.2 Motivation

Clutter measurements and models have been mostly limited to monostatic radar systems as the vast majority of systems in production and use are monostatic [2]. With increases to cost and time constraints on operational radar systems, a more efficient way of capturing clutter statistics is highly sought after instead of the traditional monostatic collections. The MH Algorithm being validated in this thesis brings a new option for collecting required clutter measurements from its use in post processing. The MH Algorithm will allow data collection of coarse resolution clutter cells that includes multiple clutter types to be broken down into the individual clutter type statistics. By solving for the individual clutter type statistics in a post processing environment the operational cost and time required of the radar system to collect a series of clutter type measurements will be significantly reduced. By reducing the cost and time required for an area of clutter to be measured the system can continue on and collect more variety of clutter if able. The end result of more clutter type characteristics at a cheaper rate is that clutter models can be created and updated that can be used in an operational environment to further protect against and identify targets of interest.

1.3 Contributions

The overall contribution of this thesis is to validate the degree to which the MH Algorithm can parameterize single clutter type distribution statistics from a heterogeneous scene mixture. With the validation of the assumptions and the accuracy of the MH Algorithm the redundancy of collecting single type clutter measurements can

be reduced and efficiency towards creating clutter models increased. The processing techniques incorporated in the MH Algorithm are independent of any specific radar system or requirements and thus can be used on a wide range of radar systems that can be either monostatic, bistatic, airborne, land, or sea based. Additionally, the MH Algorithm can be further tested on more complex clutter measurement scenarios.

1.4 Research Roadmap

This thesis document will explain important concepts in Chapter II that are required to understand the MH Algorithm inner workings, clutter and how the validation effort was conducted. Chapter III details simulations of the MH Algorithm to determine initial parameter settings. Chapter IV dives into the experimental radar clutter scene measurements along with the processing required. The analysis in Chapter V provides the results for the linear mixing assumption and overall MH Algorithm validation. Finally, the conclusions and recommendations are covered in Chapter VI.

II. Background

To better understand the topics covered in this thesis to validate the MH Algorithm it is necessary to review the underlying concepts that build the big picture. A basic understanding of how a radar system works is useful for further motivation for how and why the MH Algorithm is needed and is covered in Sections 2.1 and 2.2. Section 2.3 will explain what clutter is. Section 2.4 will dive into the MH Algorithm, explaining how it works, what it needs to work properly and simulations supporting the parameters used in the experiments covered in Chapter IV. Finally, a discussion on the graphical analysis needed for viewing probability density functions (PDF), cumulative distribution functions (CDF) and empirical cumulative distribution functions (ECDF) is covered in Section 2.5 which allows the analysis discussion in Chapter V to be better understood.

2.1 RADAR Overview

Radio Detection and Ranging (RADAR) has three main functions which are searching, detecting, and tracking targets [3]. The MH Algorithm being validated allows both the search and detection functions of a radar system to be enhanced with the use of clutter models that can be created from its calculations. The experiments in this thesis are also focused on the search and detection aspects of the radar system used in Chapter IV in order to build the data sets required for the method.

2.1.1 Radar Range Equation.

As previously mentioned, traditionally radar systems are monostatic which means that the transmit and receive antennae are co-located [3]. The power received at the receive antenna is the major parameter that is used for a radar system in most

scenarios of search and detection. The relationship between the system and the power received is

$$P_{Rx} = \frac{P_{Tx} G^2 \lambda^2 \sigma}{(4\pi)^3 R^4} \quad (1)$$

where P_{Tx} is the power transmitted from the system, G^2 is the gain of both the antennae, λ is the wavelength of the signal transmitted, σ is the Radar Cross Section (RCS) and R is the range of the target [3].

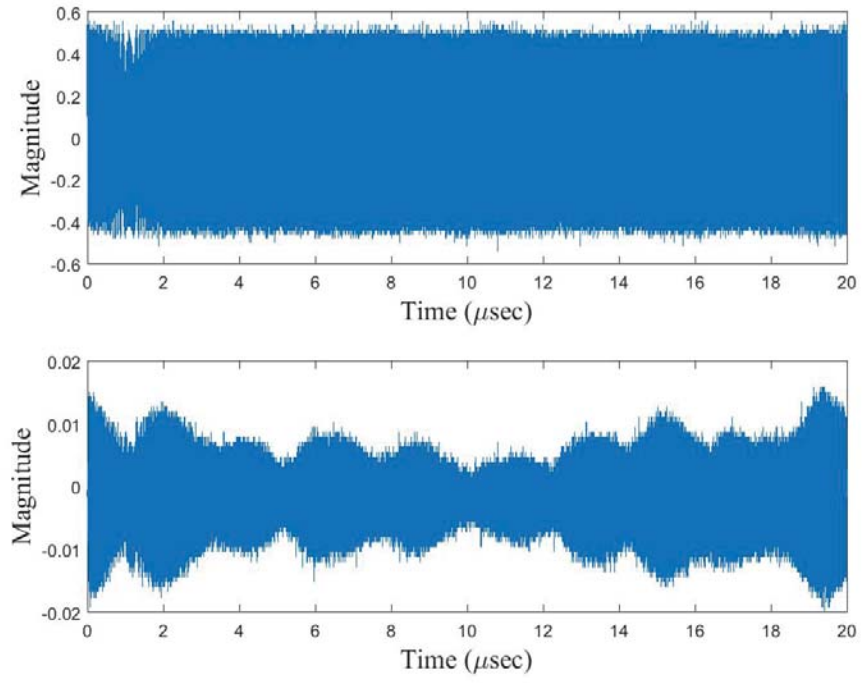
2.2 Matched Filter and the range profile

A different and more common approach to target detection using the radar signals when there are unknown parameters of the radar range equation is using a matched filter to generate a range profile. The matched filter results in a correlation of the transmitted and received radar signals.

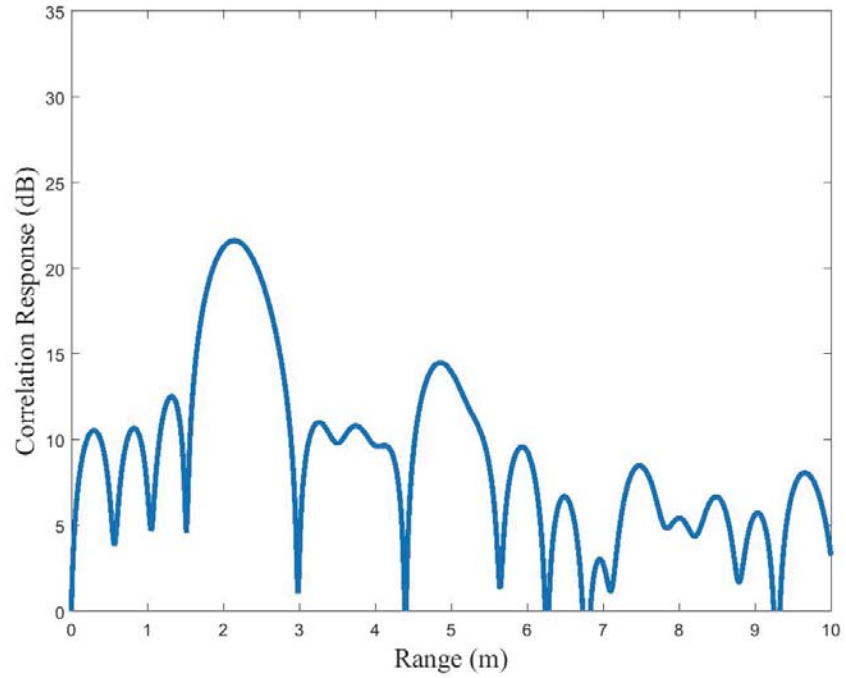
Mathematically the matched filter can be described as

$$y(t) = \int x_r(u) x^*(u - t) du \quad (2)$$

where x_r is the received signal, x^* is the time reversed transmit signal and u is the dummy variable of integration [3]. In this simplified form it is clear that the radar range equation parameters are not needed to be known and the detection can take place assuming the transmit signal is known. A simple example of a matched filter and processing that can be used is shown below in Fig. 1 which shows the transmit and receive signal (top) of an example radar signal and the calculated matched filter (bottom).



(a) Transmit(top) and receive radar signal (bottom)



(b) Range profile.

Figure 1. Range profile example (b) from the result of the transmit and receive signals (a) after matched filter.

Looking at the raw signals it would be difficult to visually locate a target of interest; however, using MATLAB's `xcorr` function, the matched filter response can be calculated using only these two signals. In the example a target is placed two meters from the antennae and is shown by the largest peak at two meters as shown in the bottom of Fig. 1, which is a range profile [3].

Another important radar feature is the range resolution of the radar signal which is important when characterizing clutter. The range resolution is a function of the signal bandwidth, B , such that

$$R_{Resolution} = \frac{c}{2B} \quad (3)$$

where c is the speed of light. At a specified bandwidth a clutter area response will be combined with the proportional range resolution area, if two clutter types are inside a range resolution bin, the range profile will show the combined response for both clutter types. It is also important to note that the bandwidth of the radar system increases hardware, calibration and signal processing complexity which in turn increases the overall cost of the system. To reduce costs based on radar system requirements the bandwidth is kept low which again creates a large, coarse resolution that creates a wider range of area that the radar captures at a time. Wide areas are more likely to contain heterogeneous clutter scenes which in turn creates the need to characterize multiple clutter types within a range resolution cell more efficiently.

2.2.1 Probability of False Alarms.

In radar detection there are two possible outcomes per range bin. Either the response received was from the surrounding clutter and noise or a target response with the surrounding environment clutter and noise [3]. The responses for these two scenarios can be modeled as two different PDFs that show the probability of a clutter

or target response amplitude, shown in Fig. 2.

The two PDFs may overlap if the signal responses are close which leads to what is known as a probability of false alarm (P_{FA}) [3]. A P_{FA} is a problem that in operational environment can cause confusion which wastes time and effort trying to work through steps to properly identify a target of interest. The P_{FA} can be more accurately characterized by a better understanding of characteristics of noise and clutter.

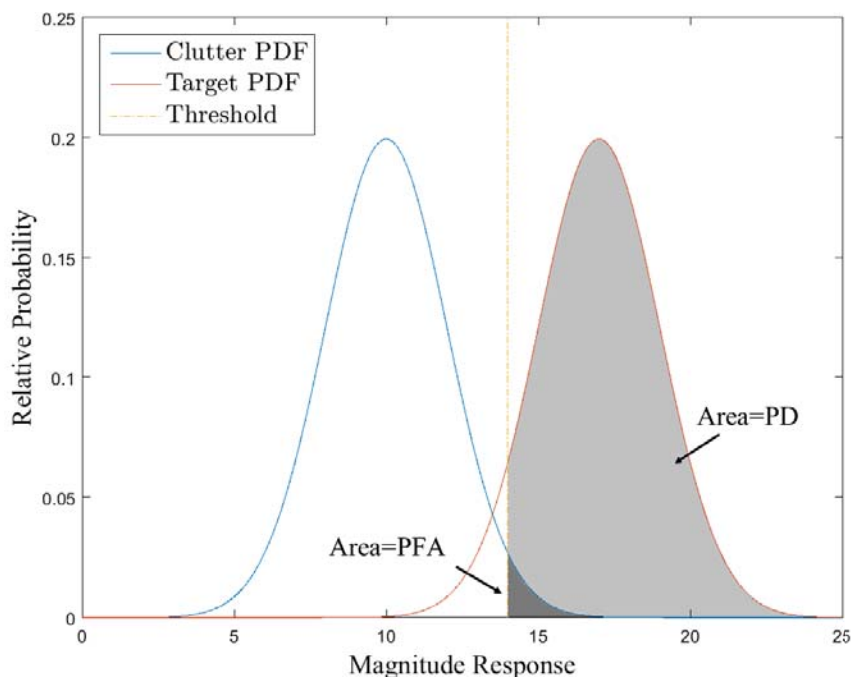


Figure 2. Clutter and target PDFs overlapping showing area of P_{FA} in a detection scenario.

2.3 Clutter

Clutter in most air to ground radar systems is an unwanted byproduct of the environment around a target of interest [2]. Examples of clutter are trees, grass, rocks, leaves, and other vegetation. In the case for this thesis, clutter is our target of interest. As shown in the previous section a good understanding of the clutter in

the environment around the target leads to improved detection through an updated clutter model used in the threshold detection parameters.

Altering the radar range equation from Section 2.1.1 for the need for determining clutter, the power received is a function of the area of the radar beam instead of a single point as previously described [2]. This is due to clutter being more distributed over an area versus a single target of interest. By integrating over the area of the radar beam the response power can be described as

$$P_{Rx} = \int_A \frac{P_{Tx} G^2 \lambda^2 \sigma_{(A)}}{(4\pi)^3 R^4} dA. \quad (4)$$

2.3.1 Homogeneous and Heterogeneous.

A clutter source is labeled homogeneous if over a specified area the material does not change when sampled over that area. Alternatively, a heterogeneous clutter source is one that varies spatially over the specified area [2].

The important difference between homogeneous and heterogeneous is that most clutter measurement campaigns have been focused on the single type homogeneous clutter with little focus on heterogeneous [2]. For example, it makes sense to only measure trees if the interest only lies in trees; however, the inefficiency of having to focus on only one clutter type at a time increases the time and cost to capture data when multiple clutter types are required to be characterized. The goal of the MH Algorithm is to be able to take heterogeneous clutter measurement data sets and calculate the single clutter type statistics to save the time and money significantly over the current traditional measurement scenarios.

2.4 MH Algorithm Overview

The MH Algorithm was created in 2015 by Scott Gabert alongside Dr. Julie Jackson and Dr. Ryan Kappedal in an attempt to estimate homogeneous clutter type statistics within a mixed proportion heterogeneous clutter scene [1]. Their research showed that for a series of simulations the MH Algorithm was successful at its estimations using goodness of fit analysis. However, with the limited measured data sets available to be evaluated, the research results were incomplete in nature.

The MH Algorithm assumes a linear mixing model of $m = 1, \dots, M$ terrain types measured in N resolution cells. Resolution cells can be described from (3) as the area enclosed by the distance of the range resolution. The RCS, is modeled as

$$\sigma_n = \sum_{m=1}^M a_{n,m} d_{n,m}, \quad (5)$$

where $a_{n,m}$ is the proportion of terrain type m in cell n and $d_{n,m}$ is a single realization from the distribution of interest, $f_{D_m}(d)$, in resolution cell N . Equation (5) can be rewritten as

$$\sigma_{N \times 1} = \mathbf{A}_{N \times NM} \mathbf{d}_{NM \times 1} \quad (6)$$

where $\mathbf{A}$ is a matrix of mixing proportions and $\mathbf{d}$ is a vector of $\mathbf{N} \times \mathbf{M}$ terrain scatter responses. The mixing proportions can be known from land use land cover maps for example. This model and approach can be used directly to solve homogeneous clutter statistic estimates and fitting techniques which is widely used for monostatic radar; however, when applied to heterogeneous clutter mixtures it becomes more complicated [4].

2.4.1 Methodology.

The Gamma distribution and PDF has been used to characterize radar clutter and as such is used to further model each clutter terrain type in the MH Algorithm [2]. The Gamma PDF for each terrain type is modeled as

$$f_{D_m}(d; K_m, \theta_m) = \frac{1}{\Gamma(K_m)\theta_m^{K_m}} d^{K_m-1} e^{-\frac{d}{\theta_m}}, \quad (7)$$

with the end goal that the MH Algorithm will estimate the K_m and θ_m parameters from each observation z_n .

The estimates are formed using a Markov Chain Monte Carlo (MCMC) Metropolis Hastings (MH) method which operates by proposing a change to each parameter and repeats for a predetermined number of iterations. The parameter that proposes the change is called the tuning parameter and the length of the repeating process is the iteration number. Gabert's thesis [1,4] covers in much greater detail the methodology and design methods for the MH Algorithm but for the focus of validation of the MH Algorithm it is sufficient to summarize it as shown in Table 1 below.

Table 1. MH Algorithm summary of the calculation steps for estimating clutter statistics using the MCMC and MH methods [1, 4].

• Initialize: $\mathbf{K} = \frac{E^2(\mathbf{z})}{\text{Var}(\mathbf{z})}$ and $\boldsymbol{\theta} = \frac{\text{Var}(\mathbf{z})}{E(\mathbf{z})}$ • For each iteration i of the Markov Chain – Randomly select a sample of observations from $\mathbf{z}$ – Randomly select orders to update $\mathbf{K}$ and $\boldsymbol{\theta}$ – For each parameter K_m * Create new parameter proposal K_m^*; accept with probability α_k – For each parameter θ_m * Create new parameter proposal θ_m^*; accept with probability α_θ – Check acceptance ratio every 100th MH iteration, adjust transition pdfs to keep acceptance ratio within 25% – 50% • Stop MH algorithm after user-selected number of iterations • Estimate parameters: mean of MH Markov chains
--

2.5 Statistics and Fits

There are a few basic statistical concepts that need to be addressed to fully understand the calculations in the MH Algorithm, outlined in Table 1, as well as the comparison techniques used in the analysis for validation. The key concepts include histograms, PDFs, CDFs, ECDFs and the goodness of fit tests.

A histogram is a mathematical tool that allows a history of distribution data to be

used as either a graphical display or binned to approximate a PDF [5]. An example histogram, below in Fig. 3, shows a series of binned magnitudes along the x axis and the quantity of data points within each bin along the y axis.

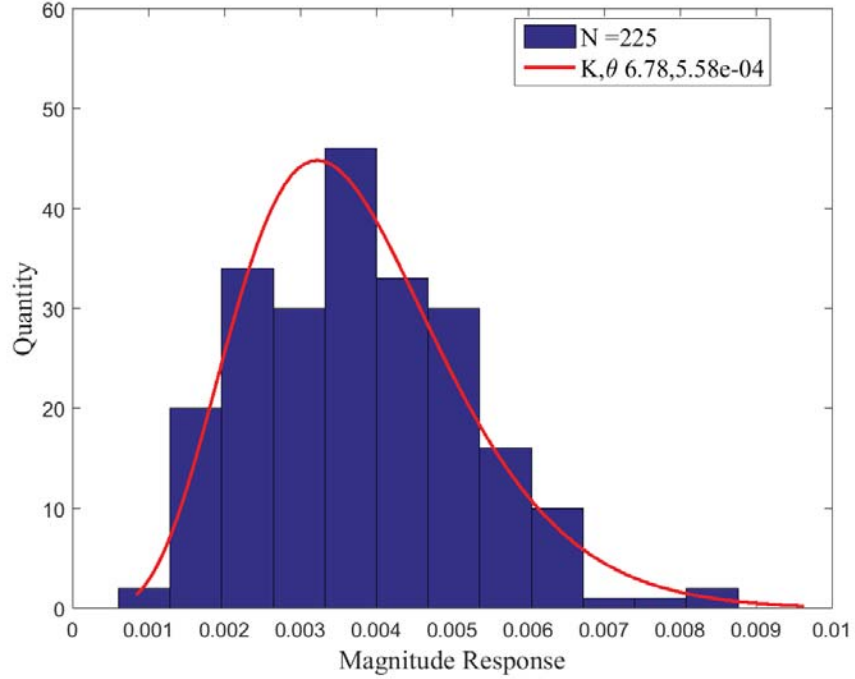


Figure 3. Histogram example with Gamma PDF fit.

The histogram also shows the calculated Gamma distribution PDF fit that is based on the maximum likelihood estimation for the data set. The PDF fit calculated from the histogram in this manner is just one way to determine the statistical distribution function for the data and is not the primary choice for analysis used in this thesis.

The alternative way, which is the primary source for our comparison analysis, is the CDF. The CDF shows the probability for the expected value of the data distribution for the probability between 0 and 1 [5]. The CDF allows us to compare the magnitudes that we can expect to get for each data set. In reality the CDF is a theoretical curve and since our experimental measurements will be a discrete data set the correct approach for analysis is using ECDFs. With a random sample Z_j drawn from a

distribution CDF F , the ECDF is defined as

$$F_n(z) = \frac{\#(Z_j \leq z)}{n}, -\infty < z < \infty \quad (8)$$

where $\#(Z_j \leq z)$ means the number of Z_j 's less than or equal to z with n being the number of samples [6]. Graphically what this creates is a stair step function that with each data sample creates the CDF range from 0 to 1 which is shown below in Fig. 4.

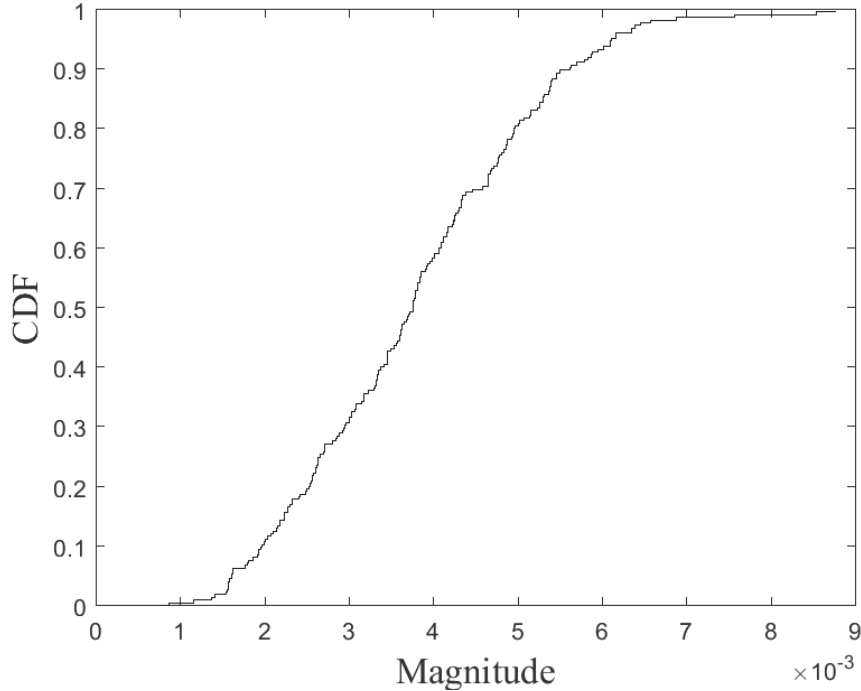


Figure 4. ECDF Example showing stair step function from 0 to 1 based on the number of samples in the data set.

The goodness of fit tests that we will use in our analysis use the CDF/ECDFs fits that are generated from experimentally measured or simulated data. These fits are tested using a two-sample Kolmogorov-Smirnov (KS) goodness of fit test [7]. The two-sample KS test is appropriate for the analysis of comparing two ECDF data sets versus other goodness of fit tests that compare a known truth to a single ECDF [7].

The two-sample KS test statistic

$$D = \sup_z |F_{1,N}(z) - F_{2,N'}(z)| \quad (9)$$

is used to determine whether the two distributions $F_{1,N}$ (having N samples) and $F_{2,N'}$ (with N' samples) differ. The null hypothesis that the two distributions are the same is rejected at a significance level of α_{reject} if

$$D > c(\alpha_{reject}) \sqrt{\frac{N + N'}{NN'}} \quad (10)$$

for critical values $c(\alpha_{reject})$ which are shown below in Table 2 [7].

Table 2. Two sample KS Test Critical values.

Significance Level					
α_{reject}	0.01	0.05	0.10	0.15	0.20
$c(\alpha_{reject})$	1.48	1.36	1.22	1.14	1.07

An example scenario, Fig. 5, shows a CDF which is derived from the ECDF and a separate ECDF fit with the calculated D value of 0.05. Each data set has 225 samples; therefore, from (10) and Table 2 the threshold of rejection is calculated to be 0.1282 for a α_{reject} value of 0.05. The two sample KS D value for the fit is less than the rejection level and thus is not rejected. It is important to note that we cannot say we accept the fit, or that it is good, because this type of test only allows us to reject the null hypothesis.

