



**RADIO TOMOGRAPHIC IMAGING USING A MODIFIED
MAXIMUM LIKELIHOOD ESTIMATOR FOR IMAGE
RECONSTRUCTION IN VARIOUS ENVIRONMENTS**

THESIS

Antwon R. Gallagher, Captain, USAF

AFIT-ENG-MS-18-M-028

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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Antwon R. Gallagher, B.S.E.E.

Captain, USAF

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Antwon R. Gallagher, B.S.E.E.
Captain, USAF

Committee Membership:

Richard K. Martin, PhD
Chair

Julie A. Jackson, PhD
Member

Michael A. Temple, PhD
Member

Capt Jeffery K. Nishida, MS
Member

Abstract

Radio Tomographic Imaging (RTI) is an emerging Device-Free Passive Localization (DFPL) technology. Radio Tomographic Imaging (RTI) involves using a set of small low cost wireless transceivers to create a Wireless Sensor Network (WSN) around an Area of Interest (AoI). Furthermore, the Received Signal Strength (RSS) between transceiver pairs is utilized to reconstruct an image from the signal attenuation caused by an object disrupting the links. This image can then be utilized for multiple applications ranging from localization to target detection and tracking. This enhances the importance of image resolution in order to capture the actual size of the objects as well as the ability to resolve multiple objects in an AoI.

The objective of this research is to propose a new image formation technique for a reconstructed image within a WSN. This was accomplished using a modified Maximum Likelihood Estimate (MLE) function that forces the desired solution to be positive. Other regularization techniques must implement different methods to mitigate the undesired singular values caused from a non-invertible matrix. Additionally, the research highlights the performance of the modified MLE estimator and the robustness of improved image resolution in three different environments.

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List of Abbreviations

AFIT	Air Force Institute of Technology
AFRL	Air Force Research Laboratory
AoI	Area of Interest
AWGN	Additive White Gaussian Noise
BSD	Berkely Software Distribution
CCD	Charge-Coupled-Device
dB	decibels
dBm	decibel milliwatts
DF	device-free
DFL	Device-Free Localization
DFPL	Device-Free Passive Localization
ft	foot
FSPL	Free Space Path Loss
GHz	Gigahertz
GPS	Global Positioning System
GUI	Graphical User Interface
ICD	Informed Consent Document
IEEE	Institute of Electrical and Electronics Engineers
IFA	Inverted-F Antenna
IID	Independent and Identically Distributed
Inc.	Incorporated
IR	Infrared
IRB	Institutional Review Board
ISM	Industrial, Scientific, and Medical

ITU	International Telecommunication Union
JDK	Java Development Kit
JRE	Java Runtime Environment
kB	kilobyte
kbps	kilobits per second
KRTI	Kernel Distance-Based RTI
LOS	Line-of-Sight
LS	Least Squares
LSVRT	Least Squares Variance-Based Radio Tomography
MRTI	Mean-Based Radio Tomographic Imaging
m	meters
mph	miles per hour
mA	milliamps
MEMS	Micro Electro-Mechanical Systems
MHz	megahertz
MIMO	Multiple Input, Multiple Output
min	minute
ML	Maximum Likelihood
MLE	Maximum Likelihood Estimate
mnRTI	Multiple-Networks RTI
MRI	Magnetic Resonance Imaging
MSE	Mean Squared Error
mW	milliwatt
NaN	Not a Number
NeSh	Network Shadowing
NLOS	Non-Line-of-Sight

NP	Neyman-Pearson
NMSE	Normalized Mean Squared Error
O&M	Operations and Management
OMP	Orthogonal Matching Pursuit
OS	Operating System
PCA	Principal Component Analysis
PDF	Probability Density Function
PVC	Polyvinyl Chloride
RAM	Random Access Memory
RF	Radio Frequency
RFIC	Radio Frequency Integrated Circuit
RFID	Radio Frequency Identification
RTI	Radio Tomographic Imaging
RSS	Received Signal Strength
s	seconds
SNR	Signal-to-Noise Ratio
SOCHE	Southwestern Ohio Council for Higher Education
SPAN	Sensing and Processing Across Networks
SVD	Singular Value Decomposition
TinyOS	Tiny Operating System
TSVD	Truncated Singular Value Decomposition
TTW	Through-The-Wall
TV	Total Variation
UC	University of California
USB	Universal Serial Bus
UWB	Ultra-Wideband

VRTI Variance-Based RTI

Wi-Fi Wireless Fidelity

WLAN Wireless Local Area Networks

WPAFB Wright Patterson Air Force Base

WPAN Wireless Personal Area Network

WSN Wireless Sensor Network

RADIO TOMOGRAPHIC IMAGING USING A MODIFIED MAXIMUM LIKELIHOOD ESTIMATOR FOR IMAGE RECONSTRUCTION IN VARIOUS ENVIRONMENTS

I. Introduction

This chapter provides a brief introduction and overview of Wireless Sensor Networks (WSNs) and Radio Tomographic Imaging (RTI). The chapter will discuss different applications of RTI as well as some of the reconstruction methods used to produce an image.

1.1 Background and Research Motivation

The ability to see through walls is highly desired for a variety of defense and security related reasons. Fortunately, with the exponential climb of technological advancements, this once thought-to-be science-fiction attribute has become a reality. Using Radio Frequency (RF) devices, a WSN can be constructed for the use of geolocating objects and/or people through the walls of a room. This concept is known as Device-Free Passive Localization (DFPL), where the target is not required to wear a device for tracking. The basic concept of DFPL involves the use of low-cost wireless radios that are set-up to create a WSN. The transceivers have multiple designating terms that are used interchangeably. Notably, the transceivers are referred to as a radio, node, or mote. The transceivers are capable of sending and receiving information over a RF communication channel while a “Basestation” transceiver collects the data [1]. Furthermore, a WSN, when used for RTI, is a collection of motes that are set up as a perimeter around a certain Area of Interest (AoI). The basis of RTI utilizes the WSN

links and the Received Signal Strength (RSS) between pairs of transceivers to reconstruct an image from the signal attenuation caused by an object [2], [3], [4]. Since the transceivers use RF to create links, which can be either Line-of-Sight (LOS) or Non-Line-of-Sight (NLOS), the mote links possess the ability to pass through most obstructions like walls, furniture and even concrete [4]. Furthermore, a WSN can be set up to track objects in various outside environments (i.e. wooded areas, neighborhoods, etc.). This is highly desirable for military target tracking and localization, as well as law enforcement and emergency responders to aid in object location within a hazardous smoke-filled building.