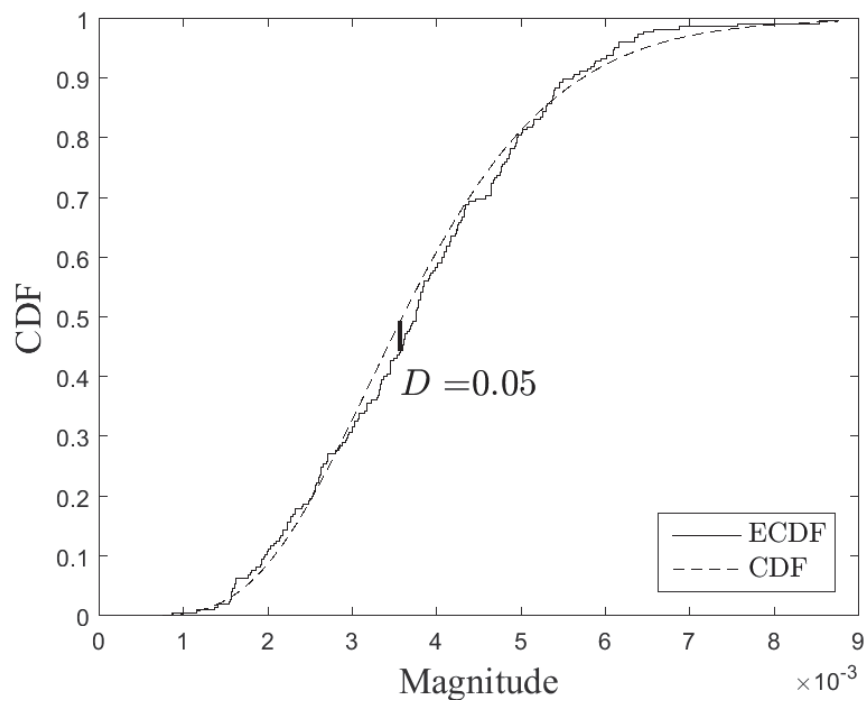


Figure 5. CDF and ECDF comparison with goodness of fit calculation showing no reason to reject that the two data sets differ significantly.

III. Simulations

Simulations were accomplished in order to properly assess how many data samples, N , are required to result in a solution from the MH Algorithm that would not be rejected in the goodness of fit test for the case when $M=2$ clutter types. A randomized set of gamma distributed data samples with specified shape (K) and scale (θ) parameters were generated in MATLAB in a varied amount of data samples for two different simulated clutter types. Two data inputs are required for the MH Algorithm in order for the calculation and fitting estimates to work properly. The K and θ values chosen for both simulated clutter types were based on an initial set of measurements collected in the RAIL Lab but excluded in the thesis discussion. Five sample sizes $N= 2500, 1000, 500, 250$ and 120 and four iteration lengths of $1000, 5000, 10000$ and 15000 were chosen for the hypothetical data collection simulations. Two sets of Gamma distributed samples with different K and θ parameters are input into the MH Algorithm, along with the required proportion matrix, tuning parameter and iteration count. The Homogeneous simulation trials are outlined below in Table 3.

Initial results from the series of purely homogeneous simulations show that the minimum sample size for the two clutter type scenario is 250 . Additionally, the iteration count required is determined to be sufficient at 5000 since the increased count made little to no difference in the two-sample KS test statistic calculations. Figs. 6 and 7 show the CDF comparison, clutter A on top and clutter B bottom, of the MH Algorithm results for the 250 and 120 sample for each iteration variable. The 120 sample size CDF fit shows an over and under estimated result for each simulated clutter type whilst the 250 sample CDF fit shows a close fit. The two sample KS test D values, not shown, also show no justification for a rejection of the fit for the 250 sample scenario. Again from these CDF figures the iteration count does not seem to

Table 3. MH Algorithm Homogeneous Simulation Scenarios

Scenario	N	Iterations	Scenario	N	Iterations	Scenario	N	Iterations	Scenario	N	Iterations
A	120	1000	F	120	5000	K	120	10000	P	120	15000
B	250	1000	G	250	5000	L	250	10000	Q	250	15000
C	500	1000	H	500	5000	M	500	10000	R	500	15000
D	1000	1000	I	1000	5000	N	1000	10000	S	1000	15000
E	2500	1000	J	2500	5000	O	2500	10000	T	2500	15000

affect the result significantly.

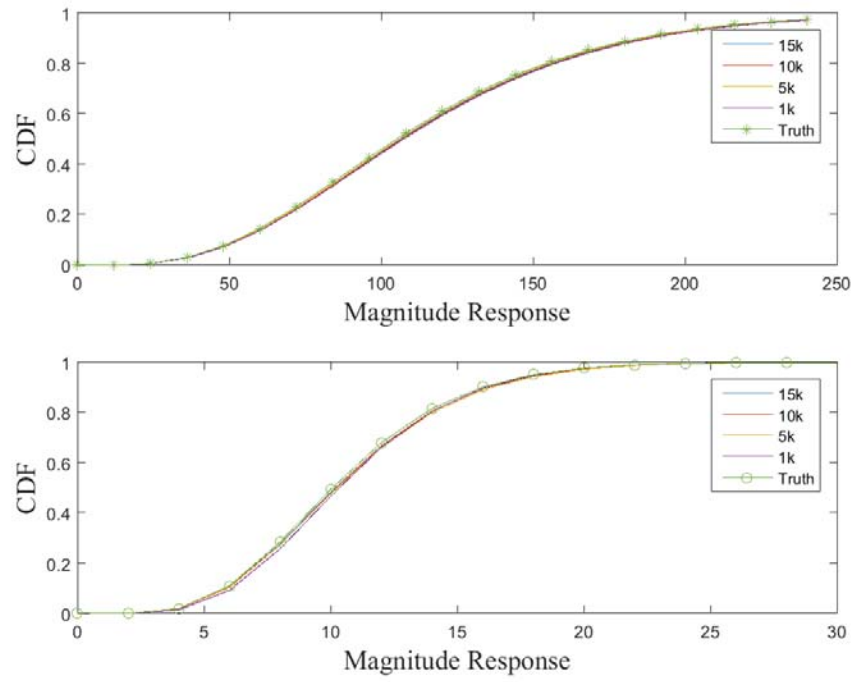


Figure 6. Homogeneous simulation results for 250 data samples show no rejection from goodness of fit results for all iterations scenarios 1k to 15k.

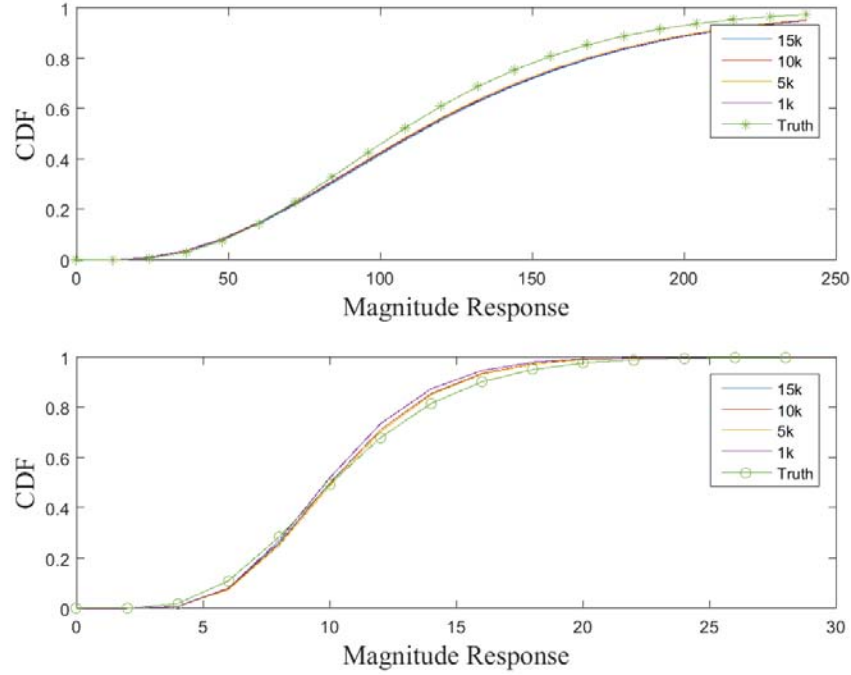


Figure 7. Homogeneous simulation results for 120 data samples show rejection from goodness of fit results for all iterations scenarios 1k to 15k.

Heterogeneous clutter simulations were similarly structured with the sample size for the simulated clutter distributions being $N = 120, 200, 250, 300, 400,$ and 500 . However, the iteration count was held constant at 5000 and was not explored further in simulation for the heterogeneous scenarios. The heterogeneous mixture proportions were simulated to be 75% and 25% for each clutter type. To further test the limitations of the MH Algorithm the tuning parameter was altered between 0.15, 0.35 and 0.55. Choices for this were an arbitrary starting point since the only requirement based on the mathematical limitations of the MH Algorithm is that it remains between 0 and 1. The results for the heterogeneous simulations, including the tuning parameter, are shown below in Fig. 8. Only one of the MH Algorithm estimates for one of the simulated clutter types is shown since the other simulated clutter type results were almost identical. The simulations were repeated 200 times. From the

trials results, the MH algorithm does not show any result average that crosses the two sample KS test D threshold for $\alpha=0.05$ for each sample size. The inclusion of the standard deviation intervals, however, does show that at certain sample sizes there is a possibility the clutter D values will be greater than the D threshold for the specific sample size and as such would be rejected. Based on the results, the required minimum sample size was selected to be 250 and the tuning parameter of 0.15 to be used in the experiments covered in Chapter IV.

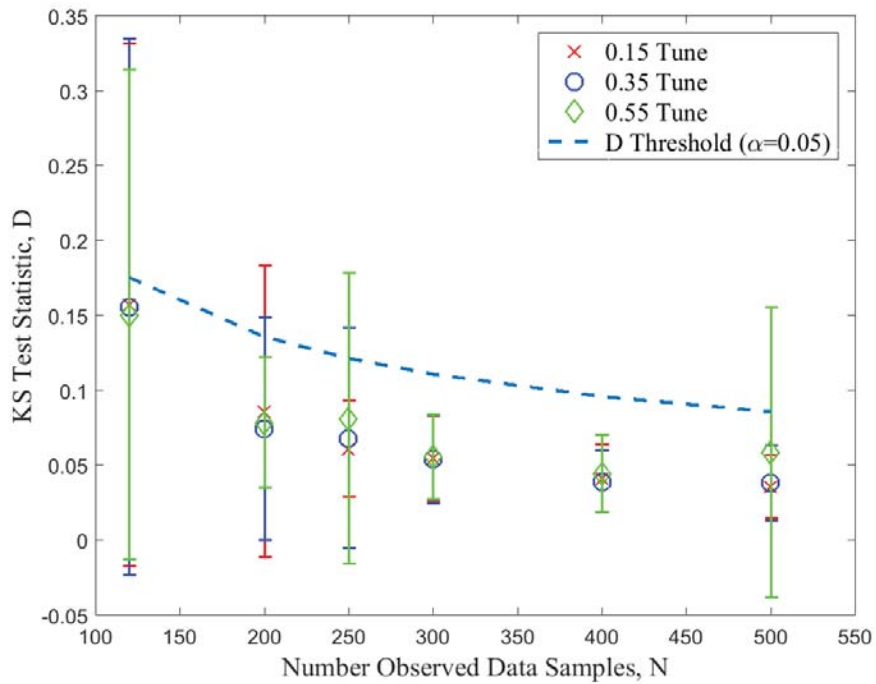


Figure 8. Tuning parameter simulation trials show the trend of the goodness of fit D statistic verse the threshold averaged over 200 trials for each sample size.

Another simulation focused on testing the sensitivity of the input mixture proportions matrix was accomplished. The proportions were altered to include seven different error percents 1, 2, 3, 4, 5, 7.5 and 10. The simulations were again repeated 200 times for each sample size. The results, Fig. 9, show that as the percentage of error increases the further off the MH Algorithm estimate becomes. The D value

increases beyond the D value threshold for most sample sizes at around 3-4% error. The D values calculated for each sample size do show a level trend as the sample size increases; however, the two sample KS test D value threshold decreases as the sample size increases which makes the estimate fit worse off. This investigation shows the sensitivity of the MH Algorithm calculations with regards to the proportion matrix and its requirement to stay within a few percentage points in order for the goodness of fit test to be not rejected.

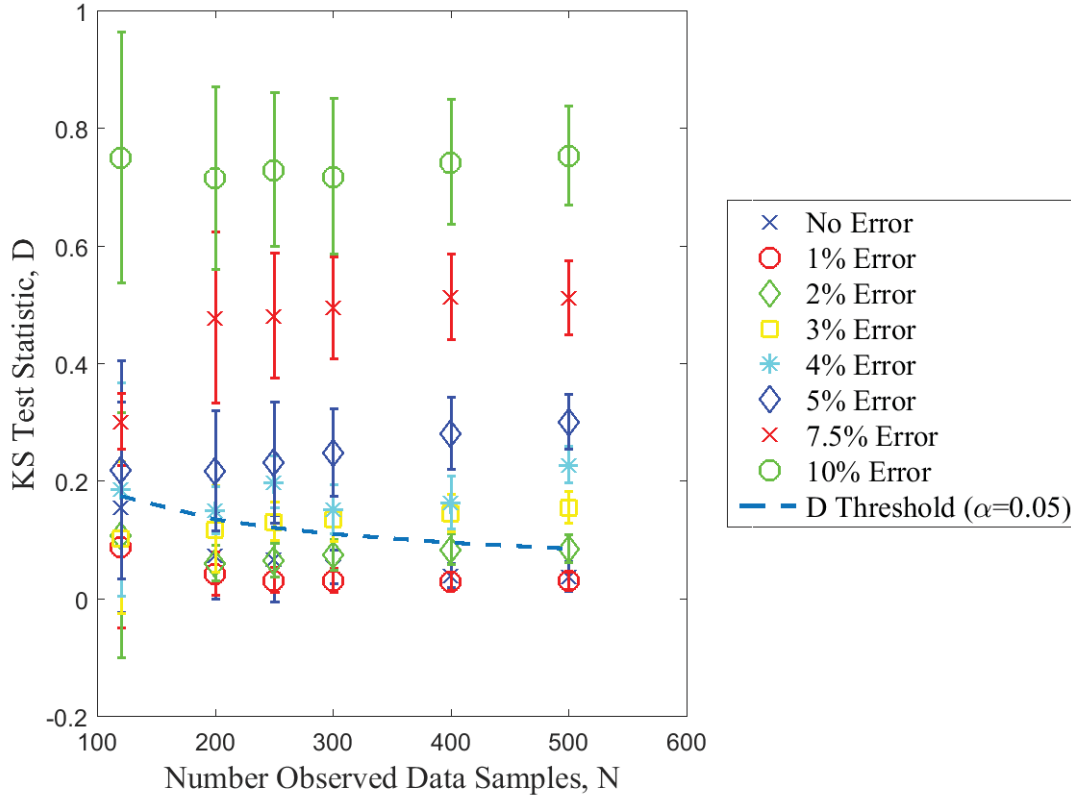


Figure 9. Heterogeneous simulation results for percent error for proportions show the trend that as the error increases the D statistic value increases. Results averaged over 200 trials for each sample size.

From these simulations the required sample size of 250, iteration of 5000, and tuning parameter of 0.15 are carried forward to be used in the experiments in Chapter IV. It is also important based on the results from the error simulations to keep

the proportions and measurements within the 3-3% error range in order to fall below the D statistic threshold.

IV. Laboratory and Experiment Setup

This chapter covers the overall development of the experiment scene and hardware setup. The details for which signal is transmitted, how the scene size is calculated and verified, data processing trials, and experiment scenarios are discussed in detail.

4.1 Laboratory Equipment Setup

The lab equipment used to conduct the experiments for this research are Tektronix Arbitrary Waveform Generator - AWG7102 (AWG), Tektronix Digital Storage Oscilloscope - TDS6214 (O-Scope), Agilent Analog Signal Generator - N5183A (Sig Gen), Agilent DC PowerSupply - E3646A (DC-PS), and various mixer and amplifier components which are shown in Fig. 10. Greater detail and setup configurations will be discussed below in the appropriate sections.

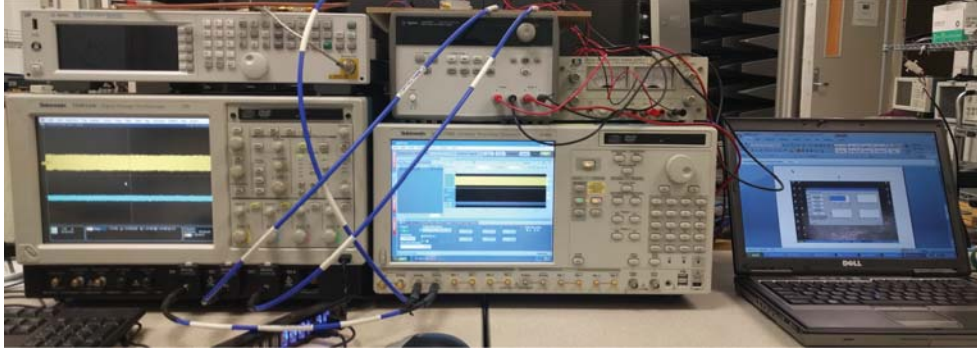


Figure 10. Lab equipment used for the radar clutter experiments.

4.1.1 AWG and Signals Generated.

As discussed in Chapter 2, match filtering is used to develop the range profile in data processing post experiment data collection. Also as discussed previously in Chapter 2, the bandwidth of the waveform is the most significant parameter of the transmitted signal. The bandwidth, B , was chosen to match the range resolution to

the size of the scene for the experiment. Using

$$B = \frac{c}{2R_{\text{Resolution}}} \quad (11)$$

and the desired range resolution of 0.5m, the bandwidth needed was determined to be 300MHz. By Using

$$TX_{LFM}(t) = A \cos(2\pi f_c t + \frac{\pi B t^2}{\tau}) \quad (12)$$

the final LFM transmit signal with a pulse length of $\tau = 20\mu s$ is created and resolution verified with another simple example data collection.

The signal itself is created in MATLAB and transmitted to the AWG through the use of the Radar Instrumentation Lab (RAIL) GUI, shown in Fig. 11 [8]. The RAIL GUI sends the LFM signal to the AWG, shown in Fig. 12, during the initial setup sequence which then allows the signal to be transmitted by enabling the transmit button on the GUI. The setup parameters stay fixed for all of the data collection scenarios with the parameters for the O-Scope set to trigger Ch1, receive on Ch2, and load waveform to AWG on Ch2. The pulse selection is always set to the 300MHz Bandwidth LFM signal for each transmit on the AWG and RAIL GUI. All of the transmitted signals for experiment data collection are accomplished using this GUI.

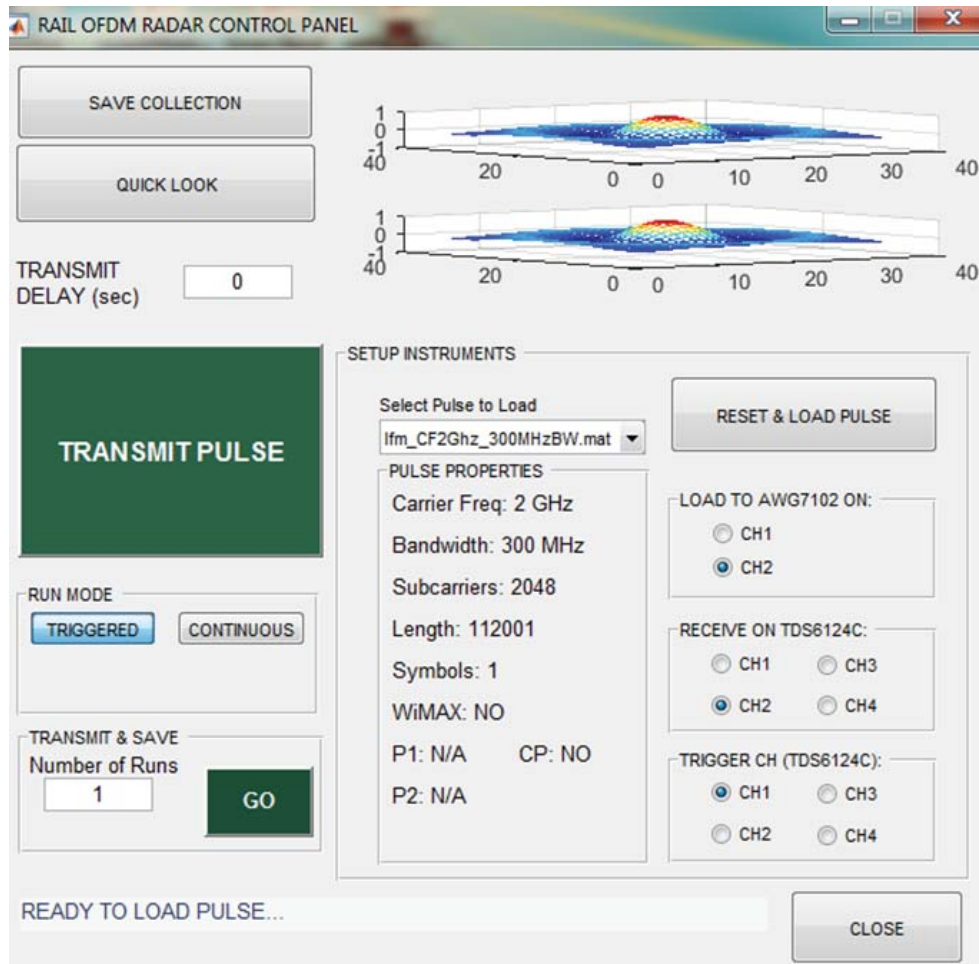


Figure 11. RAIL GUI used for experimental radar clutter data measurements.



Figure 12. Tektronix Arbitrary Waveform Generator - AWG7102 used to generate the radar LFM waveform.

4.1.2 Antennae.

The Antennae used in the experiment are two model 9535-0 Horn Antennae that were available in the RAIL lab. The antennae are part of the Lab-Volt system which in its documentation provides experimental specifications for the Half Power Beam Width (HPBW) and Gain [9]. The E-Plane HPBW is roughly 5.3 degrees and the H-Plane HPBW is 6.8 degrees. The gain of the antenna is 14.5 dB when operated in the X-Band operating range of 8-12 GHz.



Figure 13. Horn Antenna Model 9535 used as the transmit and receive antennae for the experimental radar clutter measurements. [9].

Using the HPBW information an antenna beam footprint model was created in MATLAB to determine the location and positioning of the antennae for the clutter scene in the experiment. As discussed in the previous section, the ideal scene using the 300MHz LFM signal generated using the AWG will have a range resolution of 0.5m which is the target scene size. The major factor for the horn antenna orientation

is the bore sight angle to the scene center, in other words the look down angle from the antennae to the scene. Compiling the specifications for the antenna, the model is able to give us a theoretical HPBW footprint that fits the target scene size. In Fig. 14 and Fig. 15 below, the final theoretical solution footprint is shown for each polarization. In these figures the antennae is located at coordinates (0,0) and is looking down at a boresight angle of 34 degrees. The total ground footprint distance from left to right is labeled as "X Footprint".

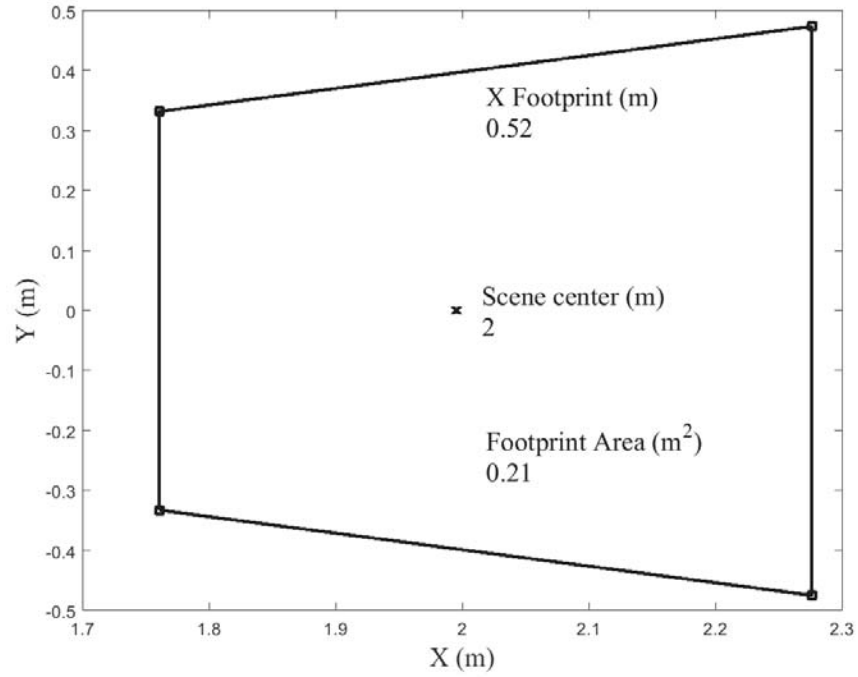


Figure 14. Horn Antenna HPBW Footprint Model for Vertical Polarization (orientation not used in experiments).

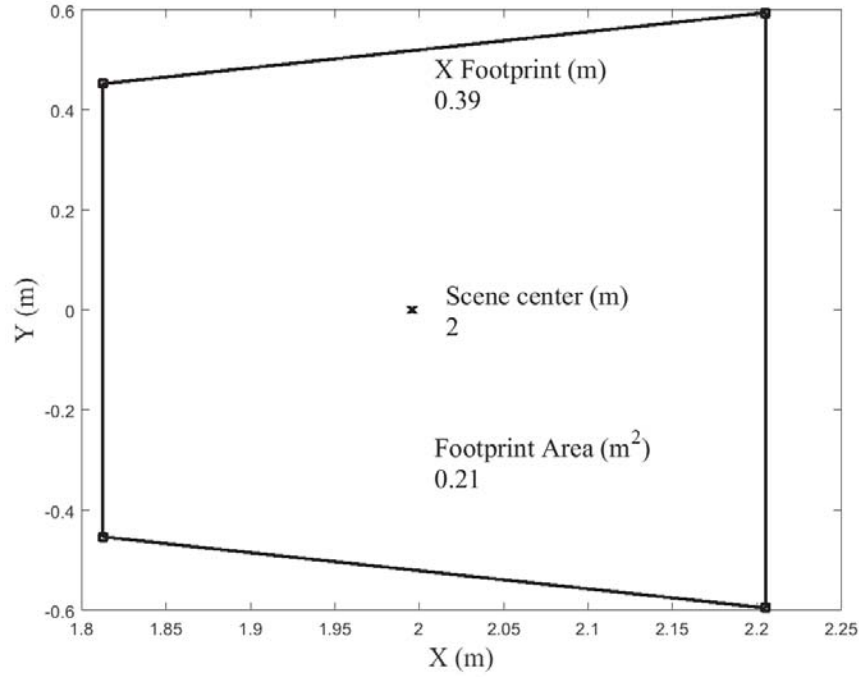
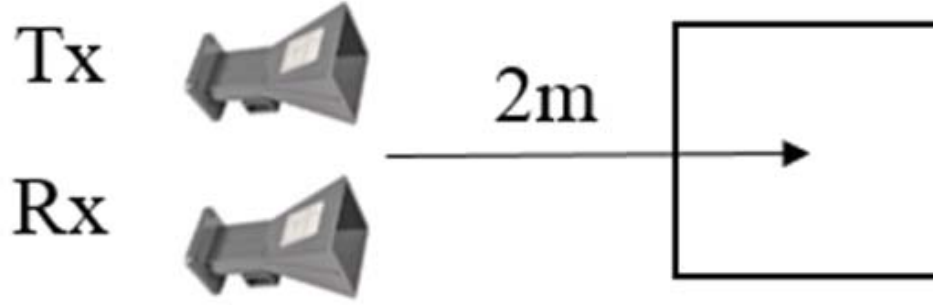
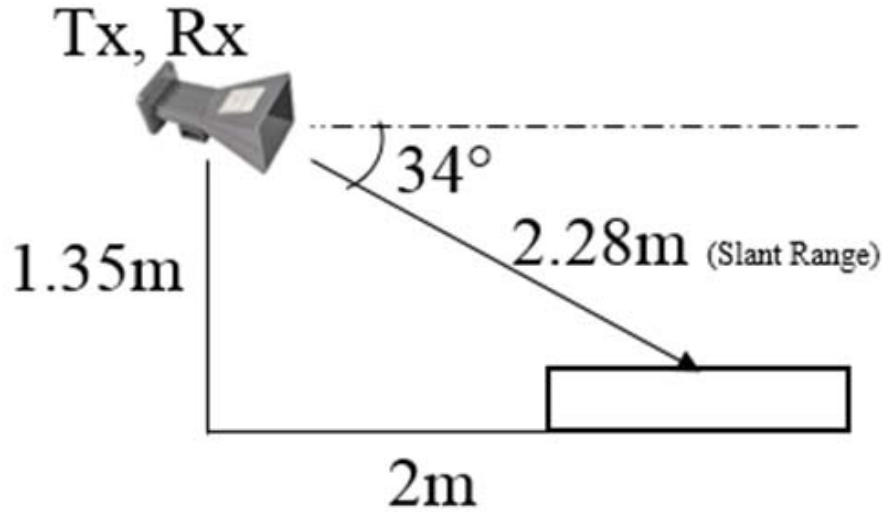


Figure 15. Horn Antenna HPBW Footprint Model for Horizontal Polarization which was chosen to be used for the experimental radar clutter measurements.

The footprint gives us the initial setup parameters to set the scene 2m away from the antennae with a bore sight angle of 34 degrees. With this geometry a 0.5m range resolution is met for the vertical polarization. However, as shown in Fig. 15 the range resolution in conjunction with the same boresight angle of 34 degrees the X footprint is less than the desired 0.5m. The difference in footprint size due from the HPBW difference and the rotation of the antennae. Due to considerations of scene layout consistency and organization this reduced theoretical HPBW footprint was chosen to be acceptable as the data for each polarization is only compared to its own polarization. A separate transmit and receive antenna are used and can be assumed as a mono static system due to having approximately less than 5 degrees of separation with regards to the scene. The final scene setup diagram is shown below in Fig. 16.



(a) Top down view of antennae scene showing 2m distance to scene center and negligible (3in) spacing between Tx and Rx Antennae.(Drawing not to scale)



(b) Side view of antennae scene showing scene 2m, 2.28m slant range with boresight angle of 34 degrees.

Figure 16. Antennae scene diagram shown top down and side view of experiment setup.

4.1.3 Hardware Circuits and Signal Generator.

The combination of the X-Band Horn antennae and limitations of the AWG require the use of an up conversion circuit to transmit the LFM signal at 10 GHz. The 10 GHz frequency was chosen for simplicity in math for the circuit and post processing

filtering later on as well as the important feature that at 10 GHz the wavelength of the signal is 3 cm which is proportional to the size of the clutter being used in the scene.

To obtain a signal at 10 GHz a circuit, shown in Fig. 17, is created and the steps to reach the desired outcome discussed below. The signal generator is set to 8 GHz with the maximum output of the signal generator set to 15 dBm and is connected to a 2 way splitter model (ZX10-2-126-SH). The splitter allows two signals to be mixed up and down in conjunction with the LFM signal. The LFM signal is set to a carrier frequency of 2 GHz to be mixed up to 10 GHz, via standard nature of mixing architecture

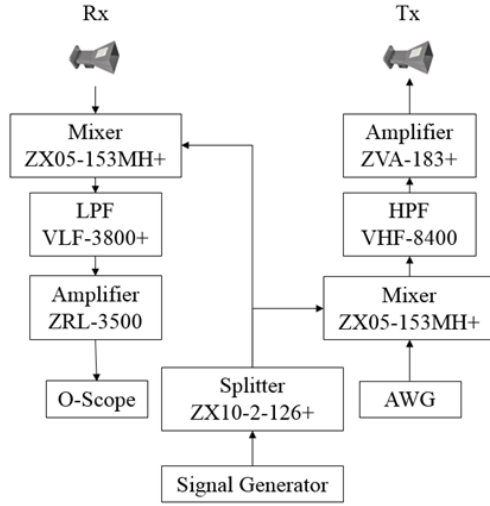
$$MixSignal = 0.5[\cos(\alpha + \beta) + \cos(\alpha - \beta)] \quad (13)$$

where α is 8 GHz and β is 2 GHz using mixer model (ZX05-153MH-S+). A high pass filter (HPF) model (VHF-8400+) is added after the up conversion mixer to delete the signal byproduct created at 6 GHz. Once the signal is transmitted at 10 GHz, the received echo signal is down converted back to 2 GHz. Again mixed using another (ZX05-153MH-S+) from 10GHz and the 8GHz signal from the signal generator to achieve the signal at the initial 2 GHz. A low pass filter (LPF) model (VLF-3800+) is added after the mixer to delete the byproduct signal that is created due to the mixing along with any higher frequencies that exist. For hardware simplicity the data saved from the O-Scope is at the same carrier frequency of 2 GHz that is transmitted.

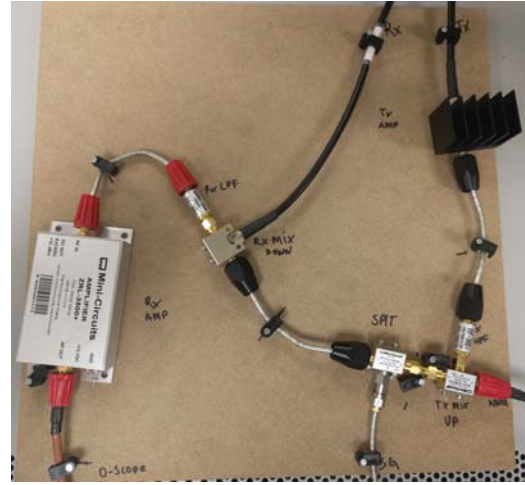
With all of the filters, mixers and splitter components adding together reducing the transmitted and receive power the final circuit includes an amplifier on both ends to increase the final signals. The transmit amp is (ZVA-183+) and is rated for a 26.23dB output at 12v when operating at 10GHz. The receive amp (ZRL-3500+) is rated for 21.54 dB output at 12v when operating at 2GHz.

Table 4. Circuit Hardware used for up and down conversion, amplification and filtering of radar signals for the experimental clutter measurements.

Component	Model	Frequency Range (GHz)	Gain/Loss (dB)
Splitter	ZX10-2-126+	7.4 - 12.6	-3.18
Mixers	ZX05-153MH+	3.2-15	-8.4
HPF (Tx)	VHF-8400	9-13	-1.47 (10GHz)
LPF (Rx)	VLF-3800+	DC-3.9	-0.35 (2GHz)
Amplifier (Tx)	ZVA-183+	0.7-18	26.23 (10GHz)
Amplifier (Rx)	ZRL-3500	0.7-3.5	21.54 (2GHz)



(a) Circuit Diagram.



(b) Circuit Picture.

Figure 17. Radar circuit hardware diagram and picture.

4.1.4 Oscilloscope Setup.

The TDS6214 Oscilloscope, Fig. 18, is used as the initial confirmation for a valid collection during the experimental data collection scenarios. The settings for the O-Scope are set to 20 giga-samples/sec sample rate, along with the horizontal division of 2 micro-seconds per division giving the total 20 micro-second pulse length, which is

what is transmitted through the AWG. Capturing the data is accomplished using the OSCOPE Export GUI, shown in Fig. 19, which was created to speed up the collection process.

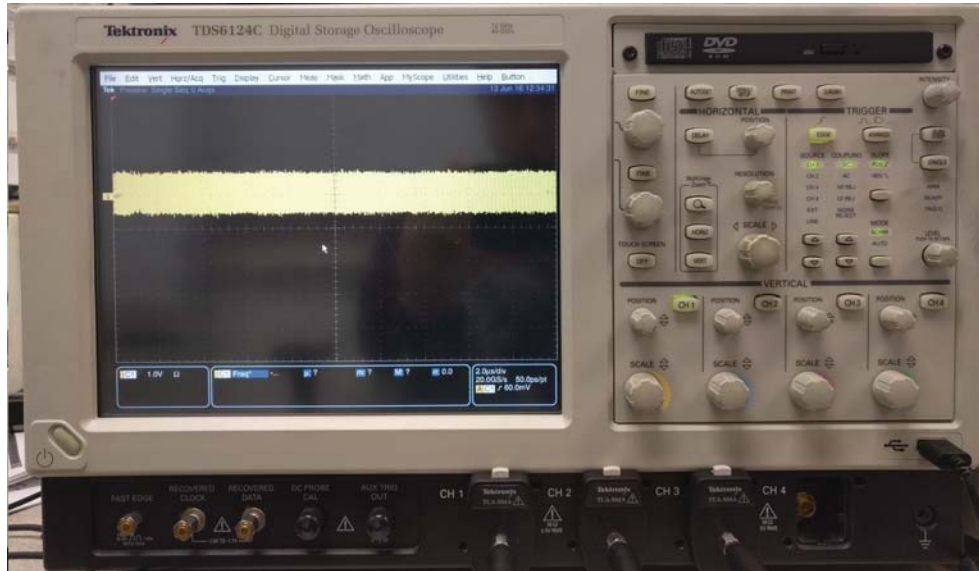


Figure 18. Tektronix Oscilloscope used for recording experimental radar clutter return signals.

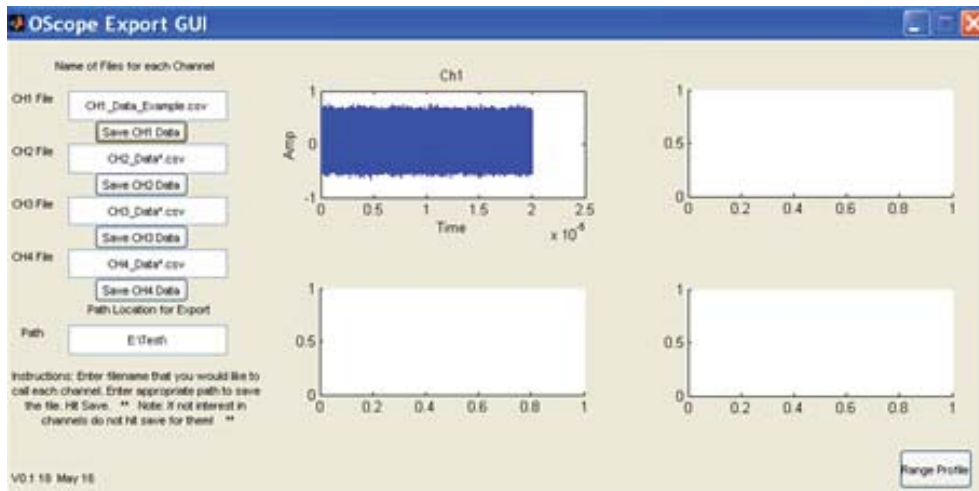


Figure 19. Data Export GUI used to record radar clutter return signals for post processing.

4.2 Safety

The power levels of the transmitted signal were investigated to confirm that there was no concern with radiation during the experiment scenarios. From the calculations in the section below it is shown that it is safe to operate.

4.2.1 Power calculations.

The transmit amplifier operating at 10 GHz produces a gain of 26.23 dB and is the highest power contributor for the entire radar circuit and hardware due to its final position in the chain. Using

$$S = \frac{Tx_{Power}\tau}{AntennaeArea} \quad (14)$$

the average power density, S , transmitted is calculated where τ is the signal pulse width. With the power of 794mW, pulse width of 20 micro-sec and 25 cm² antenna area the power density is 0.00006352 mW/cm². The maximum exposure limits for a system operating at 10 GHz are 5 mW/cm² [10]. The result shows that the system is in a safe operating zone and well within limits.

Although legally the system is operated under limits it was decided for good practice and measure to not radiate with anyone directly in front of the antennae. This prevents any unnecessary exposure and a clear piece of mind that no harm is being done to the operator or assistant.

4.3 Scene Setup

The scene used in the experiment consists of the rotator, a background radar absorbing material (RAM) wall, and the clutter itself.

4.3.1 Rotator.

A rotator is required during the experiment to vary the clutter to create the statistical data set required, which will be discussed more in an upcoming section. The rotator is constructed of 0.75 inch thick plywood with the dimensions of $48'' \times 48'' \times 6''$ for the stationary base and the rotating circle with a diameter of approximately one meter. The circle is attached to the base through a metal lazy susan which allows a full 360 degree rotation. The rotator is centered at 2m (2.28m slant range) and shown in Fig. 20 below.



(a) Rotator overhead view.



(b) Rotator with RAM wall background.

Figure 20. Experiment rotator shown from overhead and with the background RAM wall. Rotator centered at 2m (2.28m slant range) distance from the antennae (not shown).

4.3.2 Background reduction.

The environment for the experiment is not perfect which requires post processing to reduce the background clutter in order to better differentiate the signal of interest. By using background subtraction it enables the target clutter to be properly detected and recorded. This is accomplished using simple subtraction of the radar return signal for LFM signal with only the rotator in the scene from the return signal with the clutter in the scene, which will be covered in the post processing section below.

4.4 Homogeneous Setup

The purpose of the homogeneous setup and data collections are to calculate the clutter Gamma statistic parameters for shape (K) and scale (θ) in order to use as a comparison for the MH Algorithm's estimates for the same two parameters. With a known homogeneous data sample, the estimates from the algorithm can be analyzed according to the goodness of fit technique which will be covered in the analysis in Chapter V .

The two clutter types chosen for the experiment are metallic grass and river rocks. The two clutter types were selected in order for the clutter size to be on the same order of a wavelength, 3 cm, for the X-Band LFM signal. The radar scattering from the two clutter type since they are roughly the same size allows the scattering problem to be focused on the difference in clutter type instead of erroneous interaction affects that would be induced if different scaling. The scene setup for the homogeneous clutter is as follows. The Rocks or metallic grass are placed and centered on the rotator as shown in Fig. 22 and Fig. 21 below. The homogeneous data measurements are taken using the equipment and MATLAB GUIs discussed earlier, the results are shown in Chapter V analysis section 4.1.



(a) Homogeneous Grass scene overhead view.



(b) Homogeneous Grass scene with RAM wall background.

Figure 21. Experiment scene for homogeneous grass shown from overhead and with the background RAM wall.



(a) Homogeneous Rocks overhead view.



(b) Homogeneous Rocks scene with RAM wall background.

Figure 22. Experiment scene for homogeneous rocks shown from overhead and with the background RAM wall.

The measurement procedure for both the metallic grass and rocks are identical. With the clutter placed on the rotator the scene is rotated in a one degree increment counter clockwise for a full 360 degrees. At each angle the LFM signal is transmitted and the return signal is recorded.

4.5 Heterogeneous Setup

The heterogeneous setup and experiments are also identical to the homogeneous ones, with the exception that the clutter scene is split into a proportion of the rocks and metallic grass. As discussed in Chapter II with the general overview of the MH Algorithm, the clutter scene needs to be a known proportion of each clutter type, so the experiments are controlled to be the known proportions of 25% and 75% for each clutter type, Fig. 23 and Fig. 24 shown below are the two setups. The MH Algorithm and scene has the potential to be altered to different proportions but for simplicity only one combination of proportions are used in the experiments covered in this thesis.



(a) Heterogeneous Mix - $\alpha=0.75$ scene overhead view.



(b) Heterogeneous Mix - $\alpha=0.75$ scene with RAM wall background.

Figure 23. Experiment scene for heterogeneous mix $\alpha=0.75$ shown from overhead and with the background RAM wall.



(a) Heterogeneous Mix - $\alpha=0.25$ overhead view.



(b) Heterogeneous Mix - $\alpha=0.25$ scene with RAM wall background.

Figure 24. Experiment scene for heterogeneous mix $\alpha=0.25$ shown from overhead and with the background RAM wall.

The data measurements are collected and processed using the same approach as the homogeneous measurements for degrees one to 360 in one degree increments. The LFM signal is again transmitted at each angle and the return signal recorded.

4.6 Post Processing

The post processing techniques used for the experiment follow a very simple step process and only use MATLAB generic functions. The steps in post processing are repeated for each set of measurements and outlined below.

1. Load raw data files that are saved from the O-Scope for both the clutter Rx and the background Rx.
2. The background Rx is subtracted from the clutter Rx for background subtraction.
3. The transmitted LFM chirp signal is correlated with the background subtracted signal using MATLAB's `xcorr` function. The correlated signal magnitude is scaled by the LFM chirp signal energy which is calculated by

$$TX_{Energy} = \sum_0^{\tau} |(LFMSignal)|^2 \quad (15)$$

4. Peak detection of the range profile for the range bin of interest. Selection and justification of peak will be discussed below in Section 4.6.1.
5. Output result in form of a single data point from the peak detection value. An example of the final product for each measurement is shown below in Fig. 25.

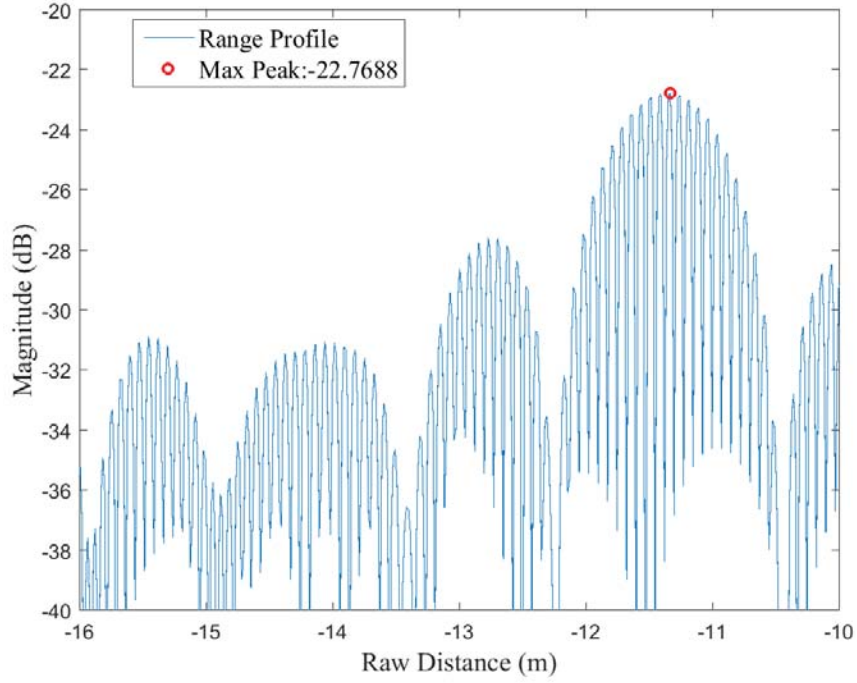


Figure 25. Range profile example showing the peak selection of the scene for a single measurement.

The final data sets for each clutter scenario are created from the single peak values for each angle which are used as the data inputs for the MH Algorithm. Using this simplified processing the entire post processing time is automated and is very efficient in providing the results for both the homogeneous and heterogeneous measurements.

4.6.1 Processing scene calibration and peak selection.

Due to wire lengths and internal system delays from the mixing circuit and equipment the range profile created in post processing shows the scene at a distance that differs from the known placement of 2.28m slant range away. To correctly identify the range bin of interest for the scene center a set of calibration measurements were taken with a single metal target placed at 1m, 2m and 3m slant range from the antennae. The results from the calibration measurements are shown in Fig. 26 below with two way distance along the x axis. From the measurements the wire length and antennae

cross talk is identified at the -8 to -7 m mark which can be thought of as the 0m mark since it directly relates the the antennae location. The peak at -9.39m represents the target at 1m, -11.15m represents the target at 2m and -14m is the target at 3m.