RTI can be characterized as a linear model, it takes the form of [2], [5], [6]

$$\mathbf{y} = \mathbf{W}\mathbf{x} + \mathbf{n}, \quad (1.1)$$

where $\mathbf{y} \in \mathbb{R}^M$ is difference in RSS values from the calibration data, $\mathbf{W} \in \mathbb{R}^{M \times N}$ is the weight matrix, $\mathbf{x} \in \mathbb{R}^N$ is the pixelated shadowing field and $\mathbf{n} \in \mathbb{R}^M$ is a measurement noise vector [6]. In order to reconstruct an image from the measured data, two main parameters are required, the weight matrix and the signal attenuation along the link paths, $\mathbf{y} \in \mathbb{R}^N$. The weight matrix is the weighting of each pixel along the path of a specific link between two nodes. The solution for the $\mathbf{x}$ vector is commonly derived using the Least Squares (LS) method. However, this involves inverting a non-invertible matrix and it is important to note that this causes RTI to be an ill-posed problem. Small traces of noise in the measurement data can be amplified to the extent where results are meaningless. This is caused by small singular values in the transfer matrix that cause certain components to quickly grow out of control upon inversion [6]. This drives the need for regularization which introduces additional information to stabilize the inverse problem. In the RTI literature, the most commonly used regularization method to improve image reconstruction is known as Tikhonov regularization.

1.1.1 Research Goal.

This research focuses on improved image resolution for RTI reconstruction in comparison to the commonly used Tikhonov approach. The research will implement a modified Maximum Likelihood Estimate (MLE) to address the ill-posed problem resulting from the inversion of a non-invertible matrix. The proposed modified MLE technique utilizes a gradient decent method that guarantees the reconstructed image estimate is always non-negative. This constraint helps produce a solution with superior resolution. In doing so, none of the desired signal will be lost, which will produce a more accurate estimate of the $\mathbf{x}$ value.

1.2 Thesis Structure

The remainder of this document includes Chapters II through VI and is organized as follows. Chapter II provides a background review of RTI, WSN, and image reconstruction. Chapter III discusses the methodology and tools used to accomplish the research goals of this thesis. Chapter IV explains the derivation of the modified MLE method. Chapter V contains the experimental results from the implementation of the methodology from Chapter III using the derivation from Chapter IV for three different environments. Finally, Chapter VI summarizes the results and presents potential areas for growth in follow-on research.

II. Related Work

This chapter covers the background and research work related to Radio Tomographic Imaging (RTI). RTI is an emerging Device-Free Passive Localization (DFPL) technology that uses a collection of wireless transceivers to form a Wireless Sensor Network (WSN). Section 2.1 introduces the concepts of DFPL as well as its history which includes references of Ultra-Wideband (UWB) and Multiple Input, Multiple Output (MIMO) radar practices. Section 2.2 will go over the use of Received Signal Strength (RSS) in RTI. Section 2.3 explains the different models used when implementing a RTI system. For this research, the Network Shadowing (NeSh) normalized ellipse model is used because of it is a better statistical comparison of the link between two transceiver pairs, however, it is important to discuss other models used for RTI applications. Section 2.4 covers the most commonly used regularization method for image reconstruction known as Tikhonov regularization. Section 2.5 highlights the different decomposition methods.

2.1 Device-Free Passive Localization

Before the discovery of DFPL, systems using Global Positioning System (GPS), ultrasound, Infrared (IR), and Radio Frequency (RF) required the use of a device on an object being tracked to interact with the corresponding system to provide sufficient localization results, which is known as device-based active localization [7]. This makes it difficult to track something that isn't wearing a device and/or actively participating in the localization system. DFPL does not require the use of a device or active participation in order to track an object within an Area of Interest (AoI). This concept was introduced in [7], using wireless RF networks that were already in place, to estimate the location of an object by calculating the changes in the signal strength of an RF environment.

DFPL is highly useful in military search, track, and intrusion applications; home security; border security; as well as an aid for emergency responders [2]. However, DFPL does have limitations and drawbacks that are worth mentioning. DFPL can not distinguish/identify the actual object. Furthermore, RF is subjected to noise and interference from outside sources. Since RF signals can be reflected and absorbed by metallic and dense materials, this could create constructive and destructive interference for both indoor and outdoor applications which can affect the received signals.

2.1.1 Ultra-Wideband.

RF imaging in the commercial realm has used UWB-based Through-The-Wall (TTW) imaging to develop products that used phased array radars that transmit UWB pulses and measure the echoes to estimate range and bearing [8]. UWB receivers measure the amplitudes, time delays, and phases of the multi-path signals, where the knowledge of time delay provides significant information about location [8]. This traditional concept of radar uses reflections as a means of localizing objects.

2.1.2 Multiple Input Multiple Output Radar.

MIMO radar is defined generally as a radar system with multiple transmitters and receivers that have the ability to jointly process signals [9]. Like traditional radar, MIMO is able to track objects within an AoI and reconstruct an image via scatter reflection. The scattering objects create a channel matrix which is comparable to the channel matrix in MIMO communication theory. While MIMO uses reflection measurements, caused by objects, for image reconstruction; RTI differs by using shadowing loss measurements [2].

2.2 Radio Tomographic Imaging & Received Signal Strength

RTI is an emerging DFPL technology that uses a collection of inexpensive wireless transceivers used to form a WSN [2]. The WSN is used to detect and track objects within a desired AoI. The transceivers can both transmit and receive signals. The transceivers are programmed to transmit one-at-a-time, sequentially, while the other motes receive the signal. Correspondingly, a weighting matrix provides a weighting for each pixel depending on the location of that pixel along the link between the current transmitting transceiver and the other receiving motes. A WSN is created when the transceivers are setup around the perimeter of a desired AoI. As an object moves through the WSN, the object disrupts the links causing a RSS attenuation, also known as shadow loss. Generally, RTI uses the measured changes of RSS in the WSN to create an image map of the AoI, thus enabling object detection.

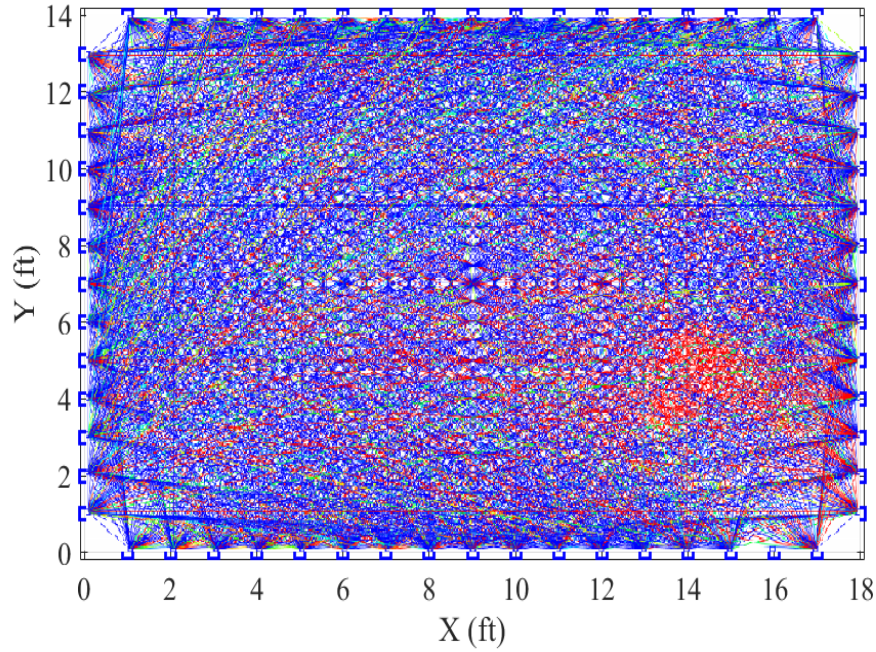


Figure 2.1. Illustration of unique links within an RTI WSN.