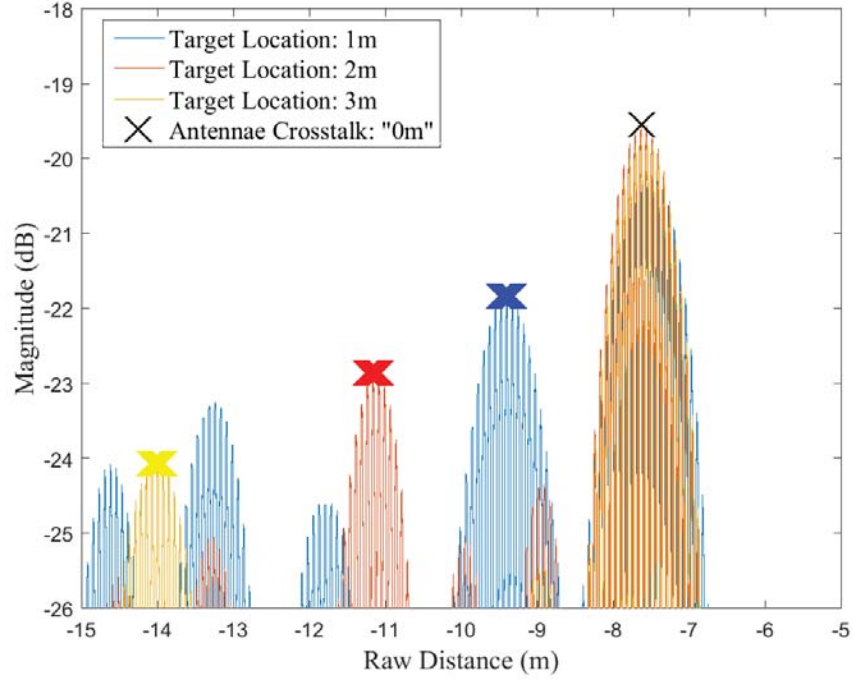


Figure 26. Range profile with calibration targets at 1m, 2m and 3m slant range from the antennae used to identify raw distance of interest for peak selection.

While the target moved from 1m to 3m the reflection angle and placement with respect from the antennae, along with the multi-path effects from the floor causes the distances to not appear as expected in 2m increments. To account for this slight error in distances and as a verification of correct peak detection in the range bin of interest the average and standard deviation for the location that is selected during processing is recorded for each clutter scene scenario. The location of scene center for the raw distance calculated using the calibration target at 2m gives a distance of -11.71m and from Figs. 27, 28, 29, 30 the average values are roughly identical. Noting the standard deviation in each of these figures, the values are a two way range

distance and all fall below the designed signal range bin resolution width of 0.5m. The standard deviation confirmation along with the average values indicates we are capturing the correct range bin of interest.

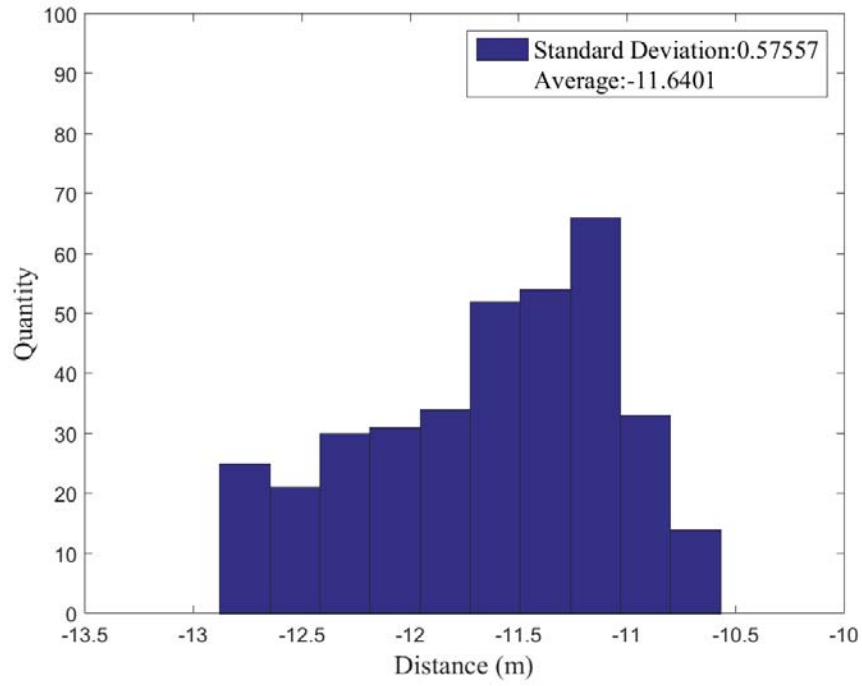


Figure 27. Range bin of interest verification from post processing for Homogeneous Grass.

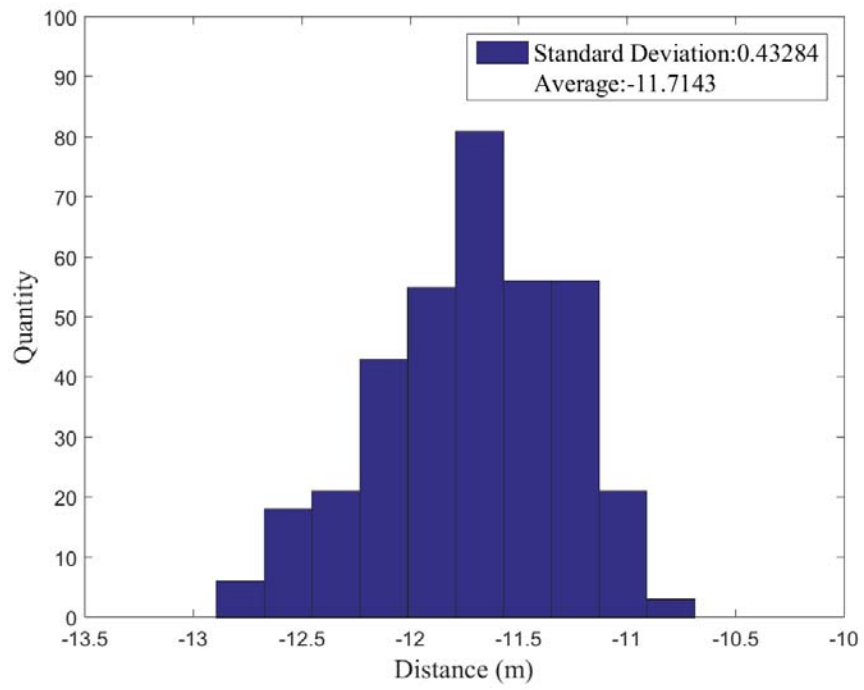


Figure 28. Range bin of interest verification from post processing for Homogeneous Rocks.

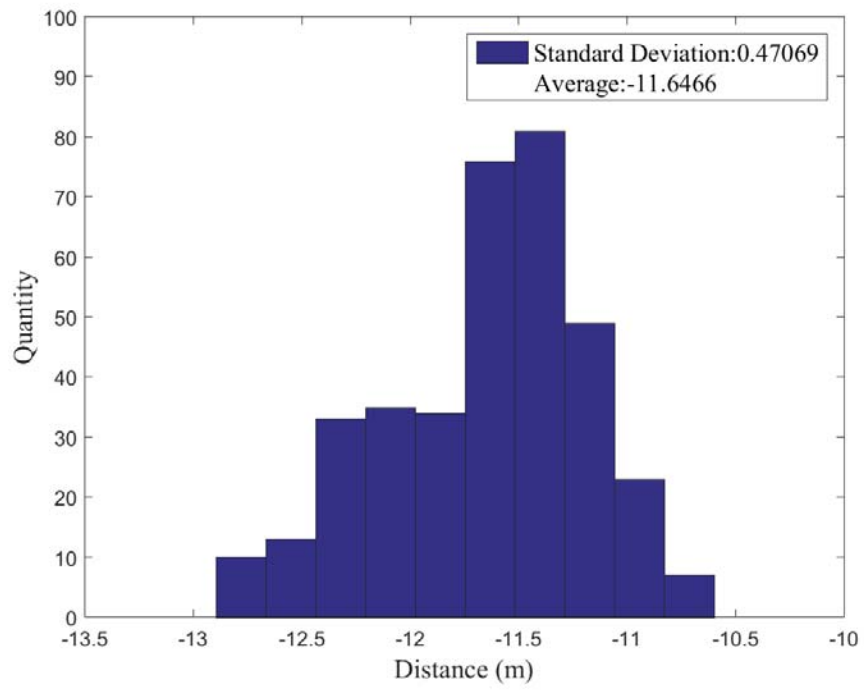


Figure 29. Range bin of interest verification from post processing for Heterogeneous Mix - $\alpha=0.75$.

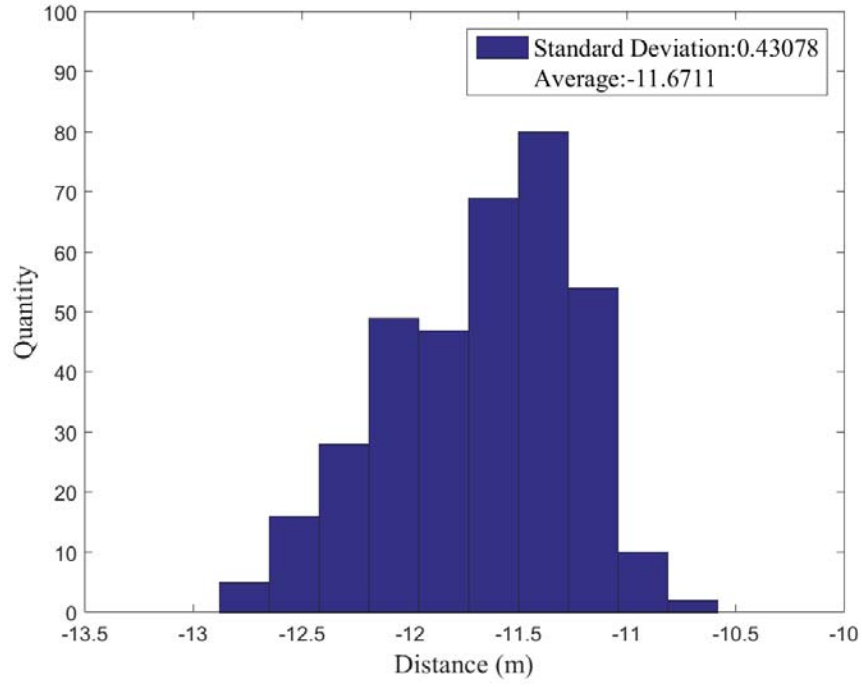


Figure 30. Range bin of interest verification from post processing for Heterogeneous Mix - $\alpha=0.25$.

The four clutter scene scenarios are measured and post processed to generate the input data for the MH Algorithm and are further analyzed in the next chapter.

V. Analysis

This chapter covers the results from the four clutter measurement scenarios for the two homogeneous cases and the two split proportion scenarios. The data sets from post processing will be explored through histogram, Gamma distribution fitting, and CDF comparisons to validate both the assumption of the linear mixing model for the MH Algorithm as well as accuracy of the algorithm itself.

5.1 Validation of Linear Mixing Model Assumption using Homogeneous and Heterogeneous Data Collections

The data sets for each clutter scene scenario, created from the peak selection post processing covered in the last chapter, are fit using MATLAB's histfit function for a Gamma distribution and shown below in Figs. 31, 32, 33, and 34.

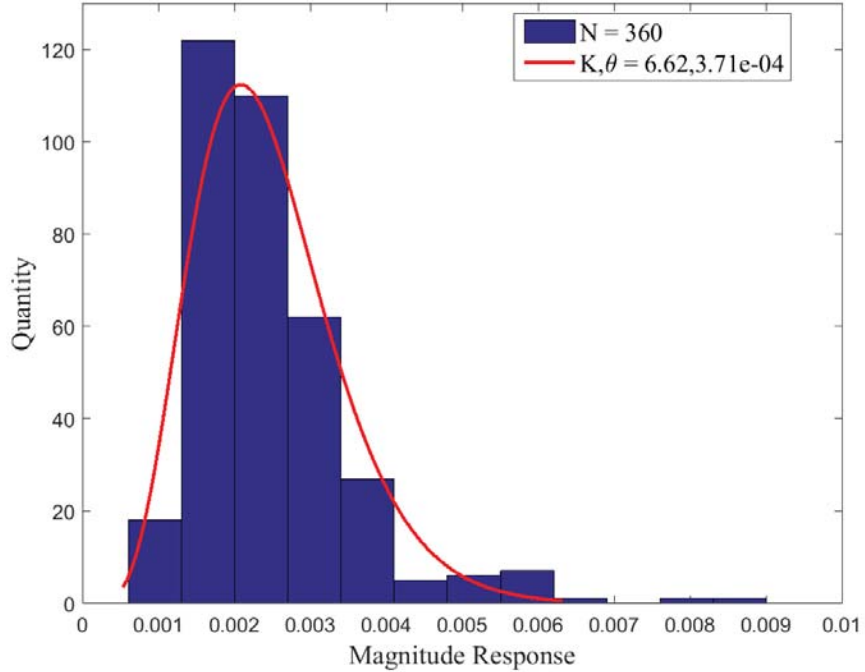


Figure 31. Homogeneous grass data collection histogram and Gamma distribution fit of $K = 6.62$, $\theta = 3.71\text{e-}4$ for the full 360 data points.

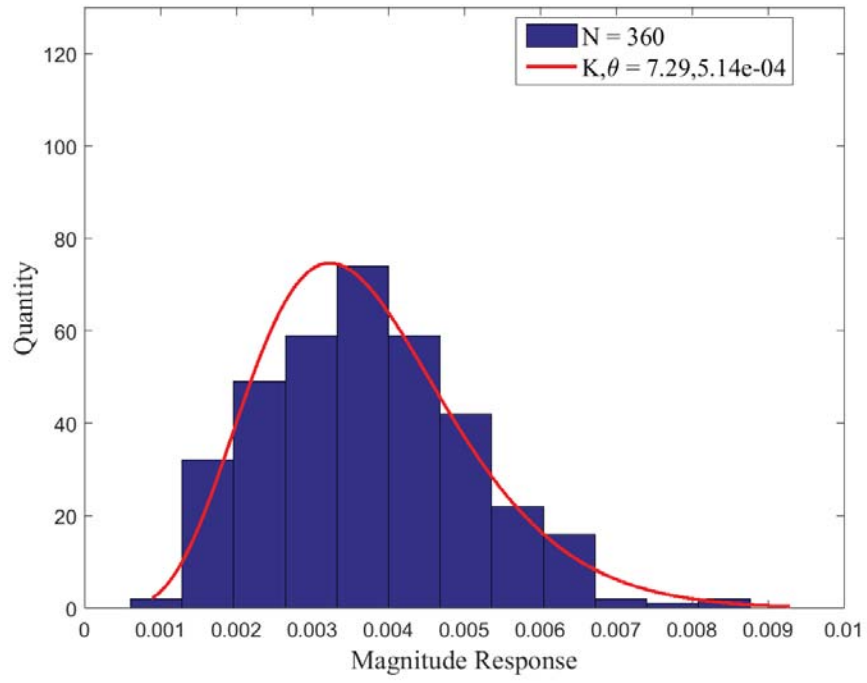


Figure 32. Homogeneous rocks data collection histogram and Gamma distribution fit of $K = 7.29$, $\theta = 5.14e-4$ for the full 360 data points.

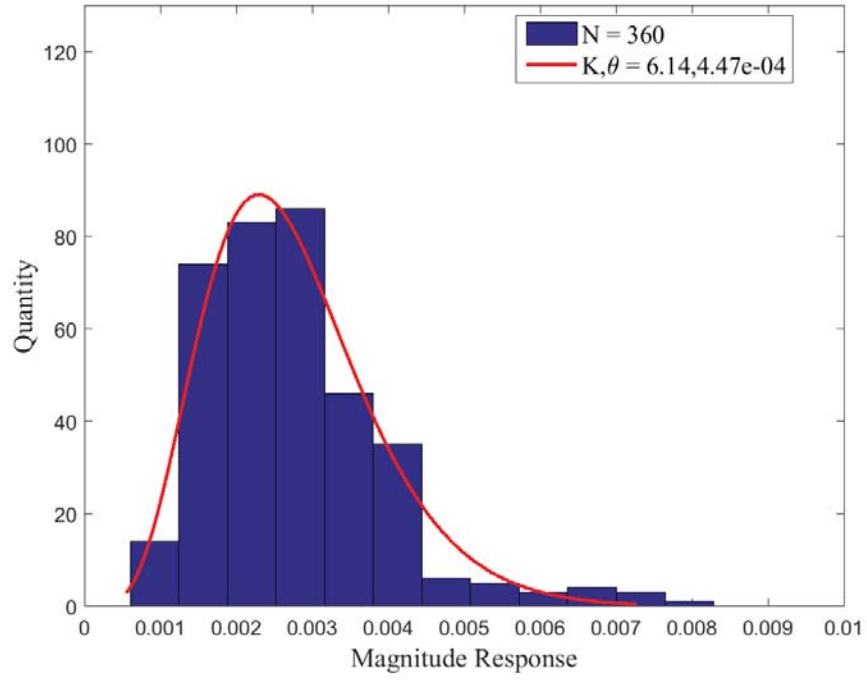


Figure 33. Heterogeneous mix - $\alpha=0.75$ data collection histogram and Gamma distribution fit of $K = 6.14$, $\theta = 4.47\text{e-}4$ for the full 360 data points.

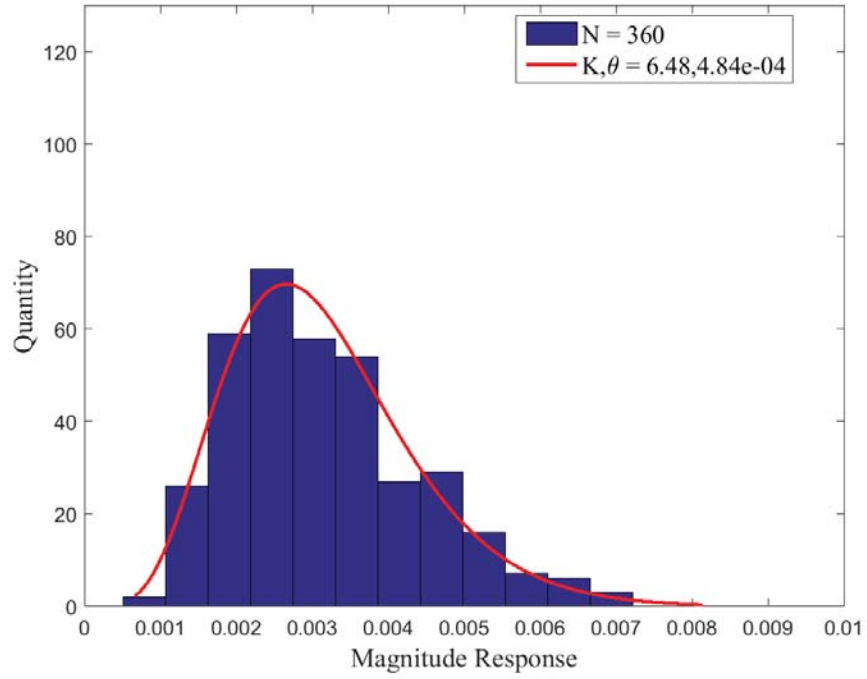


Figure 34. Heterogeneous mix - $\alpha=0.25$ data collection histogram and Gamma distribution fit of $K = 6.48$, $\theta = 4.84\text{e-}4$ for the full 360 data points.

All four of the Gamma distributions differ in both K and θ which results in different ECDFs, shown together in Fig. 35 below. Intuitively the two heterogeneous mixture ECDFs fall between the two homogeneous ECDFs due to the 25% addition of the other clutter type.

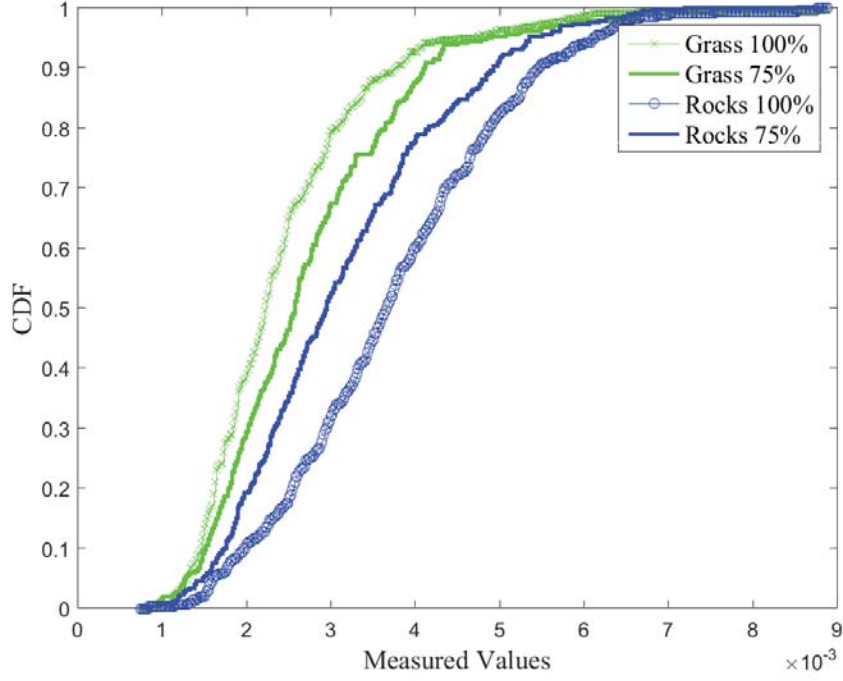


Figure 35. ECDFs overlaid showing the differences for all four clutter scene scenarios.

To validate the assumption that the clutter response mixes linearly, which is the key assumption for the MH Algorithm to work properly, the homogeneous and heterogeneous ECDFs are further compared. The heterogeneous clutter measurement ECDFs are related to the homogeneous clutter ECDFs as

$$F_{het} = \alpha_1 F_1 + \alpha_2 F_2 + \dots + \alpha_M F_M, \quad s.t. \sum_{m=1}^M \alpha_m = 1. \quad (16)$$

Combining ECDFs for the homogeneous grass, F_{Grass} , and rocks, F_{Rocks} , we predict that the ECDFs for the heterogeneous clutter should be

$$F_{het}(\alpha) = \alpha F_{Grass} + (1 - \alpha) F_{Rocks} \quad (17)$$

where $\alpha = 0.75$ for the heterogeneous mixture with grass proportion of 75% and $\alpha = 0.25$ when the mixture is only 25% grass. Using the two-sample KS goodness of fit test from Chapter II the predicted ECDF for both α values are tested. Fig. 36 below shows both the measured ECDFs along with the predicted 0.75 and 0.25 α proportions. An additional ECDF was fit that minimizes the KS test statistic D value and updates the α value to reflect an adjusted proportion value based on the measurement data. The adjusted value is used as an experimental error metric due to the fluctuation of the laboratory environment and equipment settings that change over time.