2.2.1 Unique Links.

The system model for an RTI is laid out in [2]. The number of unique two-way links can be calculated as $M = \frac{K^2-K}{2}$, where K is the number of transceivers used in the WSN and M is the number of unique links. Figure 2.1 illustrates the unique links in a given WSN.

2.2.2 Frame Rate.

The frame rate is the time inverse, $\frac{1}{T}$, it takes all the transceivers in a WSN to transmit one time, while the other motes are receiving the signal, which creates one frame of data. Thus the physical size of a WSN increases, T increases and the frame rate decreases. Frame rate is an important factor for real-time RTI applications. A high frame rate is desirable in order to process data for image reconstruction quickly for emergency situations or dynamic scenes.

2.2.3 Received Signal Strength.

RSS is the measurement of signal amplitude from one transceiver to another. As mentioned before, the premise of RTI is to measure the signal attenuation between a RF link between transceiver pairs. The equation for RSS between two transceivers where $y_l(t)$ is the signal strength of a specific link l at time t is defined as [2]

$$y_l(t) = P_l - L_l - S_l(t) - F_l(t) - v_l(t). \quad (2.1)$$

where [2]

- P_l : Transmitted power (Decibels (dB))
- L_l : Static losses due to distance, hardware inconsistencies, antenna patterns, etc. (Decibels (dB))

- $S_l(t)$: Shadowing loss caused by obstructions attenuating the signal (Decibels (dB))
- $F_l(t)$: Fading loss caused by interference (constructive and destructive) in a multipath environment (Decibels (dB))
- $\nu_l(t)$: Measurement noise (Decibels (dB))

The shadowing loss $S_p(t)$ is calculated as the sum of attenuation in each pixel inside a WSN [2]. The mathematical equation for the shadowing loss for a single link is given by

$$S_l(t) = \sum_{p=1}^N w_{p,l} x_l(t), \quad (2.2)$$

where $w_{p,l}$ is the weight on pixel p in link l and $x_l(t)$ is the attenuation on l at time t and N is the amount of pixels within the WSN.

2.3 Measurement Models

2.3.1 Mean-Based RTI.

Mean-Based Radio Tomographic Imaging (MRTI) also known as shadowing-based RTI, generally described in Section 2.2, is the most common and least complex RTI measurement technique, utilizing only the changes in attenuation when compared to a baseline calibration that aids in target localization. The baseline calibration is considered a collection of RSS signals within the WSN before a target is introduced into the AoI [2]. The baseline calibration consists of the RSS data collection for the desired environment of interest, including all static objects contained inside said environment. The calibrated data is then compared to the data collection during target introduction.

Since all static losses can be removed, imaging the attenuation is simplified. Let Δy_l be the change in RSS for a particular time, t . Solving for Δy_l yields

$$\Delta y_l = \sum_{p=1}^N w_{l,p} \Delta x_p + n_l(t) \quad (2.3)$$

where Δx_p represents the changes in attenuation at each pixel between the current time and calibration time and N is the amount of pixels within the WSN [2].

Finally, in matrix form, the linear system is defined as [2], [5], [6]

$$\mathbf{y} = \mathbf{W}\mathbf{x} + \mathbf{n} \quad (2.4)$$

where

$$\begin{aligned} \mathbf{y} &= [\Delta y_1, \Delta y_2, \dots, \Delta y_M]^T, \\ [\mathbf{W}]_{p,l} &= w_{p,l}, \\ \mathbf{x} &= [\Delta x_1, \Delta x_2, \dots, \Delta x_N]^T, \\ \mathbf{n} &= [n_1, n_2, \dots, n_M]^T \end{aligned} \quad (2.5)$$

2.3.2 Variance-Based RTI.

Rather than RSS baseline calibration comparison, Variance-Based RTI (VRTI) involves utilization of the variance between the calculated RSS frames to estimate the target's location. This is beneficial due to the fact that a baseline calibration is no longer needed to track targets. This approach is stated to provide more accuracy in target tracking for through-wall and Non-Line-of-Sight (NLOS) applications [10].

For the VRTI system, the variance caused by moving objects on each link can be es-

estimated as a linear combination at each pixel. The RSS variance on each link is mathematically shown as [10]

$$Var[y_{dB}] = \sum_p w_p x_p + n \quad (2.6)$$

where y_{dB} is the RSS, n is noise and modeling error, and w_l is the contribution to the link variance caused by the moving object in pixel p [10]. Consequently, when including all the links in a WSN the system can be set-up mathematically as a linear model, similar to Equation (2.4).

$$\mathbf{s} = \mathbf{W}\mathbf{x} + \mathbf{n} \quad (2.7)$$

where $\mathbf{s}^{M \times 1}$ is the variance for each link, $\mathbf{W}^{M \times N}$ is the variance weight transfer matrix, $\mathbf{x}^{N \times 1}$ is the motion image to be estimated and $\mathbf{n}^{M \times 1}$ is noise [10].

The experiments in [10] showed VRTI was capable of identifying areas of motion in through-wall scenarios where shadowing-based RTI was not as effective. VRTI also does not require a calibration time to collect RSS without any targets of interest in the network, making it more applicable for real-world situations. However, the limitation with VRTI is that it is less accurate for targets with little or no motion.

2.3.3 Weight Models.

It would be desirable to have prior knowledge of an environment. The data being collected would aid in estimation of weights for each link. This would improve overall accuracy. However, for real-world RTI applications, prior knowledge of the environment will most likely be unavailable. This is why there are numerous weight model proposals in the literature. Generally, the weighting matrix can be defined as

$$\mathbf{W} = \mathbf{S} \odot \mathbf{\Omega} \quad (2.8)$$

where $\mathbf{\Omega}$ is a matrix of how much weight to assign each pixel within a link, $\odot$ is an element-wise Hadamard multiplication, and $\mathbf{S}$ is a binary selection matrix that determines which pixels are affected by its corresponding link [3], [11].

Additionally, $\mathbf{W}$ can be characterized as a Singular Value Decomposition (SVD) seen as

$$\mathbf{W} = \mathbf{U}\mathbf{\Lambda}\mathbf{V}^T \quad (2.9)$$

where $\mathbf{U}$ and $\mathbf{V}$ are both unitary matrices, and $\mathbf{\Lambda}$ is a diagonal matrix of singular values [2]. The use of this equation will be explained further in section 2.5

2.3.4 NeSh Normalized Ellipse Model.

The NeSh normalized ellipse model made its initial debut in [2] and it is now the most widely used weight model for RTI. NeSh suggests that as the link distance decreases the accuracy of the data increases, consequently adding more weight to the affected pixels. The magnitude matrix of $\mathbf{\Omega}^{NeSh}$ is defined as

$$\mathbf{\Omega}^{NeSh} = \frac{1}{\sqrt{d_l}} \quad (2.10)$$

where d_l is the link distance.

In previous studies it has been shown that the variance of shadowing does not vary with distance. Furthermore, we can take the square root of the link distance to ensure that the pixel weighting takes this into account. An ellipsoid foci is used at each transceiver to determine the weighting for each link in the WSN. If a pixel is outside the ellipsoid the weighting for that pixel is zero. The mathematical description of the weight is [2], [11]

$$\mathbf{w}^{Ellipse} = \frac{1}{\sqrt{d_l}} \begin{cases} 1, & \text{if } d_{l,p}(1) + d_{l,p}(2) < d_l + \lambda \\ 0, & \text{otherwise} \end{cases}, \quad (2.11)$$

where $d_{p,l}(1)$ and $d_{p,l}(2)$ are the Euclidean distances from the transceivers to the center pixel of link l , and λ is a tunable parameter that dictates the width of the ellipse. Normally, the width is set low so that it is similar to using the Line model which will be discussed in the following section [2]. Furthermore, Equation (2.11) contains a normalization factor, $\frac{1}{\sqrt{d_l}}$ that minimizes the variance as the distance increases [12]. Figure 2.2 shows an example of the pixels selected according to the $\mathbf{S}^{Ellipse}$ selection matrix for a particular ellipse width [2].

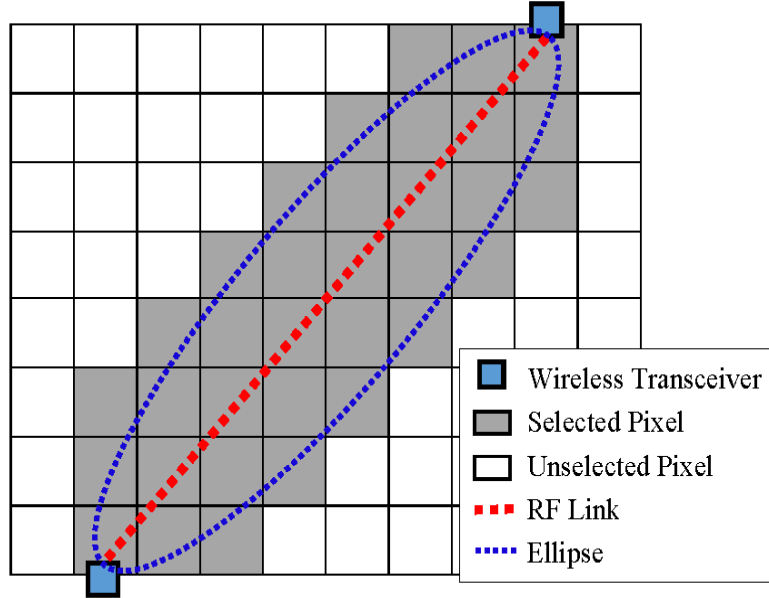


Figure 2.2. Illustration of a single link between two transceivers in a direct LOS path showing the shaded pixels with a non-zero weighting for the $\mathbf{S}^{Ellipse}$ selection matrix.

2.3.5 Line Model.

The Line model is regularly used in RTI applications due to its computational efficiency. It has been used in [3] and [13]. The Line model proposes that only the pixels that the link transverses through are affected with a magnitude matrix, Ω^{Line} , of [4]

$$\Omega_{l,p}^{Line} = SL_{l,p}, \quad (2.12)$$

where $SL_{p,l}$ is the segment length of the link l that traverses through pixel p . The selection matrix, $\mathbf{S}^{Line}$, for this model is [4]

$$S_{l,p}^{Line} = \begin{cases} 1, & \text{if link } i \text{ traverses through pixel } j \\ 0, & \text{otherwise} \end{cases}. \quad (2.13)$$

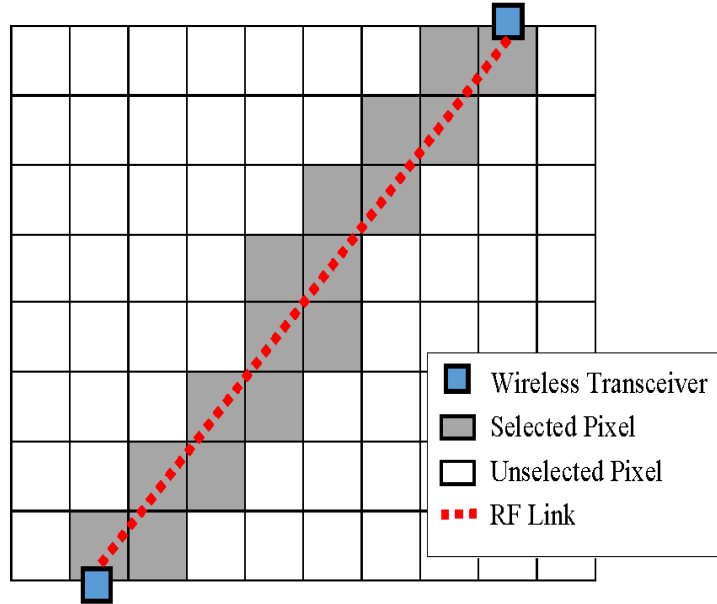


Figure 2.3. Illustration of a single link between two transceivers in a direct LOS path showing the shadowed pixels with a non-zero weighting for the $\mathbf{S}^{Line}$ selection matrix.