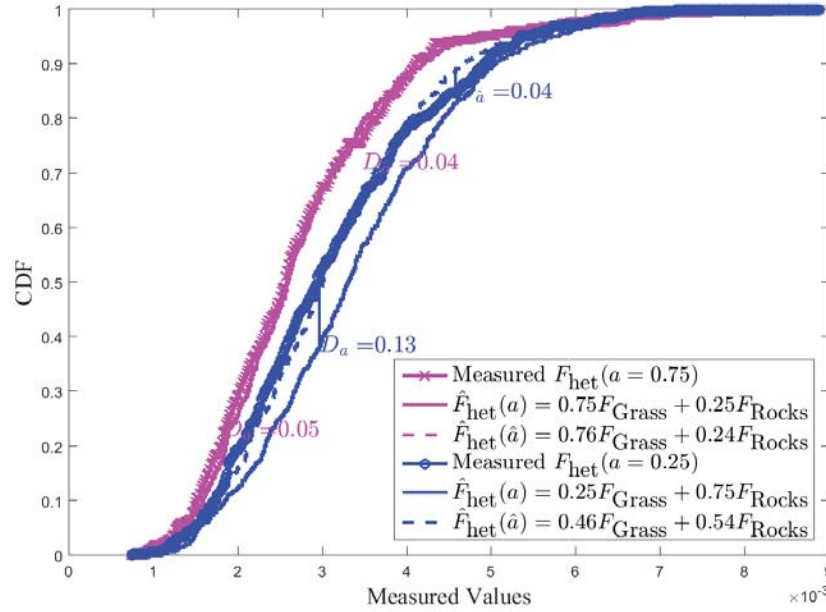


Figure 36. Linear mixing assumption for heterogeneous ECDF Fits showing the theoretical and measured ECDF for mixed proportions.

From the comparison in Fig. 36, the fit appears to be valid for the $\alpha=0.75$ but rejected for $\alpha=0.25$. Rejection not due to the D value but because of the adjusted ECDF fit proportion of 0.46 and 0.54. From this fit the data is showing almost a 50/50 split which is not the true proportion of 25% grass and 75% rocks.

Exploring the processed data for the 100% and 75% grass it becomes clear that

at certain angles the magnitude response is significantly higher than the rest. Due to the orientation of the grass at certain angles facing directly back at the antennae a “flat plate” response which at the peak is 9.5 times the standard deviation when compared to the average response value. Fig. 37 below shows that from angles 229 to 288 the response values for both data sets are higher and whilst included in the averaging alter the K and θ significantly. To account for this “flat plate” effect we truncate the data sets down to 225 samples (angles) instead of the full 360.

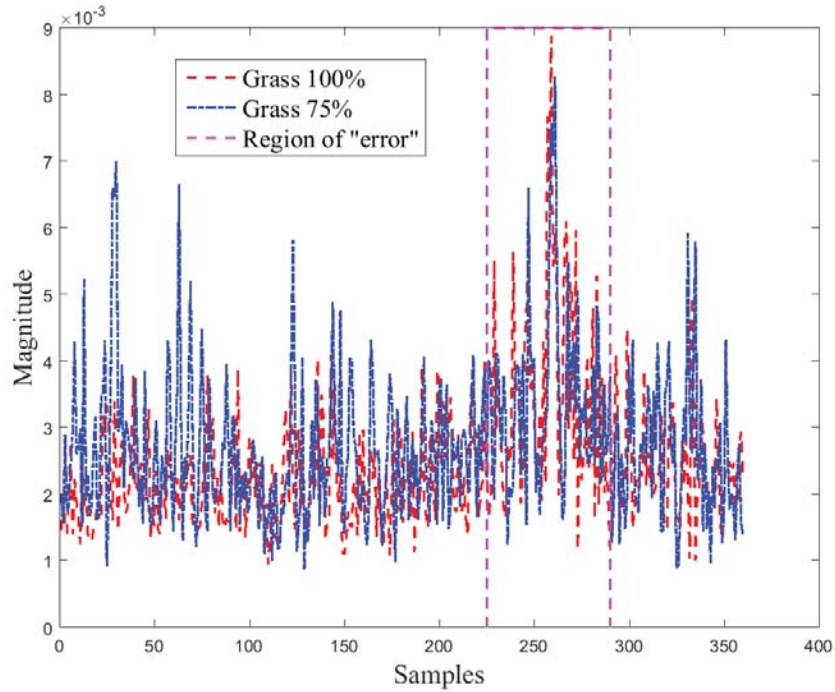


Figure 37. Homogeneous and Heterogeneous Grass measurement data reduction justification for angles 225 to 360 due to extreme magnitude inconsistency.

By reducing the angle and sample count to 225 the ECDFs are compared again and the fit is much more appropriate to the known proportions of the lab experiments, shown in Fig. 38. Both the D values for the two-sample KS statistics fall below the rejection threshold of 0.1249 for the $\alpha_{Reject}=0.05$ significance level for the predicted and adjusted ECDFs for the sample size of 225.

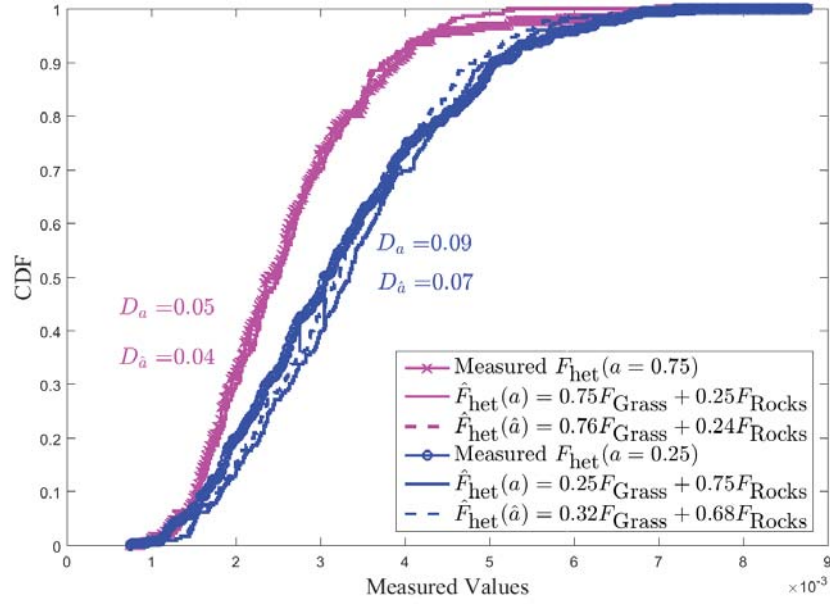


Figure 38. Linear mixing assumption for heterogeneous ECDF Fits showing the theoretical and measured ECDF for mixed proportions for the truncated 225pts.

The histogram and Gamma distribution fits are re-calculated for the down sampled data sets and shown below in Figs. 39, 40, 41, and 42. All of the scenario data set K and θ values reflect a change in magnitude due to the down sampling. Again the overlay of all four scenario ECDFs is shown in Fig. 43 and still show the intuitive pattern as with the full 360 point data set.

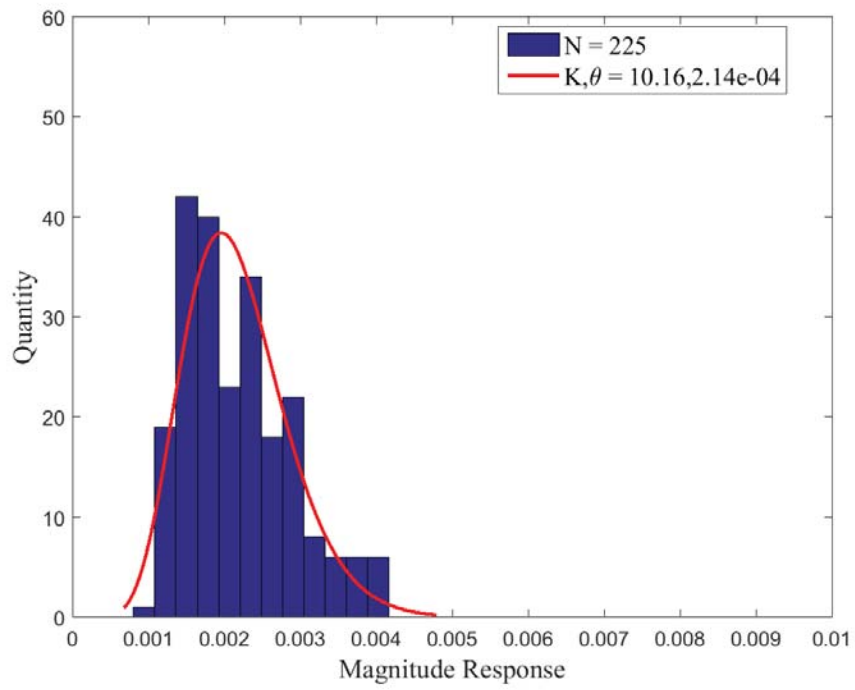


Figure 39. Homogeneous grass data collection histogram and Gamma distribution fit of $K = 10.16$, $\theta = 2.14e-4$ for 225 data points.

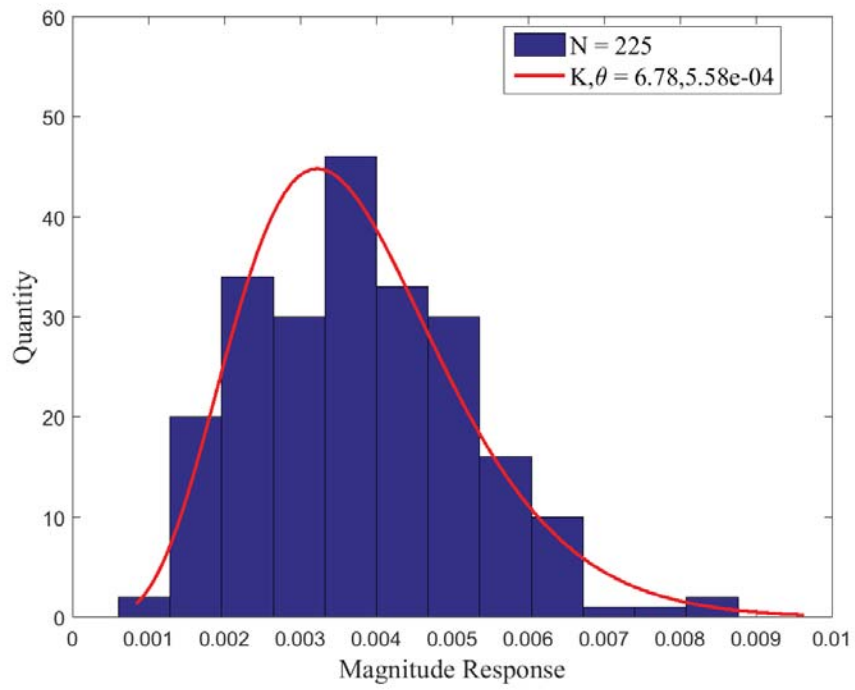


Figure 40. Homogeneous rocks data collection histogram and Gamma distribution fit of $K = 6.78$, $\theta = 5.58e-4$ for 225 data points.

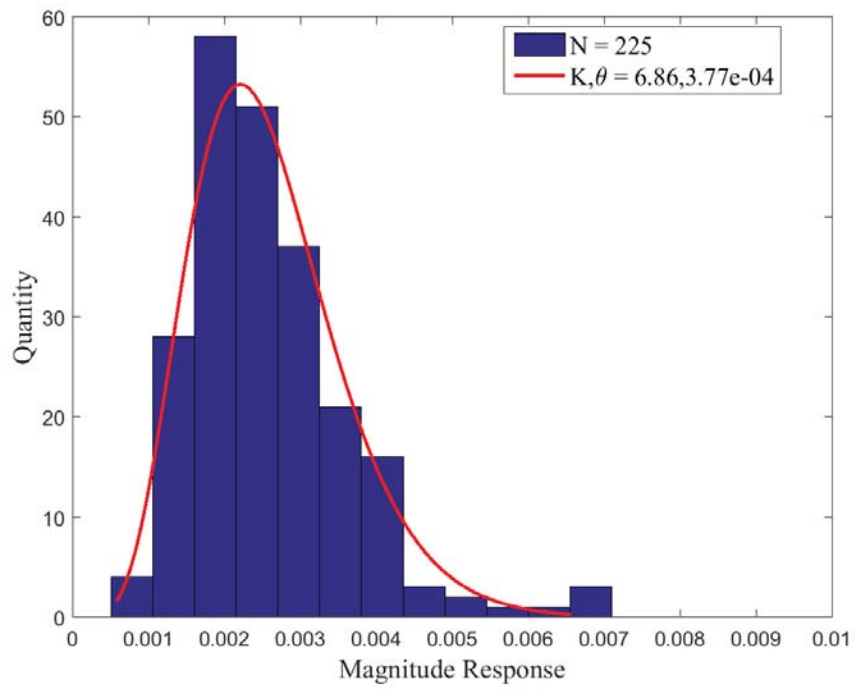


Figure 41. Heterogeneous grass data collection histogram and Gamma distribution fit of $K = 6.86$, $\theta = 3.77\text{e-}4$ for 225 data points.

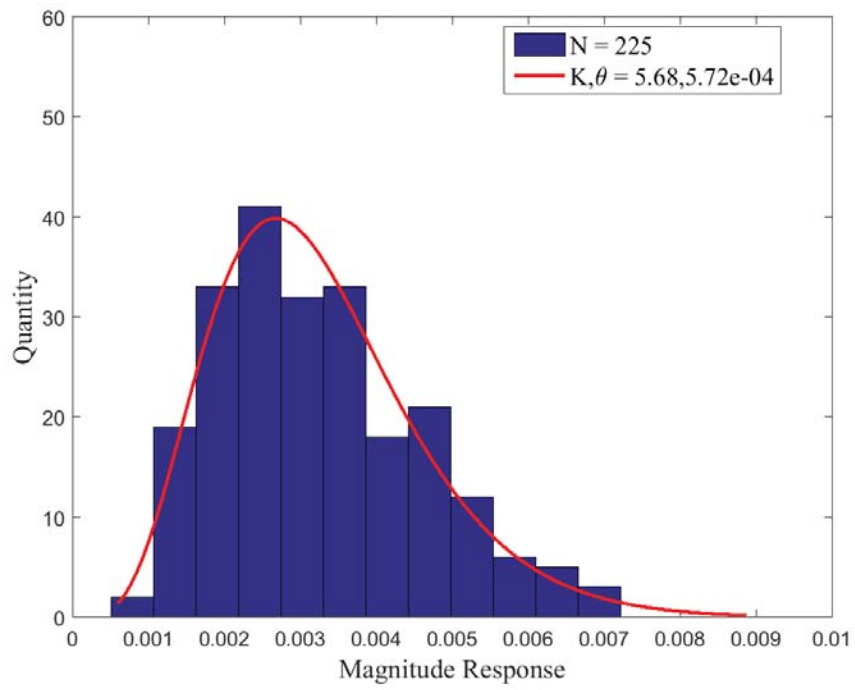


Figure 42. Heterogeneous rocks data collection histogram and Gamma distribution fit of $K = 5.68$, $\theta = 5.72\text{e-}4$ for the full 360 data points.

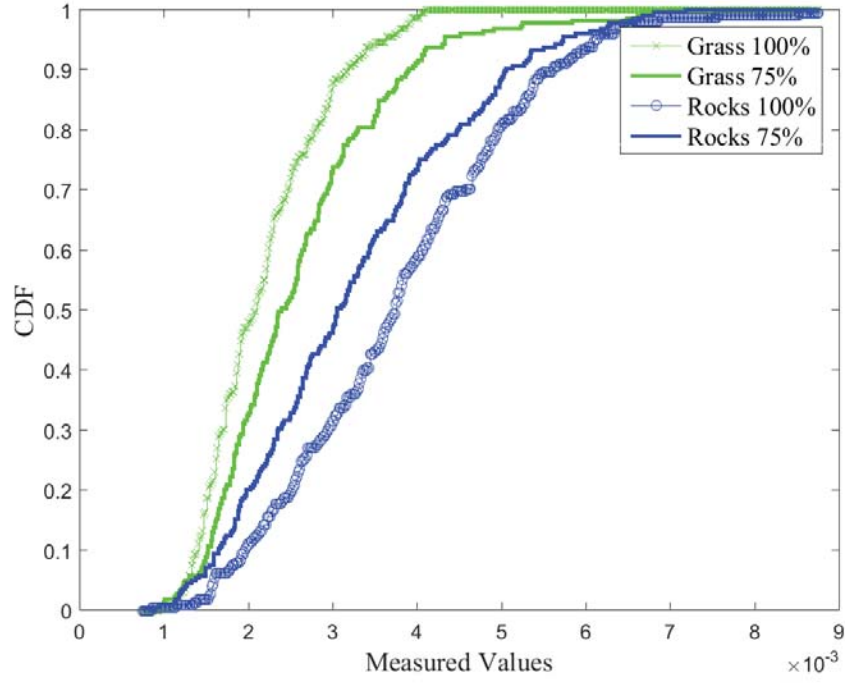


Figure 43. ECDFs overlaid showing the differences for all four clutter scene scenarios for the data from angles 1-225 degrees.

The summary of the data collection Gamma distribution fits is outlined below in Table 5 below.

Table 5. Gamma fit distribution summary for all four scenarios for both the full 360 pts and truncated 225 pts.

Data Set	K	θ	N
100% Grass	6.62	3.71E-04	360
100% Rocks	7.29	5.14E-04	360
$\alpha=0.75$	6.14	4.47E-04	360
$\alpha=0.25$	6.48	4.84E-04	360
Truncated			
100% Grass	10.16	2.14E-04	225
100% Rocks	6.78	5.58E-04	225
$\alpha=0.75$	6.86	3.77E-04	225
$\alpha=0.25$	5.68	5.72E-04	225

5.2 MH Algorithm Results

As discussed in Chapter II the MH Algorithm requires the clutter measurements along with the proportions as inputs in order to function. Along with these data sets the tuning parameter and iteration count for the Monte-Carlo aspect of the function are set and held constant for all of the following validation scenarios. From the results in simulations, also covered in Chapter II, the tuning parameter is set to 0.15 and the iteration count is set to 5000.

The goal of the validation scenarios is to test the MH Algorithm's ability to accurately estimate the Gamma distribution fit for both the homogeneous grass and homogeneous rocks simultaneously through different measurement data set and proportion combinations. In total there are eleven validation scenarios and are outlined below in Table 6. The scenarios cover the range of combinations available for the four different measurement sets of two homogeneous and two heterogeneous along with the additional repeat of each scenario for the adjusted proportion estimates from the previous section. The primary scenario of interest is scenario F for the two heterogeneous inputs, however, all combinations are included for completeness. The validation metric used to test for rejection of of MH Algorithm fit is the two-sample KS test. The threshold D value for rejection is set for the $\alpha_{Reject}=0.05$ value of 0.1249 as previously stated in the previous section.

Table 6. MH Algorithm validation scenario matrix

Scenario	Input 1	Input 2	Input 1 Proportions (G/R)%	Input 2 Proportions (G/R)%
A	100% Grass	100% Rocks	100/0	0/100
B	$\alpha=0.75$	100% Rocks	75/25	0/100
B (Adjusted)	$\alpha=0.75$	100% Rocks	76/24	0/100
C	$\alpha=0.25$	100% Rocks	25/75	0/100
C (Adjusted)	$\alpha=0.25$	100% Rocks	32/68	0/100
D	100% Grass	$\alpha=0.75$	100/0	75/25
D (Adjusted)	100% Grass	$\alpha=0.75$	100/0	76/24
E	100% Grass	$\alpha=0.25$	100/0	25/75
E (Adjusted)	100% Grass	$\alpha=0.25$	100/0	32/68
F	$\alpha=0.75$	$\alpha=0.25$	75/25	25/75
F (Adjusted)	$\alpha=0.75$	$\alpha=0.25$	76/24	32/68

Each scenario is analyzed using a traditional CDF comparison plot and a K versus θ image plot that are evaluated for rejection based on the two-sample KS test statistic D value for the $\alpha_{Reject}=0.05$ level. The image plot is generated by calculating the two-sample KS test D value threshold values for $\alpha_{Reject}=0$ to $\alpha_{Reject}=0.2$ levels for both the homogeneous grass and rocks based on the histogram fit values.

The first scenario, A, tests the MH Algorithm's ability to fit the distributions when it is given both homogeneous measurement data sets for the grass and rocks along with a proportion of 100% for each set. Fig. 44 shows that the $D_{Grass}=0.10$ and $D_{Rocks}=0.04$ both fall below the threshold value of 0.1249 and are not rejected.

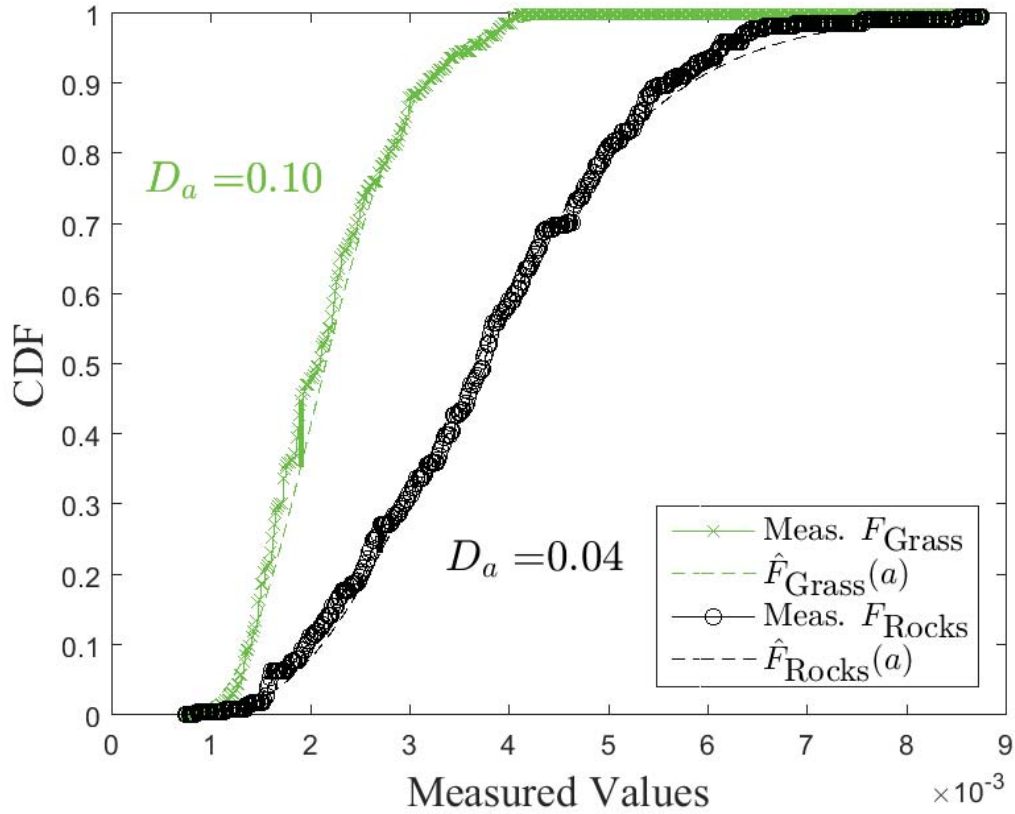
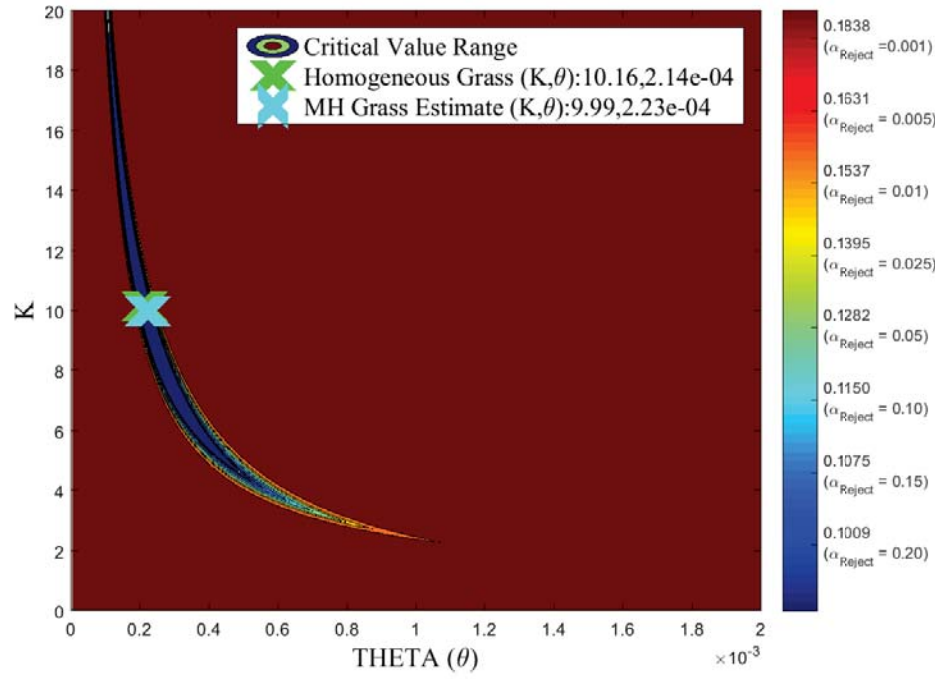
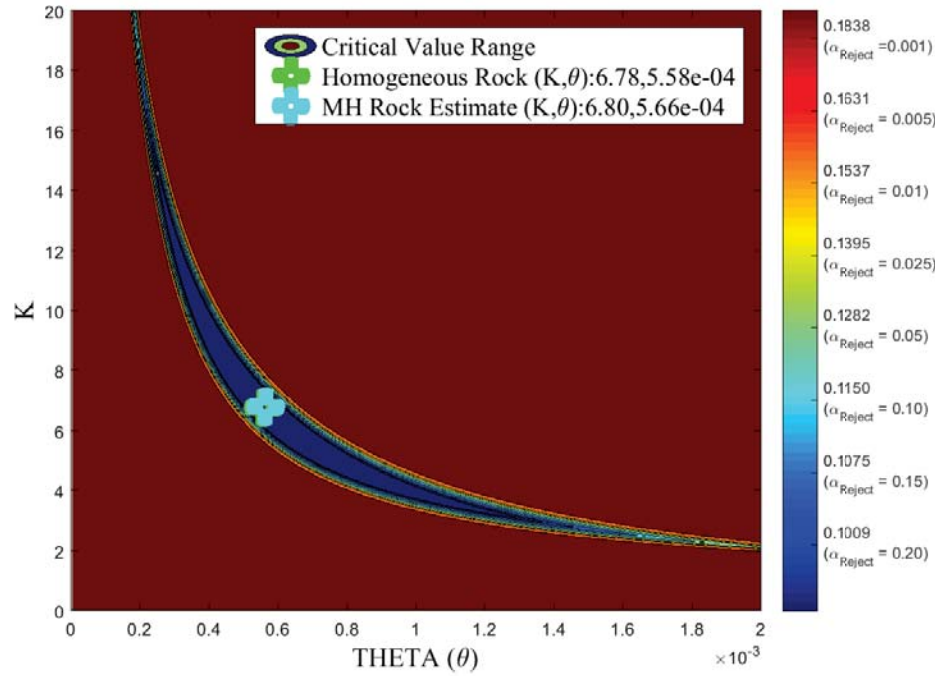


Figure 44. Scenario A CDF comparison for MH Algorithm results and Homogeneous distribution fits for Grass and rocks.