Figure 2.3 shows an example of the pixels selected according to the $\mathbf{S}^{Line}$ selection ma-

trix. The final equation for the Line model is represented as [2]

$$\mathbf{W}_{l,p}^{Line} = SL_{l,p} \begin{cases} 1, & \text{if link } l \text{ traverses through pixel } p \\ 0, & \text{otherwise} \end{cases}. \quad (2.14)$$

2.3.6 NeSh-Line Model.

As the name suggest, the NeSh-Line model is a combination of both the Line and NeSh model in the previous sections. This model makes use of the line selection matrix, $\mathbf{S}^{Line}$ from the line model and the magnitude matrices from the NeSh model. This model was used both in [14] and [15]. The mathematical model is described as

$$\mathbf{W}_{l,p}^{NeShLine} = \frac{SL_{l,p}}{\sqrt{d_l}} \begin{cases} 1, & \text{if link } l \text{ traverses through pixel } p \\ 0, & \text{otherwise} \end{cases} \quad (2.15)$$

2.3.7 Noise.

Noise in RTI is normally modeled as Additive White Gaussian Noise (AWGN) [16], [16], [15], [17]. Research in [18] suggested that noise in RTI could be characterized as AWGN, even though the skew-Laplacian is a more accurate representation of the distribution. In [2] a normal mixture model was used in the decibels (dB) scale which is a two-part Gaussian Mixture Model, shown as

$$f_{n_i}(u) = \sum_{k \in [1,2]} \frac{p_k}{\sqrt{2\pi\sigma_k^2}} \exp \frac{-u^2}{2\sigma_k^2} \quad (2.16)$$

where $f_{n_i}(u)$ is the Probability Density Function (PDF) of the noise random variable n_i ; p_k is the probability of k , $p_2 = 1 - p_1$ and σ_k^2 are the variance.

2.4 Tikhonov Regularization

Regularization is the concept of introducing additional information into the mathematical cost function to handle ill-posed problems. With most regularization techniques having high computational cost, regularization is needed to de-amplify the noise measurement to make the data more useful [2]. The Least Squares (LS) solution is used regularly for estimation to find an optimal solution. The LS solution to Equation (2.4) is [2], [6]

$$\hat{\mathbf{x}}_{LS} = \underset{x}{\operatorname{argmin}} \|\mathbf{W}\mathbf{x} - \mathbf{y}\|_2^2. \quad (2.17)$$

Taking the gradient of (2.17) and setting it to equal zero yields [2]

$$\hat{\mathbf{x}}_{LS} = (\mathbf{W}^T \mathbf{W})^{-1} \mathbf{W}^T \mathbf{y}. \quad (2.18)$$

An important note is that $(\mathbf{W}^T \mathbf{W})^{-1}$ exists only if $\mathbf{W}$ is full rank. RTI is an ill-posed inverse problem where small singular values can potentially lead to large errors and meaningless estimates [2].

Tikhonov is a well-known and widely used regularization method used in most RTI applications. The Tikhonov regularization adds an energy term to the LS formula, resulting in the following objective function [2]

$$f(x) = \frac{1}{2} \|\mathbf{W}\mathbf{x} - \mathbf{y}\|^2 + \alpha \|\mathbf{Q}\mathbf{x}\|^2, \quad (2.19)$$

where $\mathbf{Q}$ is the difference operator known as the Tikhonov matrix, that forces a solution, shown in Equation (2.20). The α value is a tunable regularization parameter that affects the quality of the regularization by adding a scale factor to the $\mathbf{Q}$ matrix [19]. As α increases, the noise spikes are suppressed and the image becomes smooth. If α is too

high the attenuation caused by the object is eventually lost. Conversely, as α decreases, the noise within the image increases, in which the object can be masked by noise. The regularization parameter must be fine tuned to find a balance for image quality.

$$\mathbf{Q} = \mathbf{D}_H^T \mathbf{D}_H + \mathbf{D}_V^T \mathbf{D}_V \quad (2.20)$$

The derivative of (2.19) can be taken and set it equal to zero. This results in the regularized LS solution [2]

$$\hat{\mathbf{x}}_{TIK} = \mathbf{\Pi}_{TIK} \mathbf{y}, \quad (2.21)$$

$$\mathbf{\Pi}_{TIK} = (\mathbf{W}^T \mathbf{W} + \alpha \mathbf{Q}^T \mathbf{Q})^{-1} \mathbf{W}^T. \quad (2.22)$$

2.5 Truncated Singular Value Decomposition

Truncated Singular Value Decomposition (TSVD) is a commonly used regularization technique. TSVD removes the small singular values that are contained in the weighting matrix $\mathbf{W}$ which simplifies the computation. However, research from [6] shows that TSVD produces noisier results in comparison to the Tikhonov method. The linear transformation matrix is derived when (2.9) is plugged into (2.18), shown as

$$\hat{\mathbf{x}}_{TSVD} = \mathbf{V} \mathbf{\Lambda}^{-1} \mathbf{U}^T \mathbf{y} = \sum_{j=1}^N \frac{1}{\sigma_j} \mathbf{u}_j^T \mathbf{y} \mathbf{v}_j, \quad (2.23)$$

where σ_j is the j th diagonal element of $\mathbf{\Lambda}$. In TSVD, only the largest j singular values are computed to recreate the image and $\mathbf{u}$ and $\mathbf{v}$ are matrices that contain singular vectors. Consequently, (2.23) can be rewritten as [6]

$$\hat{\mathbf{x}}_{TSVD} = \mathbf{\Pi}_{TSVD} \mathbf{y}, \quad (2.24)$$

$$\mathbf{\Pi}_{TSVD} = \sum_{j=1}^{i < N} \frac{1}{\sigma_j} \mathbf{u}_j^T \mathbf{v}_j = \mathbf{V} \mathbf{\Lambda}_i^{-1} \mathbf{U}^T. \quad (2.25)$$

III. Methodology

This chapter provides the methodology utilized in this research for data collections for a specific Radio Tomographic Imaging (RTI) network setup in various environments. The research will cover image reconstruction for penetration in foliage and other dense object. For this research, two estimators used to compute the $\hat{x}$ value will be compared, the Tikhonov Regularization method and the modified Maximum Likelihood Estimate (MLE). These estimators are used to calculate the changes in Received Signal Strength (RSS) values on a particular pixel, which aid in image reconstruction and resolution. The following section outlines the specific equipment and tools used to facilitate data collections, as well as the software used to process said data. Throughout all experiments the distance unit that was used is foot (ft) with all RSS values assumed to be measured in decibel milliwatts (dBm). Furthermore, all coordinates for target tracking will be denoted by the target's corresponding (x,y) coordinates in feet. Additionally, all data collection was performed on a laptop in MATLAB® 2016a running Microsoft Windows® 7. All data processing was accomplished on a desktop computer in MATLAB® 2017a running Microsoft Windows® 10.

3.1 Equipment and Tools

Memsic TelosB TPR2400. Made by Crossbow Technology Incorporated (Inc.) based in San Jose, California, and developed by the University of California (UC) Berkeley; the TelosB mote TPR2400 [20] will be the open-source wireless radio used in this experiment, shown in Fig. 3.1. The radios are compatible with the Tiny Operating System (TinyOS) distribution which will be explained in the next section. The TelosB mote is an Institute of Electrical and Electronics Engineers (IEEE) 802.15.4 compliant platform with an integrated on-board inverted-F antenna, CC2420 transceiver radio

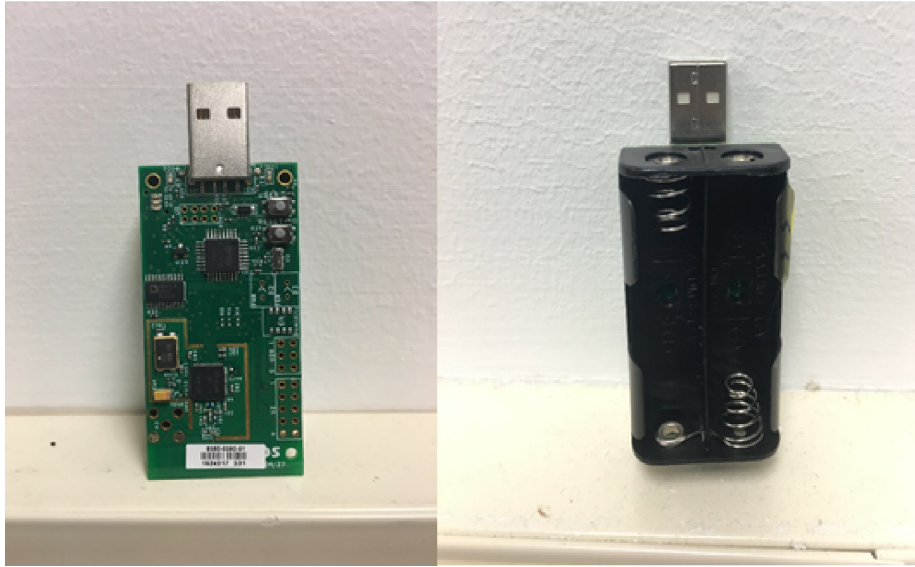


Figure 3.1. TelosB Transceiver TPR2400.

chip, data rate of 250 kilobits per second (kbps), and an 8 megahertz (MHz) micro-controller with 10 kilobytes (kB) of RAM [20]. The Radio Frequency (RF) transceiver power ranges from -24 dBm to 0 dBm and has an indoor transmission range of 65.6 to 98.4 ft. Universal Serial Bus (USB) on the TPR2400 is used for data collection, powering, and programming the mote. The mote can also be powered by two AA batteries. More information about the TelosB can be found in [20].

TinyOS. TinyOS is an open-source operating system designed for low-power wireless devices. The TelosB motes are programmed with TinyOS which is written in NesC. TinyOS includes the program file titled “BaseStation”, for programming the mote acting as the network base station. Any mote can act as either a wireless radio in the network or the base station, but the mote that is being used as the base station must be programmed as such on initial installation [21].

Spin. Spin is an open-source TinyOS protocol written in NesC and loaded to the TelosBs. Spin was created by the Sensing and Processing Across Networks (SPAN)



Figure 3.2. Image showing the stakes being level and parking marker at location [0,0]

lab in the Department of Electrical and Computer Engineering at the University of Utah. Spin collects RSS information from a Wireless Sensor Network (WSN) using a token passing protocol. This allows the user to program the motes to arbitrarily dictate the transmission order of the motes. For this experiment, the motes will transmit one at a time in sequential order while the other motes are receiving the signal. For more information on the Spin protocol, refer to [22].

RTI Link GUI. RTI Link Graphical User Interface (GUI) will be used to collect the desired data. The initial version was created by Mr. Alex Folkerts (Southwestern Ohio Council for Higher Education (SOCHE Intern)), Mr. Tyler Heintz (SOCHE Intern), and Dr. Richard K. Martin (Professor of Electrical Engineering at the Air Force Institute of Technology (AFIT)) [23]. The RTI Link GUI is a MATLAB[®] based application designed to collect and save package data from the RTI network. The GUI collects the raw link data at each frame in real-time and uses a created raw data matrix as a linear operator to output the estimated image $\mathbf{x}$ near real-time. The calibration data and final recorded

data can be saved in the form of raw link RSS data to provide the flexibility to compare different user parameters such as pixel size and regularization values [2].

Mounting TelosBs. In order to preserve consistency, all motes were mounted vertically with the USBs pointed up, 4 ft from the ground surface. The motes were attached to 1/2 inch Polyvinyl Chloride (PVC) pipes with 1 ft spacing. For outdoor data collections, each mote was powered using AA batteries and secured to the PVCs using velcro with adhesive on the back. Setting up outdoors required a 4 ft level, two measuring tapes, four parking markers and a hammer. Since most terrains are not perfectly flat, it was essential to use the level to make sure the staked PVCs, which were 5 ft in length, were consistently even and level. Each PVC stake had a screw 2 inches from the top of the PVC and a line drawn 4 feet down from the screw. This provided an extra 10" inches of PVC to ensure the WSN was setup 4 ft above the ground on uneven terrain. The screws were used to hang an orthogonal PVC pipe, in which the motes were secured 1 ft apart. The two tape measures were used to measure the sides of the rectangle to ensure length accuracy. The orange parking markers, shown in Fig. 3.2, were used to mark the corners of the WSN.

3.2 WSN Setup

The WSN was set up using $K = 60$ motes. The total network perimeter dimensions are in correspondence $[L \times W \times H]$ and are 18 ft $\times$ 14 ft $\times$ 4 ft. There were no transceivers mounted at the corners of the WSN perimeter. The actual transceiver

Table 3.1. Hypotenuse Measurement of WSN for each Environment

Environments	Calculated	Open Field	Woods	Playground
Length (ft)	22.8	22.3	23.7	23.2

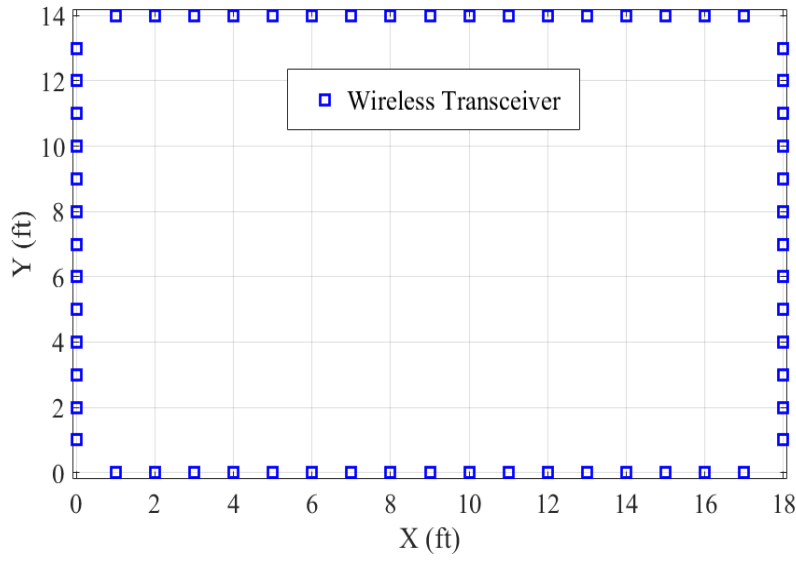


Figure 3.3. Aerial view of mote locations for the WSN.