The results when looking at the K versus θ image plot, Fig. 45, show the same outcome in a more graphical approach. The MH Algorithm estimate, shown in cyan, and the homogeneous fit, shown in green, are both placed within the white area of failure to reject with very little difference between the two. Again this difference is due to the D values calculated based on the two-sample KS test.



(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.



(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 45. Scenario A: Homogeneous Grass and Rocks input to MH Algorithm. Result shows good fit of both clutter types.

The rest of the validation scenarios are a mixture of both the homogeneous and heterogeneous measurement data sets. Using the adjusted proportions from the linear mixing estimation in Section 5.1 above, the scenarios are accomplished for the designed prediction of $\alpha=0.75$ and $\alpha=0.25$ and repeated with the same data sets with the adjusted proportions appropriate for each data set.

Scenario B tests the MH Algorithm's ability to estimate both clutter types when the input includes a homogeneous measurement for rock and the $\alpha=0.75$ heterogeneous measurement. The adjusted proportion estimates are also included in this scenario and labeled as Scenario B (Adjusted). Fig. 46 shows the ECDF comparisons for both the grass and rocks. The D value calculated for the grass estimate fit is 0.26 for the predicted proportion and 0.27 for the adjusted proportion. This result exceeds the threshold level for non rejection and as such the MH Estimate is rejected as being a good fit to the homogeneous measurement data. The rock HM algorithm estimate however still conforms to the homogeneous measurement data for the rocks and does not provide any terms for rejection with the D values of 0.04 and 0.05 for both the predicted and adjusted proportions. Figures 47 and 48 show the K versus θ image plots for the predicted and adjusted proportions with the same results of rejection for the grass estimate and non-rejection for the rocks.

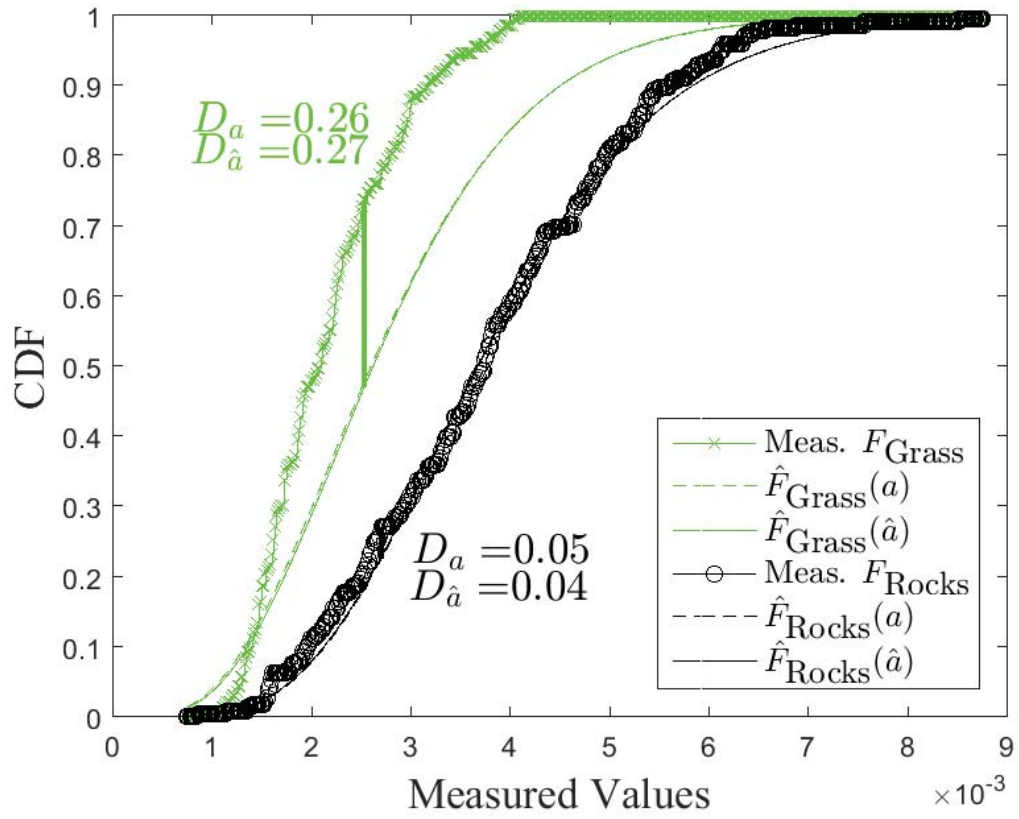
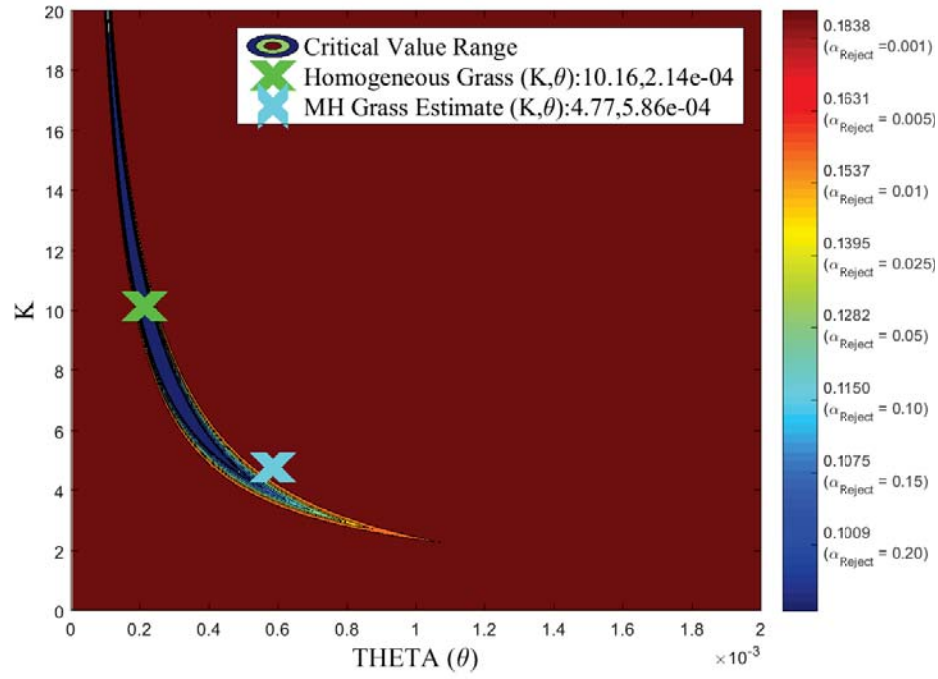
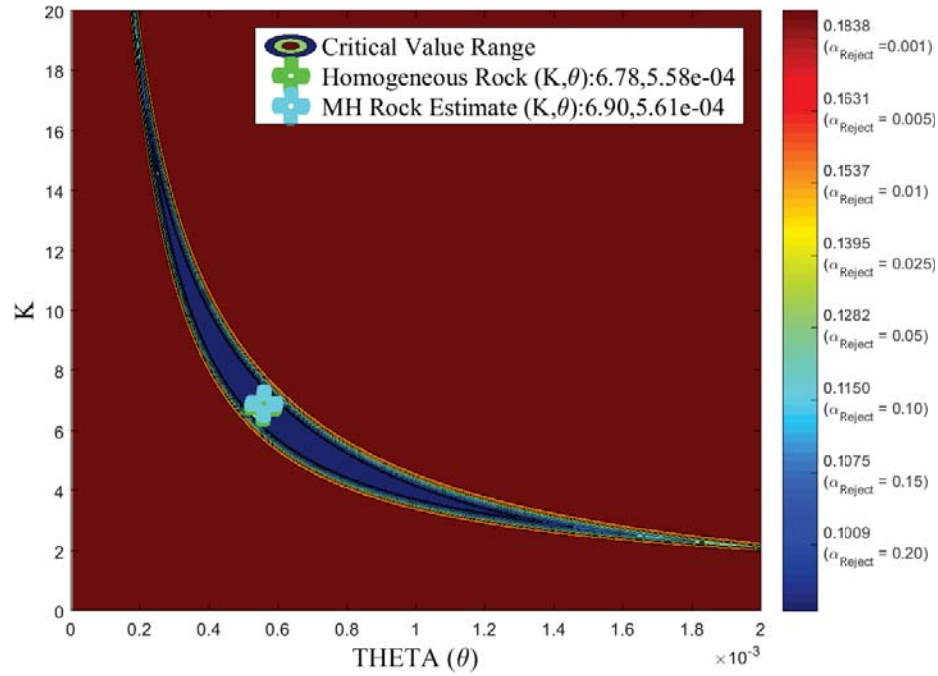


Figure 46. Scenario B CDF comparison for MH Algorithm results and Homogeneous distribution fits for Grass and rocks.

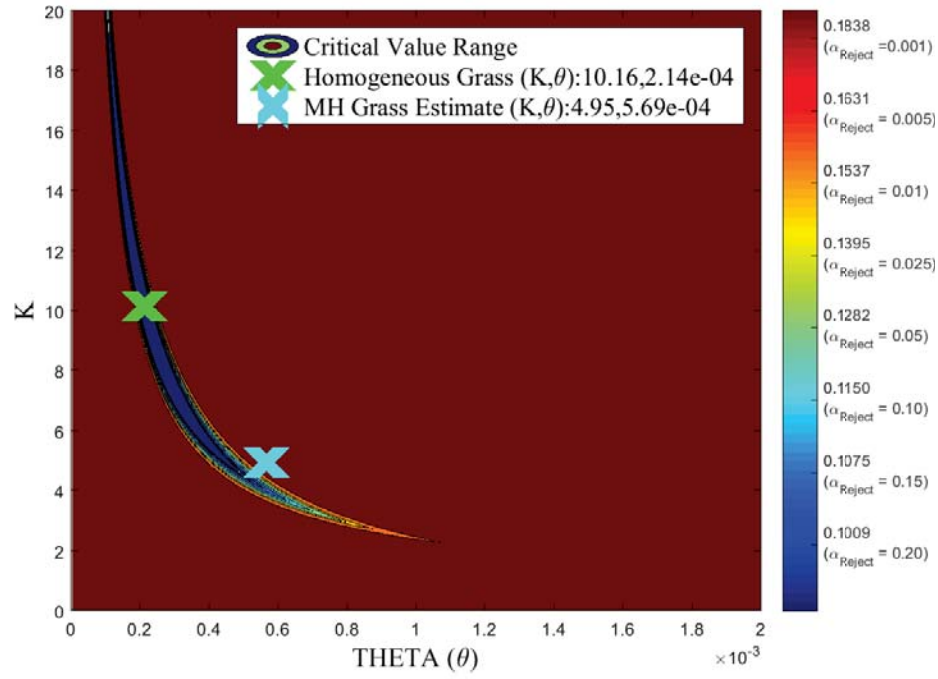


(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.

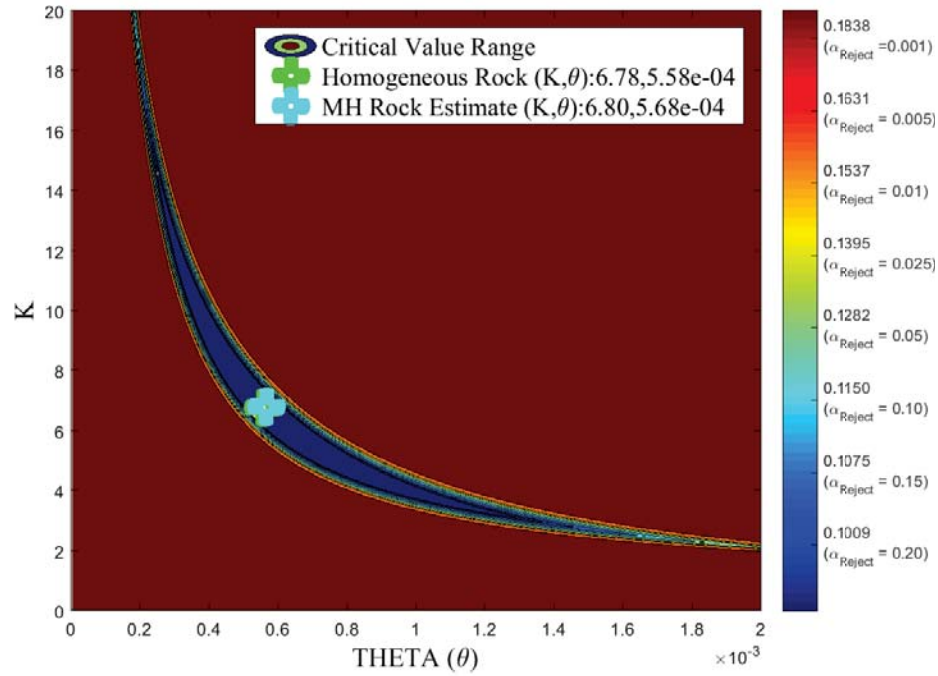


(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 47. Scenario B: Heterogeneous ($\alpha=0.75$) Grass and Homogeneous Rocks input to MH Algorithm. Result shows good fit for only Rocks.



(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.



(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 48. Scenario B (Adjusted): Heterogeneous ($\alpha=0.76$) Grass and Homogeneous Rocks input to MH Algorithm. Result shows good fit for only Rocks.

Scenario C tests the MH Algorithm's ability to estimate when given the homogeneous rock measurement data and the $\alpha=0.25$ heterogeneous measurement as inputs. Figs. 49, 50, and 51 show the results are similar to those in Scenario B. Again the MH Estimate for grass is rejected due to the D values of 0.37 and 0.58 for both the predicted and adjusted proportions. The rock estimate fails to be rejected with the D value of 0.04 and 0.05.

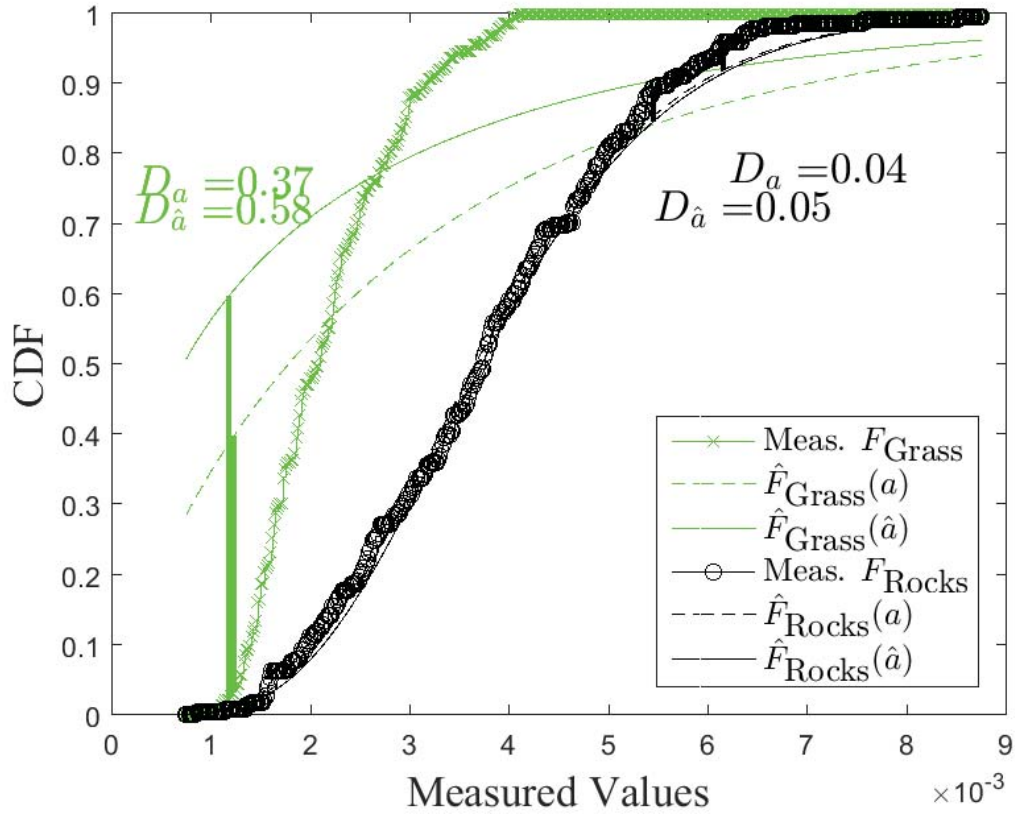
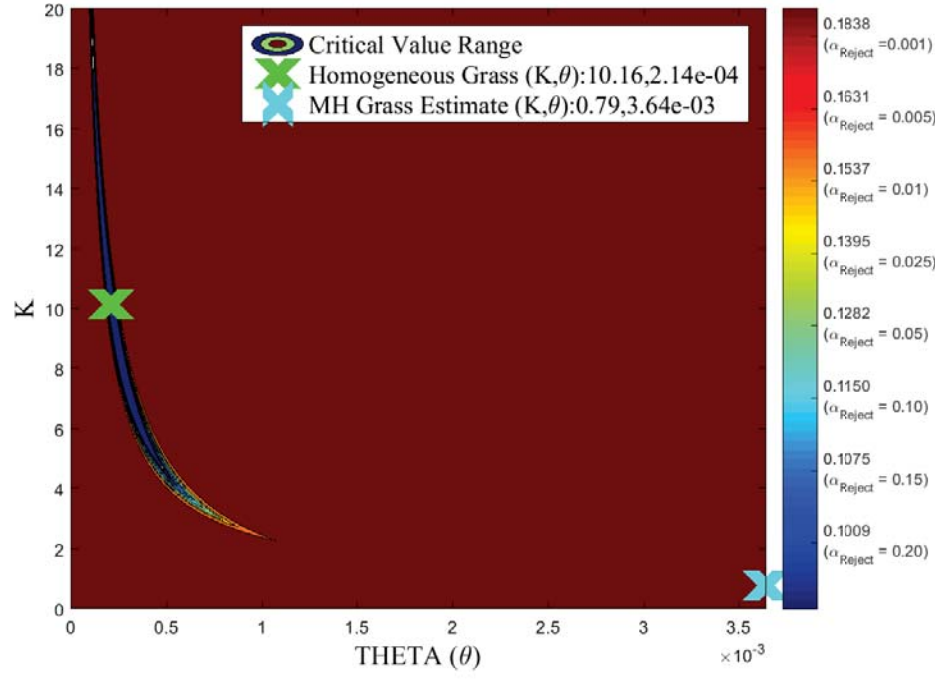
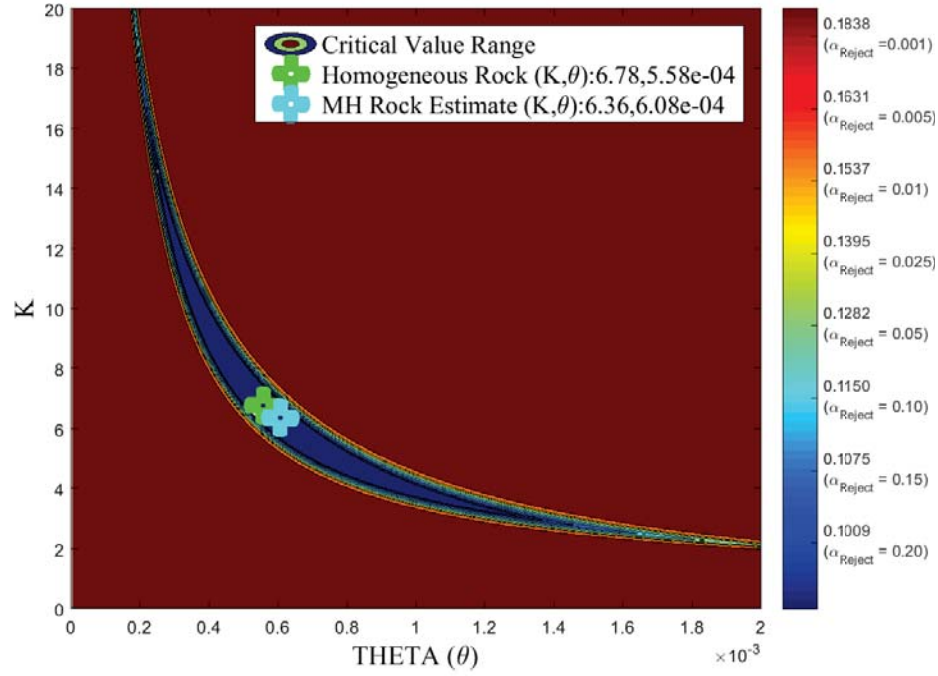


Figure 49. Scenario C: CDF comparison for MH Algorithm results and Homogeneous distribution fits for Grass and rocks.