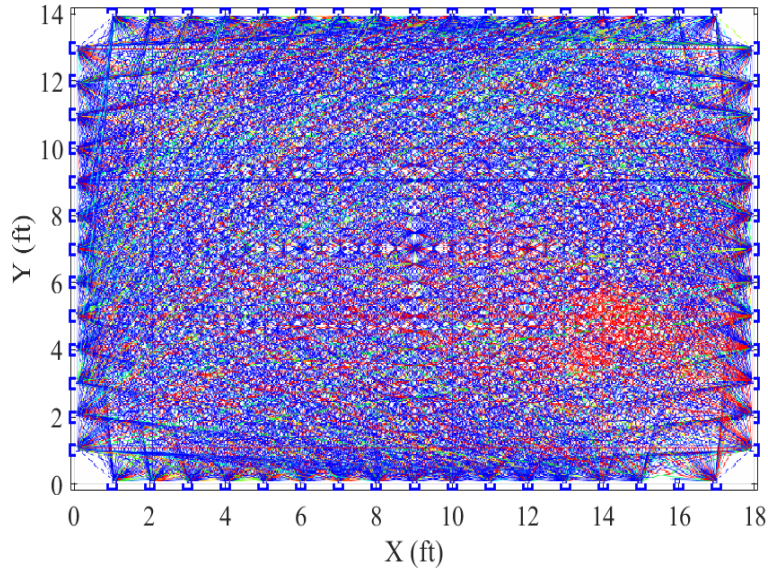


Figure 3.4. Illustration of the WSN with $M = 1770$ unique links.

mote setup around the perimeter is $17\text{ ft} \times 13\text{ ft} \times 4\text{ ft}$ with one foot spacing. For outdoor WSN setup, two tape measures allowed for use of a technique known to carpenters as “pulling corners”. This technique is used to ensure the rectangle is exact on all sides by laying one tape measure on the longest side of the rectangle, then measuring the diagonals of the rectangle, ensuring they are within a few centimeters of the calculated

hypotenuse. This method utilizes the basic concept of the well known trigonometric function, the Pythagorean Theorem. Using the Pythagorean Theorem, the diagonal should have been 22.8 feet in length. The chart below shows the diagonals for each WSN in its corresponding environment with the length being within 1 foot of the calculated value. Figure 3.3 shows the virtual setup of the mote locations around the WSN. Section 2.2.1 provided the equation for the number of unique links, M , for a specified number of transceivers, K . For this research, $K = 60$ motes are being used, making the amount of unique links, $M = 1770$. Figure 3.4 illustrates the WSN setup with $M = 1770$ links.

In this research, human subjects were used in order to provide physical obstructions within the WSN. Required human subjects training has been completed by the principal investigator per Air Force Institute of Technology (AFIT) RTI protocol. The signed Informed Consent Document (ICD) of all human subjects are approved by the Air Force Research Laboratory (AFRL) Institutional Review Board (IRB). All human subjects were briefed, voluntarily consented to participate and signed the required ICD for the experiment. The human subjects' heights were not recorded because they were taller than 4 feet; which satisfied the Line-of-Sight (LOS) link obstruction and they were approximately less than one and a half feet in width.

3.3 Environments

To highlight the robustness for image reconstruction using the modified MLE method, the data was collected in multiple environments. The first environment was an open field with no obstructions in the WSN. The second environment was a densely wooded area and contained within the WSN were various trees and bushes. The third environment was in a residential neighborhood with the WSN set up around a playground made of dense plastic and metal. This section will go over the setup and positioning of



Figure 3.5. Open field WSN setup ([0,0] right corner).

obstructions for each environment. Additionally, any object within the WSN that did not break the Line-of-Sight (LOS) of the links, at a height of 4 ft, and had a diameter less than six inches was not counted as an obstruction. This includes, but is not limited to, short bushes, various branches, swings and chains, etc.

3.3.1 Open Field.

The open field data collection took place at Rotary park in Beavercreek, Ohio. This setting was chosen because the location was far enough away from any buildings and residential neighborhoods that have Wireless Fidelity (Wi-Fi) that could cause interference and adversely affect the data collection. Additionally, there were no nearby physical structures (e.g. buildings, fences, poles, etc.) that can cause significant signal reflection. These reflections could cause uncontrollable and unmeasurable constructive and destructive interference. The temperature outside at the time of data collection was $55^{\circ}F$ and the wind was a constant 10-12 miles per hour (mph), with gusts up to 14 mph. Even though the wind was slightly aggressive in the open field setting, it had very little effect on the WSN. The wind was gusting from the east, which pushed the WSN an inch off from the initial setup site, with the height of the WSN (4 ft) still



Figure 3.6. Woods WSN setup ([0,0] center corner).

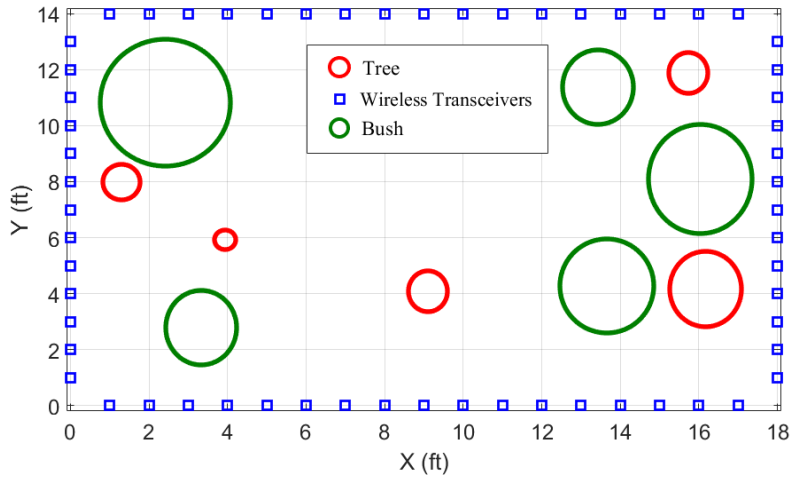


Figure 3.7. Topographical illustration of the WSN in the woods.

being preserved. We were able to stake the WSN in the shifted position securing the network in place, which eliminated the wind factor. Figure 3.5 shows the actual WSN setup and surrounding environment with no obstructions inside.

3.3.2 Wooded Terrain.

The wooded terrain data collection occurred on the next day and at the same park location as the open field collection. The wooded WSN setup was approximately 50



Figure 3.8. Playground WSN Setup in a residential neighborhood $[[0,0]$ back right corner).