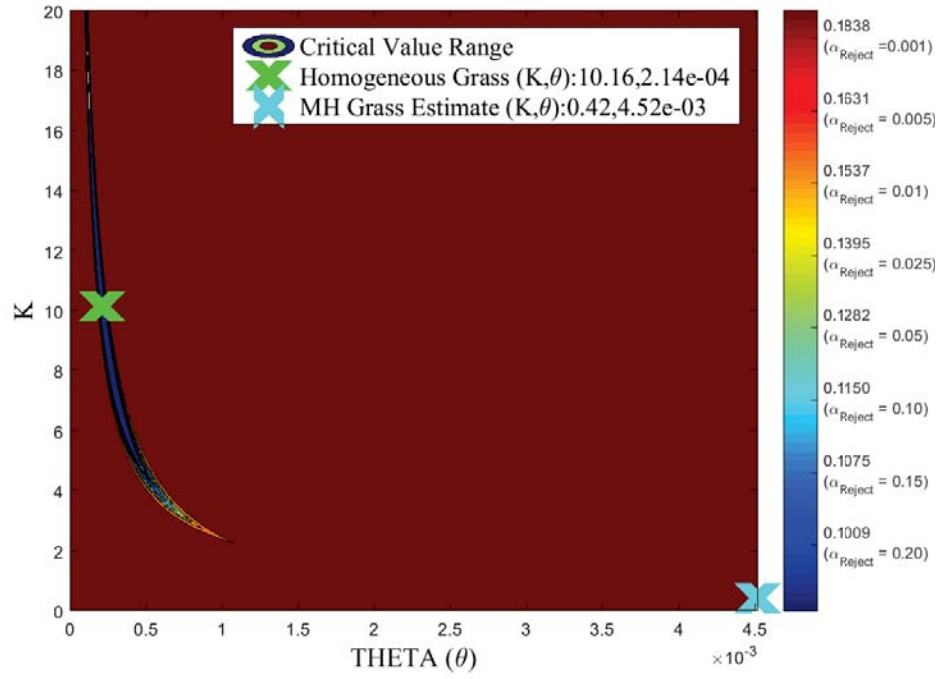


(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.

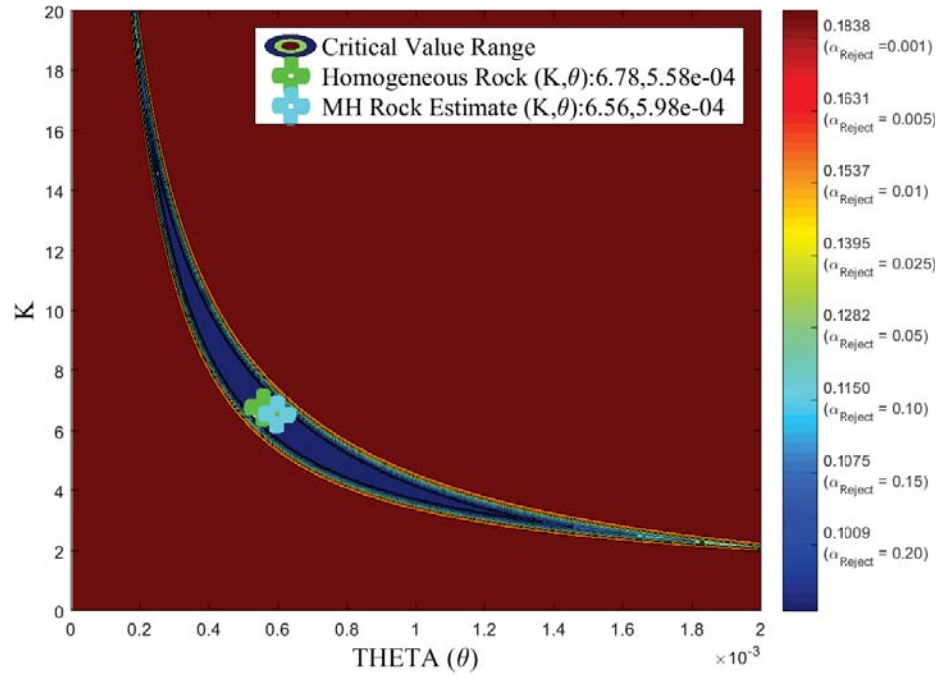


(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 50. Scenario C: Heterogeneous ($\alpha=0.25$) Grass and Homogeneous Rocks input to MH Algorithm. Result shows good fit for only rocks.



(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.



(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 51. Scenario C (Adjusted): Heterogeneous ($\alpha=0.32$) Grass and Homogeneous Rocks input to MH Algorithm. Result shows good fit for only rocks.

Scenario D tests the MH Algorithm's estimation ability when given the homogeneous grass measurement data and the $\alpha=0.75$ heterogeneous measurement data as inputs. The grass estimate for both the predicted and adjusted proportions is not rejected with the D values of 0.10 and 0.11. However, the rock estimate for both sets is rejected due to the D value of 0.37 and 0.45 for the predicted and adjusted proportions. Figs. 52, 53, and 54 show the results for this scenario below.

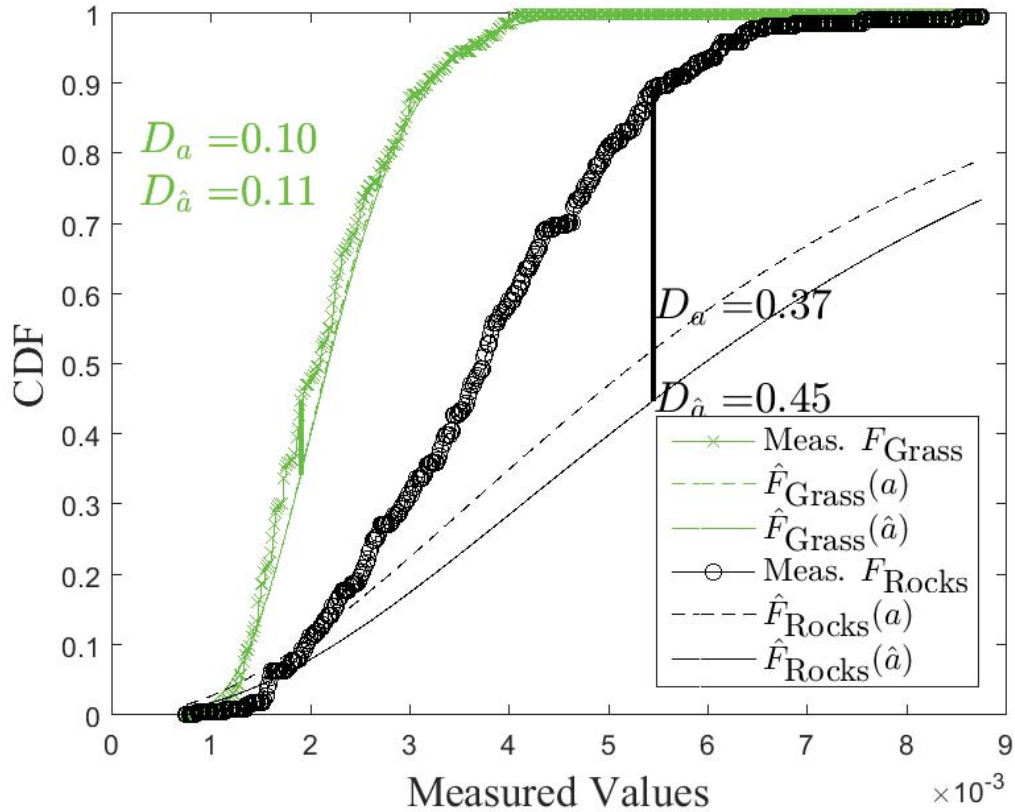
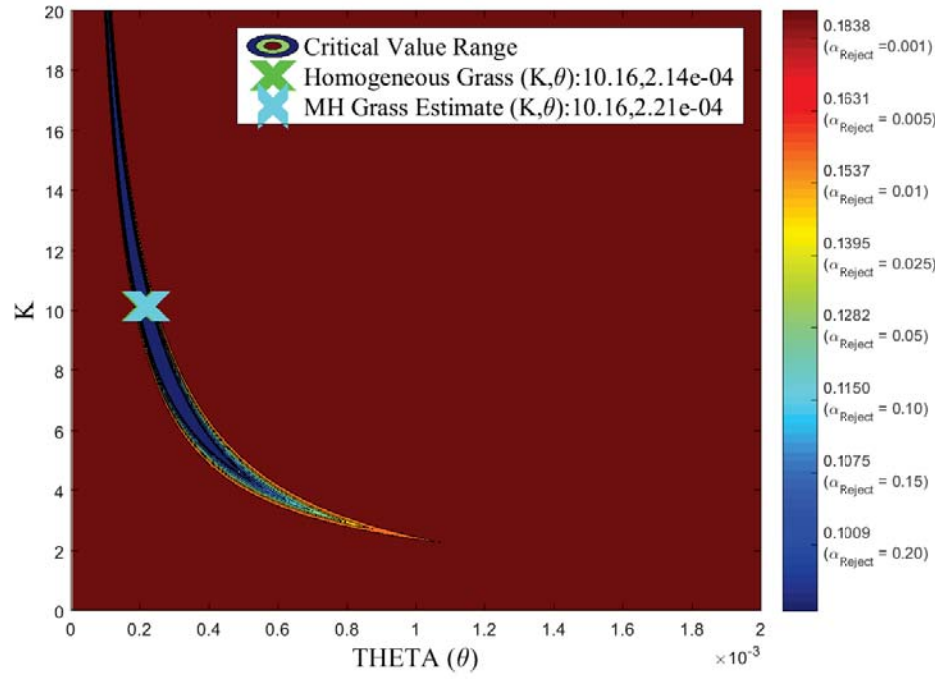
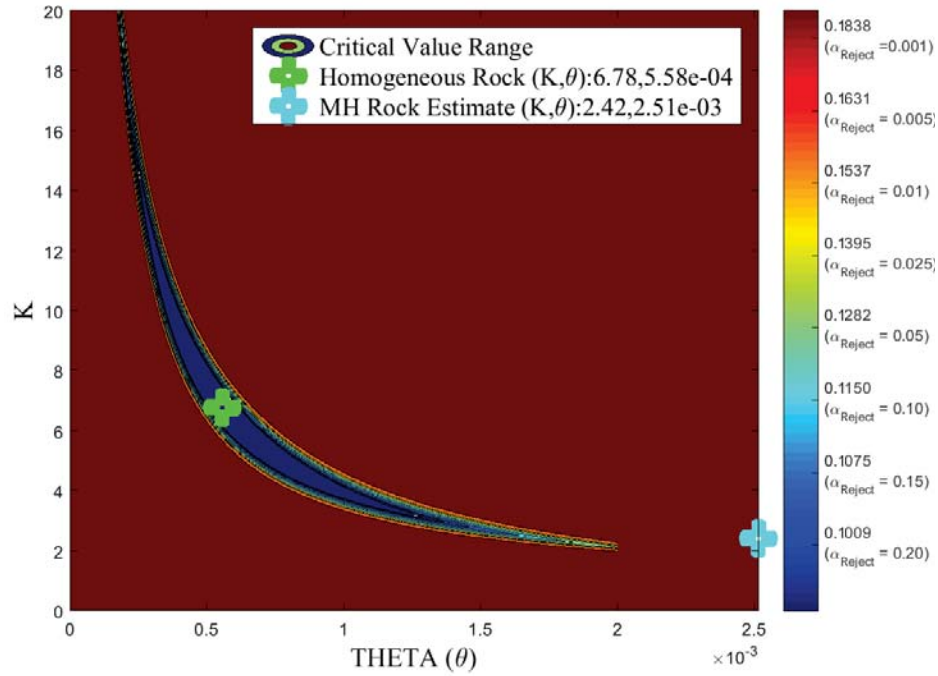


Figure 52. Scenario D CDF comparison for MH Algorithm results and Homogeneous distribution fits for grass and rocks.

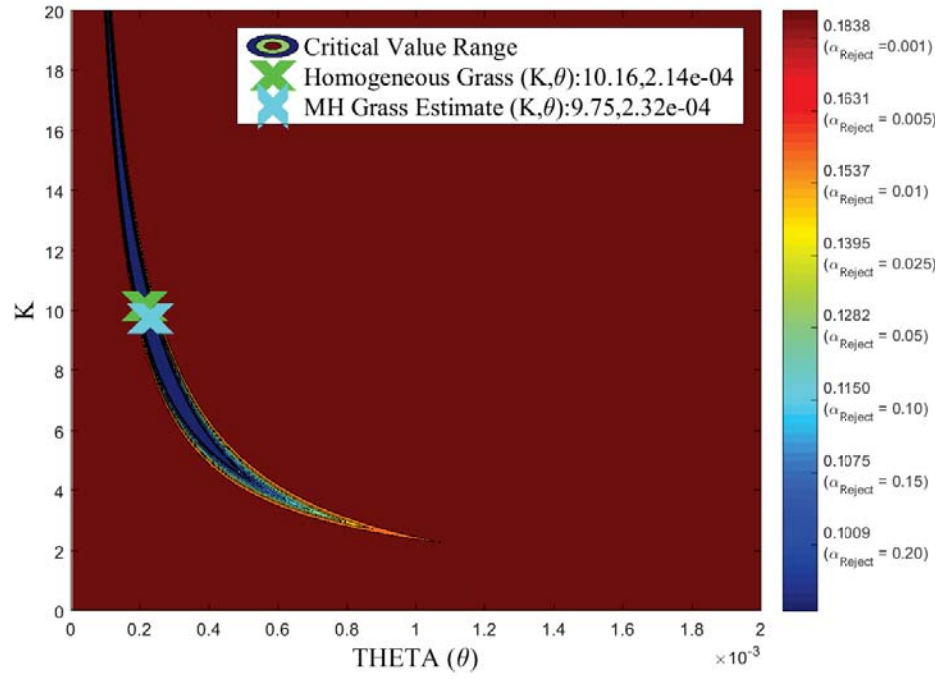


(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.

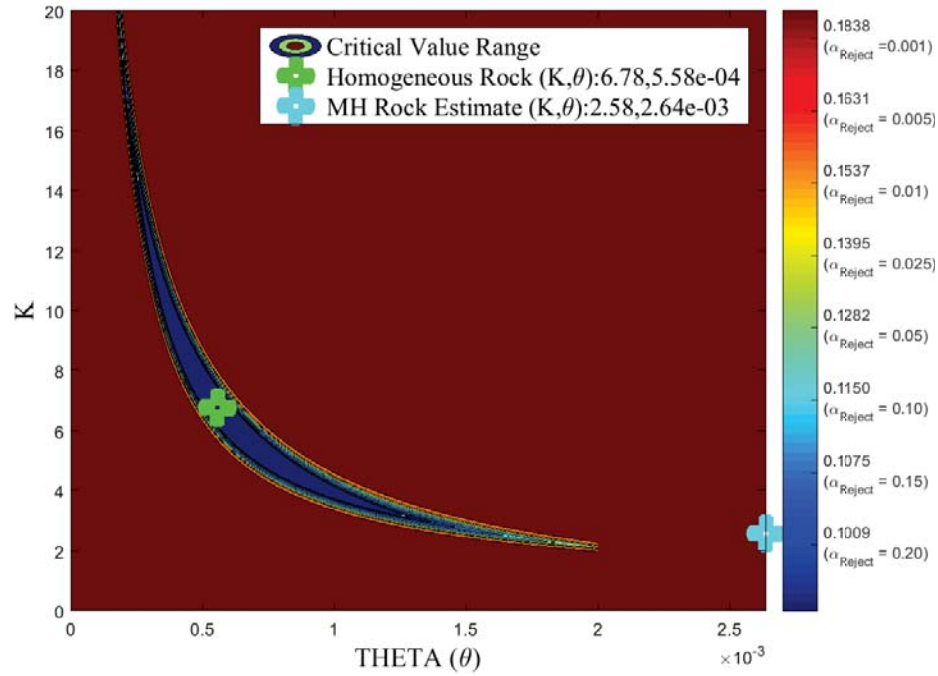


(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 53. Scenario D: Heterogeneous ($\alpha=0.75$) Grass and Homogeneous Grass input to MH Algorithm. Result shows good fit for only grass.



(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.



(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 54. Scenario D (Adjusted): Heterogeneous ($\alpha=0.76$) Grass and Homogeneous Grass input to MH Algorithm. Result shows good fit for only grass.

Scenario E again tests the MH Algorithm's ability to estimate when given the homogeneous grass and $\alpha=0.25$ heterogeneous measurement data as the inputs. As with scenario D the grass estimate is not rejected with the D values 0.09 and 0.08. The rock estimate D value of 0.11 for the predicted proportion is not rejected. However, the adjusted proportion estimate is rejected with the D value of 0.15. Figs. 55, 56, and 57 show the results for this scenario below.

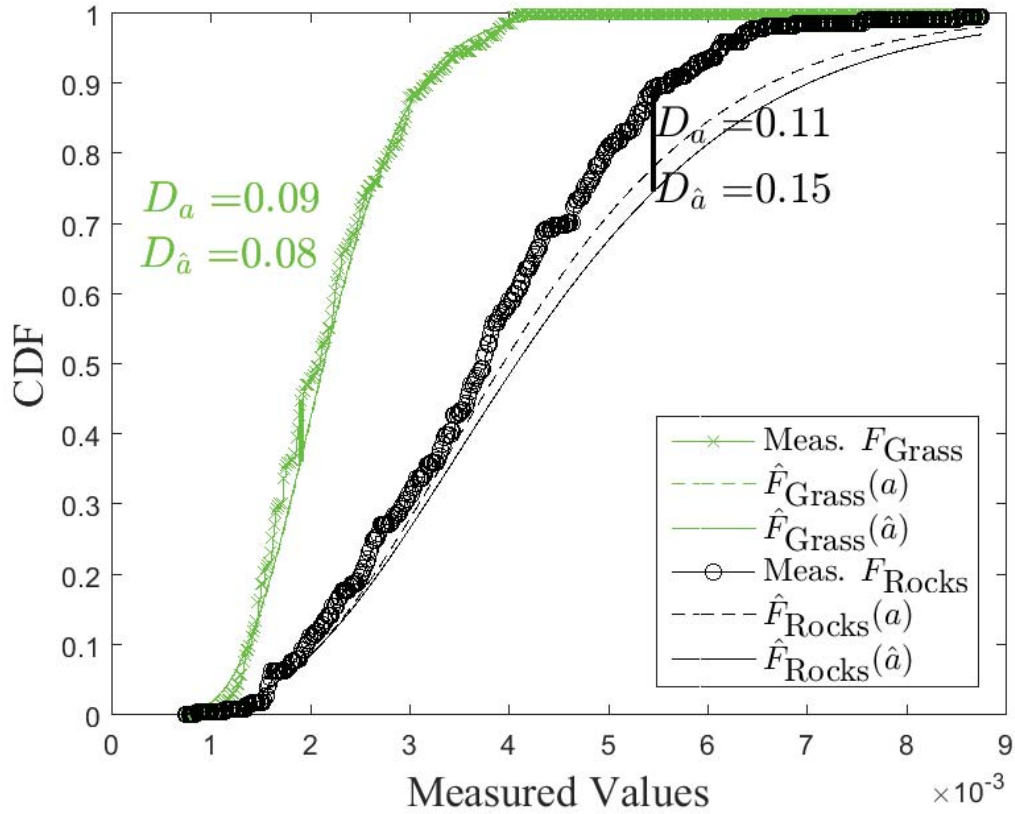
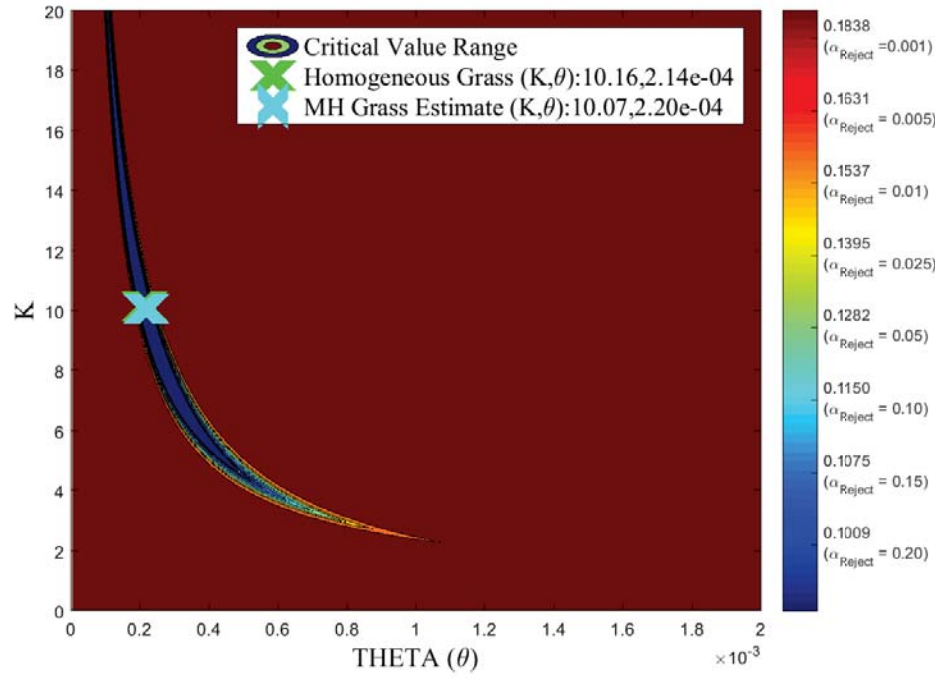
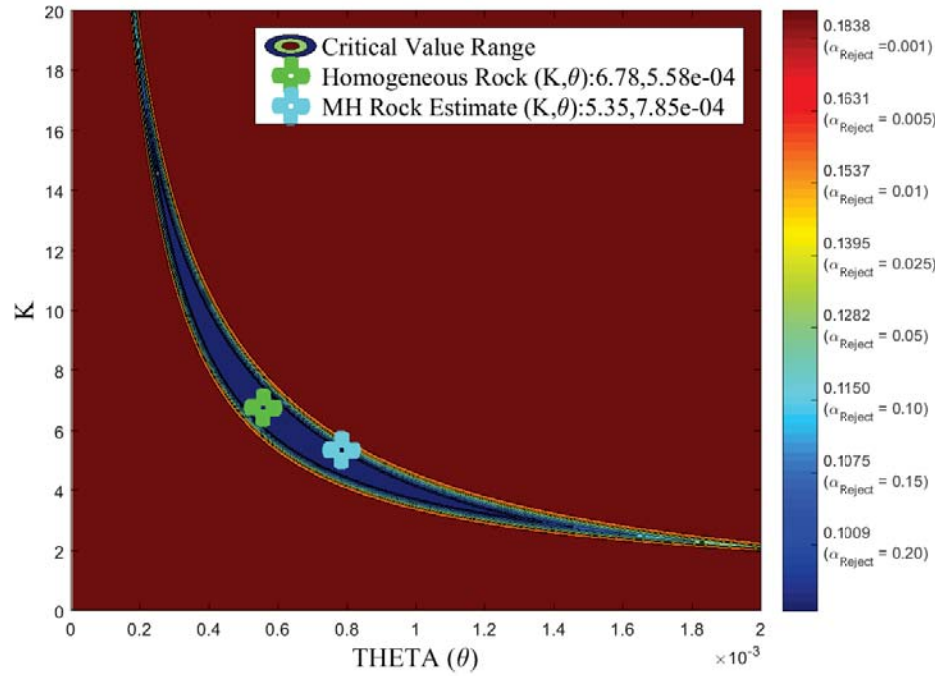


Figure 55. Scenario E CDF comparison for MH Algorithm results and Homogeneous distribution fits for grass and rocks.

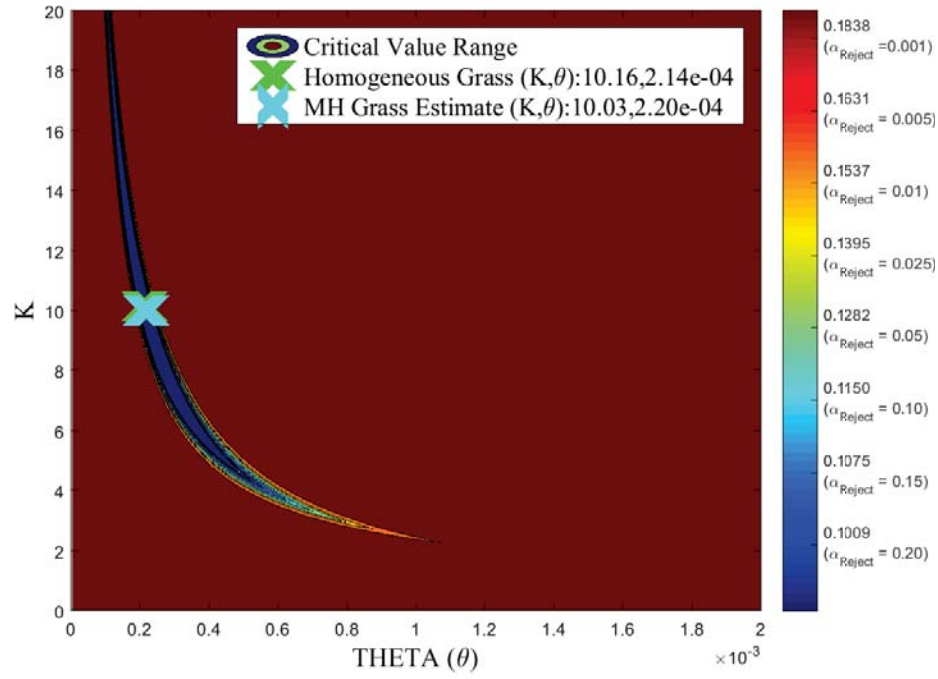


(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.

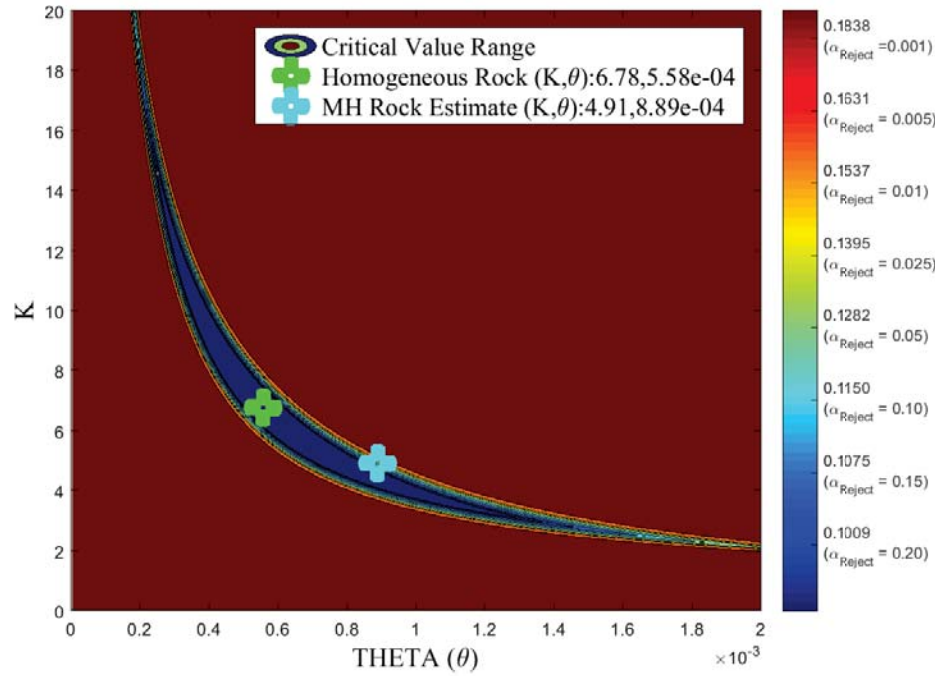


(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 56. Scenario E: Homogeneous Grass and Heterogeneous ($\alpha=0.25$) Rocks input to MH Algorithm. Result shows non-rejection for both clutter types.



(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.



(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 57. Scenario E (Adjusted): Homogeneous Grass and Heterogeneous mix ($\alpha=0.32$) input to MH Algorithm. Result shows non-rejection for grass and non-rejection for rocks at $\alpha_{Reject}=0.01$.

The final test, Scenario F, represents the case when both clutter types are unknown with no data inputs from a homogeneous case for either clutter type. Both the heterogeneous measurements $\alpha=0.75$ and $\alpha=0.25$ are the inputs to the MH Algorithm and are tested using the predicted and the adjusted proportions. The results, shown in Figs. 58, 59, and 60, indicate that the MH Algorithm estimates for the grass are rejected but the rocks are not rejected.

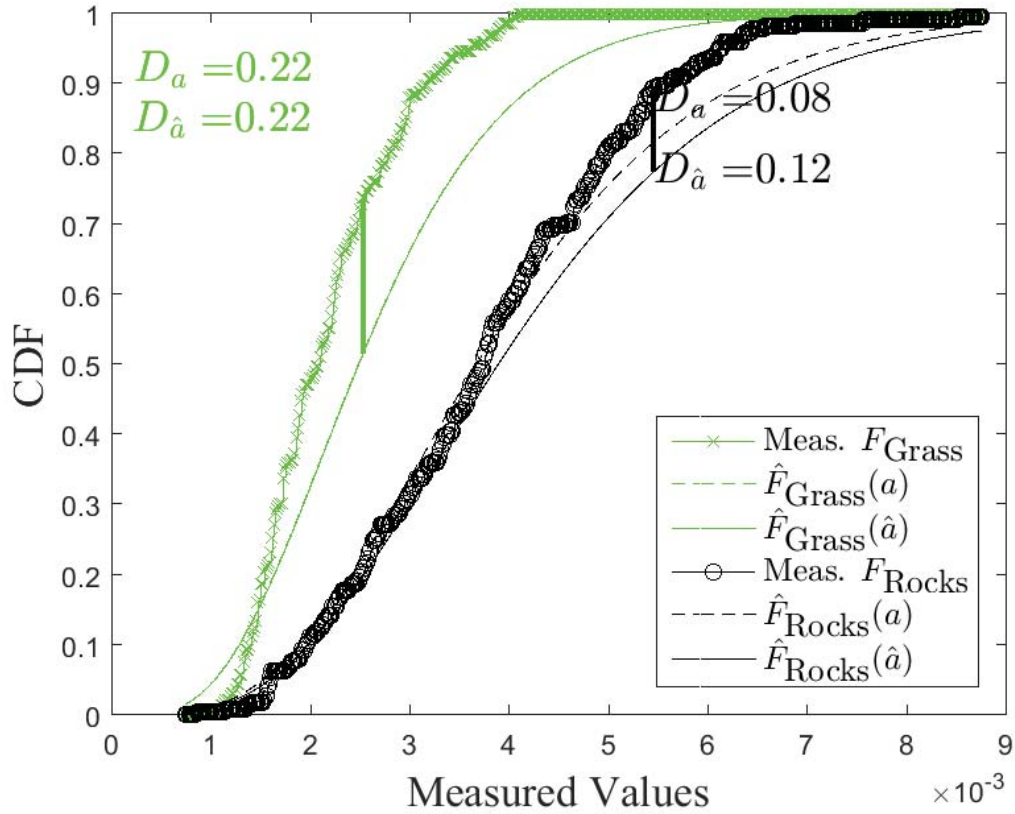
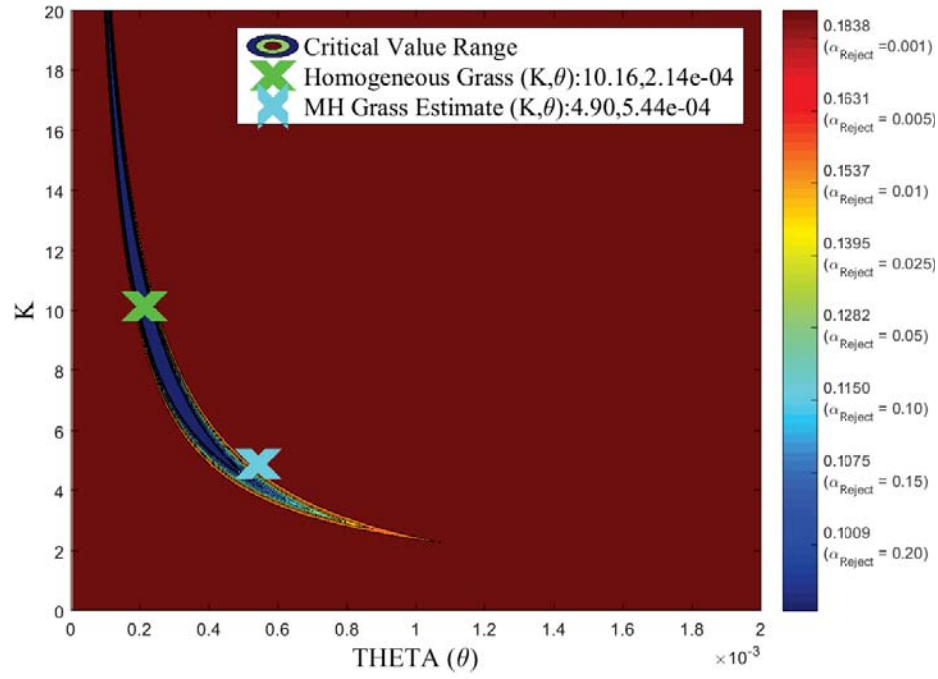
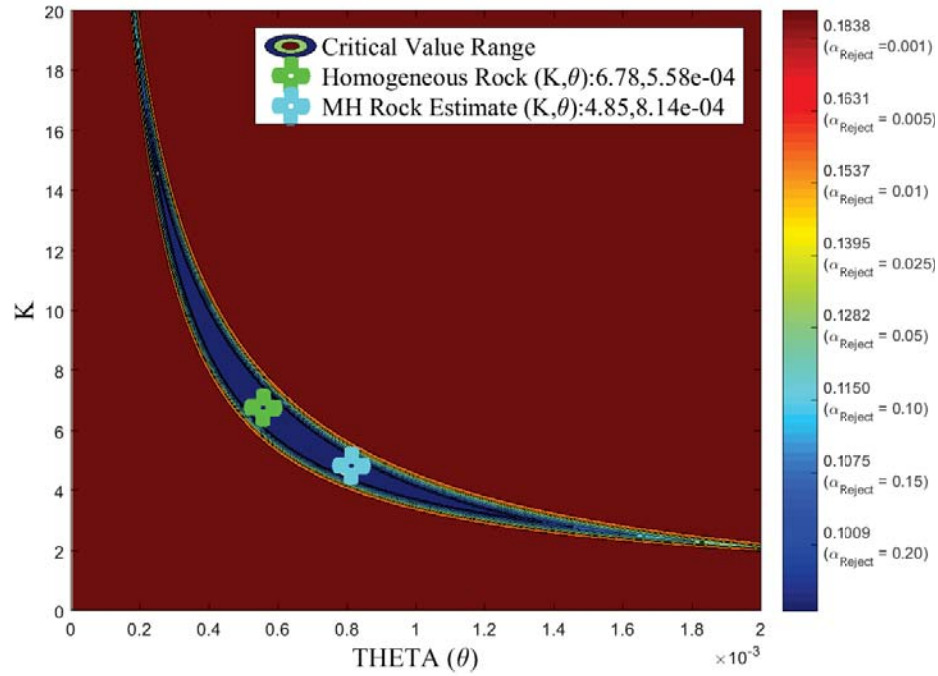


Figure 58. Scenario F CDF comparison for MH Algorithm results and Homogeneous distribution fits for grass and rocks.

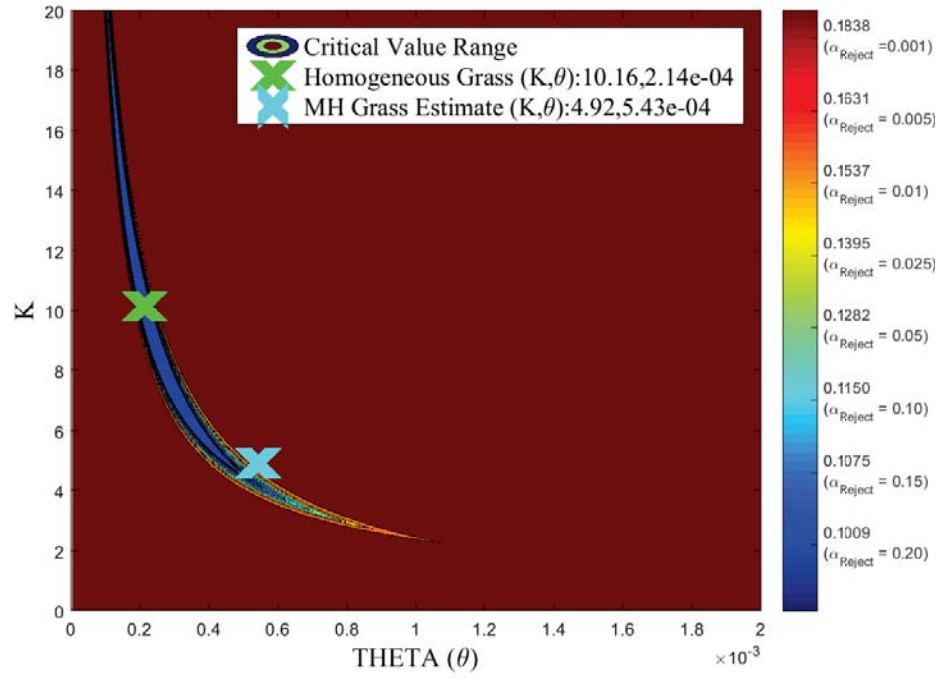


(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.

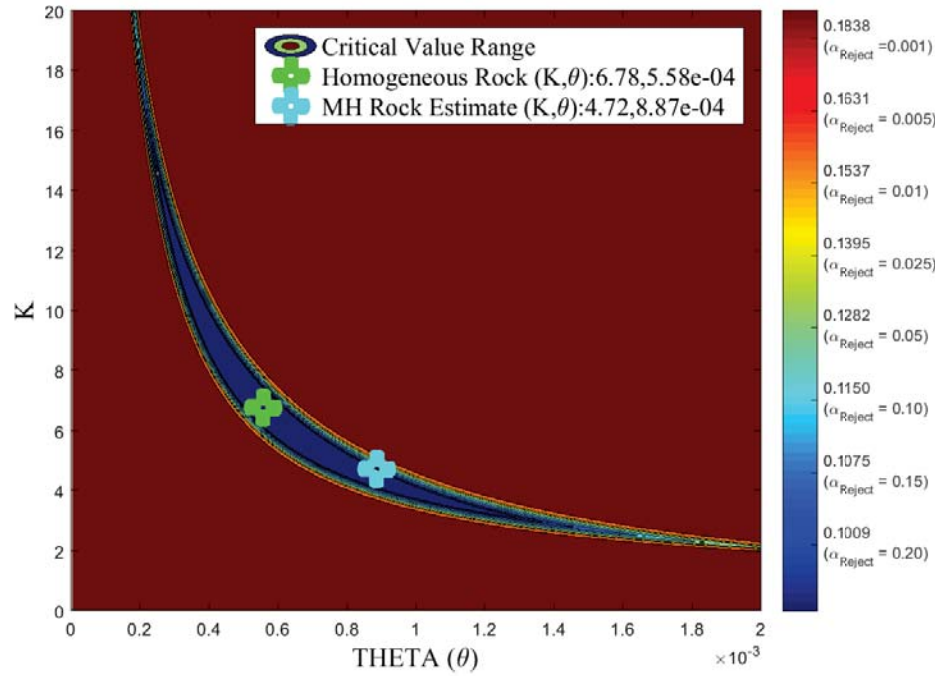


(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 59. Scenario F: Heterogeneous ($\alpha=0.75$) Grass and Heterogeneous mix ($\alpha=0.25$) input to MH Algorithm. Result shows rejection of fit for only grass estimate.



(a) Grass Gamma fit comparison for homogeneous and MH Algorithm estimate.



(b) Rock Gamma fit comparison for homogeneous and MH Algorithm estimate.

Figure 60. Scenario F (Adjusted): Heterogeneous ($\alpha=0.76$) Grass and Heterogeneous ($\alpha=0.32$) Rocks input to MH Algorithm. Result shows rejection of fit for only grass estimate.

From the results shown in each scenario above, when the homogeneous data sets are inputs the MH Algorithm estimates are accurate for that specific clutter type but for the unknown clutter type the estimate fails in most scenarios. The results shown in both Scenario E and Scenario F further indicate that there is an inconsistency in the experiment measurements as discussed in Section 4.1 due to the grass. The summary table of the results for the scenarios is shown below in Table 7.

Table 7. MH Algorithm Validation Scenario Results

Scenario	Input A	Input B	K Est Grass	θ Est Grass	K Est Rock	θ Est Rock	D Grass	D Rocks	Reject Grass?	Reject Rocks?
A	100% Grass	100% Rocks	9.99	2.23E-04	6.8	5.66E-04	0.09	0.04	no	no
B	$\alpha=0.75$	100% Rocks	4.77	5.86E-04	6.90	5.61E-04	0.26	0.05	yes	no
B (Adjusted)	$\alpha=0.75$	100% Rocks	4.95	5.69E-04	6.80	5.68E-04	0.27	0.04	yes	no
C	$\alpha=0.25$	100% Rocks	0.79	3.64E-03	6.36	6.08E-04	0.37	0.04	yes	no
C (Adjusted)	$\alpha=0.25$	100% Rocks	0.42	4.52E-03	6.56	5.98E-04	0.58	0.05	yes	no
D	100% Grass	$\alpha=0.75$	10.16	2.21E-04	2.42	2.51E-03	0.10	0.37	no	yes
D (Adjusted)	100% Grass	$\alpha=0.75$	9.75	2.32E-04	2.58	2.64E-03	0.11	0.45	no	yes
E	100% Grass	$\alpha=0.25$	10.07	2.20E-04	5.35	7.85E-04	0.09	0.11	no	no
E (Adjusted)	100% Grass	$\alpha=0.25$	10.03	2.20E-04	4.91	8.89E-04	0.08	0.15	no	yes
F	$\alpha=0.75$	$\alpha=0.25$	4.90	5.44E-04	4.85	8.14E-04	0.22	0.08	yes	no
F (Adjusted)	$\alpha=0.75$	$\alpha=0.25$	4.92	5.43E-04	4.72	8.87E-04	0.22	0.12	yes	no

5.3 Error Sources

Although the results from the previous section show that the MH Algorithm estimations are unable to accurately estimate the clutter statistics, it is not a true indication that the MH Algorithm is failing. The simulation trials and results covered in Chapter III showed us that the estimation was possible with accurate proportion splits. This leads us to believe that the data measurements for the experiments used in this validation attempt may not be the best choice to assess the MH Algorithm.

We have already shown that the “flat plate” effect, discussed in Section 4.1, had an impact on the shape and scale estimates for fitting the data and validating the linear mixing assumption which only reiterates this uncertainty that the measurement data is quality enough to be used. The anomalies in the data for the homogeneous grass and heterogeneous $\alpha=0.75$ mix which show magnitudes exceeding a higher level of standard deviation may potentially be triggering the MH Algorithm to focus on those specific data points as the unknown clutter type. A specific example of this potential error is shown in Scenario D where the rock θ is estimated higher when the heterogeneous $\alpha=0.75$ mix is the input along with the homogeneous grass.

Another potential error source may be the separation of the clutter type distributions for both the grass and the rocks. In simulations the K and θ were held constant during the tuning and error trials for each set of sampled data. Without any further simulations, the experiment measured data may be inside the range of overlap for the MH Algorithm to properly estimate.

VI. Conclusions and Future Work

This thesis covers a series of experimental data measurements of radar clutter to validate a clutter statistic estimation algorithm [1]. This chapter summarizes the experiments, outlines the validation analysis and concludes with future research efforts that can be included to improve the outcome of this effort.

6.1 Experiment Overview

Four sets of radar clutter measurements were taken that included a set of homogeneous grass, homogeneous rocks, and two heterogeneous mixtures of the grass and rocks at a split proportion of 75% and 25%. The measurements were accomplished using the AFIT RAIL radar system in conjunction with a target rotator and background RAM wall. The measurements were processed and compiled together using basic matched filter and range profile techniques. Each data set included 360 points, one for each angle of the rotator, but due to clutter inconsistency the sample size was truncated down to 225 samples per set.

The MH Algorithm uses these four data sets along with their proportion matrix to estimate the underlying clutter statistics for each single clutter type. The MH Algorithm assumes a linear mixing model in order to correctly determine the statistics from heterogeneous clutter data sets.

6.2 Results and Conclusion

Comparing the homogeneous measurements for grass and rocks when scaled by the appropriate proportion percent to the heterogeneous clutter mixture measurements showed the goodness of fit statistics that could not be rejected. This result validated that the assumption that clutter linearly mixes and is a function of the physical

proportions.

Running the four sets of measured data in a series of validation tests showed the MH Algorithm could successfully, with no goodness of fit rejection, calculate the clutter statistics for the cases when it was given a homogeneous data set. However, for each test the estimate based on the heterogeneous data sets were rejected most of the time based on the goodness of fit results. We cannot justify with a high level of confidence that the failure is due to the MH Algorithm since there have been multiple errors in data collection due to clutter choices and the collection environment. Unfortunately the results from this research effort did not provide enough justification to fully accept or reject the MH Algorithm.

6.3 Future Work

Future work to further investigate the MH Algorithm should include a more rigorous set of simulations. The simulations should test the limitations of magnitudes, K and θ spacing of the gamma distributions and to re-evaluate the tuning and error factors when the distributions are altered. The results from these simulations will better layout the areas in which the MH Algorithm can be expected to work and where it may not be at an acceptable range for a solution.

Additionally, based on the results from using grass and its inconsistency at varied angles it is recommended to use a different material as a clutter source that is more isotropic in its scattering response. The rock response proved to be consistent for each angle that the rotator was moved to and can be reused as a clutter source.

Once these two items can be corrected, the MH Algorithm can be tested again using the same scenarios that were accomplished in Chapter V. If the results prove to be within an acceptable goodness of fit threshold the next step in validation would be to further expand the tests with an additional clutter source added for scenarios where

up to three clutter types are unknown. From the conclusions of the two unknown as well as the three unknown clutter types the MH Algorithm can be validated with the assumption that for these two types of scenarios the results are either acceptable or rejected.

AWG Tektronix Arbitrary Waveform Generator - AWG7102

O-Scope Tektronix Digital Storage Oscilloscope - TDS6214

Sig Gen Agilent Analog Signal Generator - N5183A

DC-PS Agilent DC PowerSupply - E3646A

Tx Transmit

Rx Receive

USAF United States Air Force

CDF Cumulative Distribution Functions

PDF Probability Density Functions

RADAR Radio Detection and Ranging

RCS Radar Cross Section

CDF Cumulative Distribution Function

ECDF Empirical Cumulative Distribution Function

PDF Probability Density Function

MH Metropolis Hastings

MCMC Markov Chain Monte Carlo

PFA Probability of False Alarm

PD Probability of Detection

KS Kolmogorov-Smirnov

HPBW Half Power Beam Width

HPF High Pass Filter

LPF Low Pass Filter

RAM Radar Absorbing Material

LFM Linear Frequency Modulation

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EXPERIMENTAL VALIDATION OF A HETEROGENEOUS RADAR CLUTTER STATISTICAL ESTIMATION METHOD

Elliot R. Erstein

March 2017

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14. ABSTRACT Radar clutter models are important for radar target detection when clutter is present. A new method for estimating single clutter type, homogeneous, radar clutter statistics through measurement of a multiple type, heterogeneous clutter was developed in 2015 by researchers at the Air Force Institute of Technology. The estimation method is greatly valued in the clutter research and modeling world for reducing clutter campaign measurement time and cost. This thesis looks at validation steps for the estimation method through the use of simulations and experimental radar clutter measurements.						
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