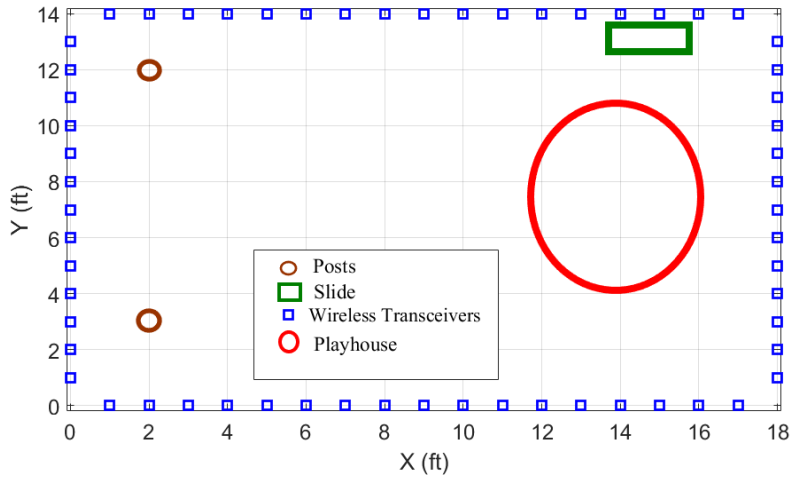


Figure 3.9. Topographical illustration of the WSN around residential neighborhood playground.

yards south-west from the center of the open field WSN. Performing both collections in approximately the same area minimized some of the variances caused from environmental factors, including Wi-Fi interference. Similar to the open-field, there were no Wi-Fi signals in the local area from adjacent residential neighborhoods or buildings. Also, the outside temperature at collection time was approximately $55^{\circ}F$ with no wind. Figure 3.6 shows the actual WSN set-up and surrounding environment, while Fig. 3.7 illustrates the virtual topographical view of the WSN.

3.3.3 Playground.

The playground data collection took place in a residential neighborhood. The temperature outside at the time of data collection was $52^{\circ}F$ and the wind was a constant from 9-10 mph, with gusts up to 14 mph. The playground was a good environment to collect data because of the large amount of metal and hard plastic inside the WSN which would cause a lot of destructive and constructive interference. Furthermore, the WSN is in a residential neighborhood where there are multiple Wi-Fi signals at varying strengths that add to the interference. Figure 3.8 shows the actual WSN setup and surrounding environment, while Fig. 3.9 illustrates the virtual topographical view of the WSN.

3.4 Parameters

This research applied the Mean-Based Radio Tomographic Imaging (MRTI) model, also known as shadow based modeling from Section 2.3.1. Additionally, this research utilized the most popular weighting model, the Network Shadowing (NeSh) model from Section 2.3.4. When using the NeSh model, the tunable parameter, λ , that controls the width of the ellipse must be set to a low value in order for the model to imitate the line model. For this research, since the motes were set one foot apart, the appropriate λ value was set to 0.33ft. To estimate the x -value, both the Tikhonov Regularization and the modified MLE were used for comparison. Recall from Section 2.4, Tikhonov required a tunable parameter, α , which is highly dependent on the network dimension and correlating pixel size. The best working value α value chosen through tests for specific research setup is 32.8 ft^2 .

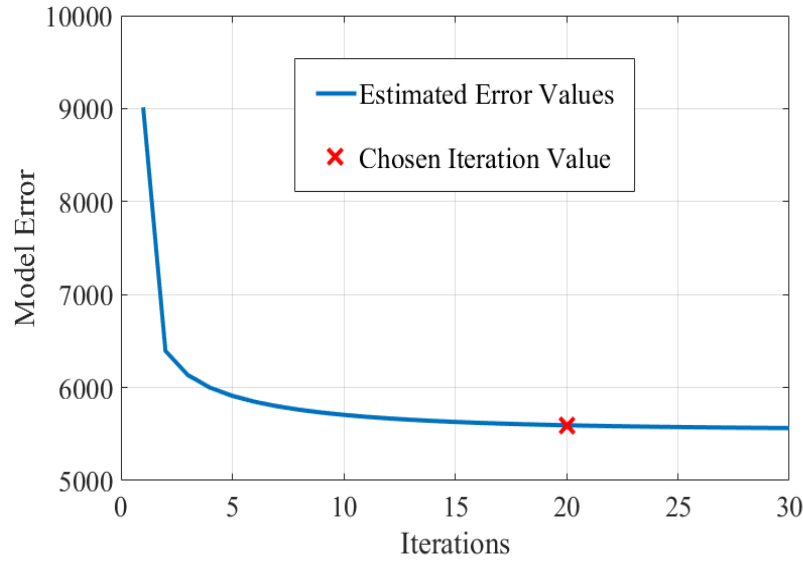


Figure 3.10. Illustration showing MLE error gradually decreasing for 30 iterations, toward the $\hat{x}$ -value.

3.4.1 Modified MLE Parameters and Processing Time.

The modified MLE, in which the modification will be explained in Chapter IV, uses a gradient accent method to estimate the $\hat{x}$ -value. Consequently, this inherently requires multiple iterations to gradually move towards the $\hat{x}$ -value, which incurs a time cost. More iterations produces improved accuracy estimation of the $\hat{x}$ -value and ultimately providing an enhanced image resolution. Figure 3.10 shows a plot of the relative error for every iteration. This is calculated simply by using the Mean Squared Error (MSE) method which sums the squared differences of the old and new y-data. Since time and image resolution are inversely proportional, it is important to select the optimal number of iterations for each data frame to save on time and provide the desired image fidelity. It is important to note that the amount of unique links within the WSN is directly proportional to the processing time as well. Averaging the errors from each environmental frame used showed that from the 20th iteration and beyond, the error begins to change by less than 1%. This is one of the reasons why 20 iterations proved to be a good number of iterations for this research. Time was also another fac-

tor for selection.

Using the “profile”, “tic” and “toc” commands in MATLAB[®] average processing time can be calculated. For the size WSN used in this research, the average time between iterations was calculated to be 0.0007 seconds (s), making the average time for 20 iterations 0.0105 s. Furthermore, The average time it takes to remove the Not a Number (NaN), which will be covered in Section 3.7, from y data and corresponding weight matrix positions can be between approximately 0.23s and 0.32s. Chapter IV will cover the average preprocessing time, which includes frame rate for each environment’s data sets.

3.4.2 Machine Specifications.

The machine used to process the data also affects the image reconstruction time. More processing power equates to faster image reconstruction. The machine used to process all of the data for this research runs Microsoft Windows[®] 10 with a Intel[®] Xeon E5-2609 v2 dual 2.5Gigahertz (GHz) processors. Figure 3.11 shows the processing time for machine used to process the data in comparison to other machines by using MATLAB’s[®] benchmark command.

3.4.3 Pixel Threshold.

Since image resolution is characterized by pixel intensity, a pixel intensity threshold was created. This is important for distinguishing and highlighting the pixels that contain a target versus the pixels that have no targets present. All of the data sets will contain fixed parameters for pixel size, number of targets within the WSN, and Tikhonov regularization value α . Additionally, when estimating $\hat{x}$ using the modified MLE there is a parameter value for the amount of iterations used for the gradient descent, explained in Section 3.4.1. Therefore, with the estimator’s parameters set, we can

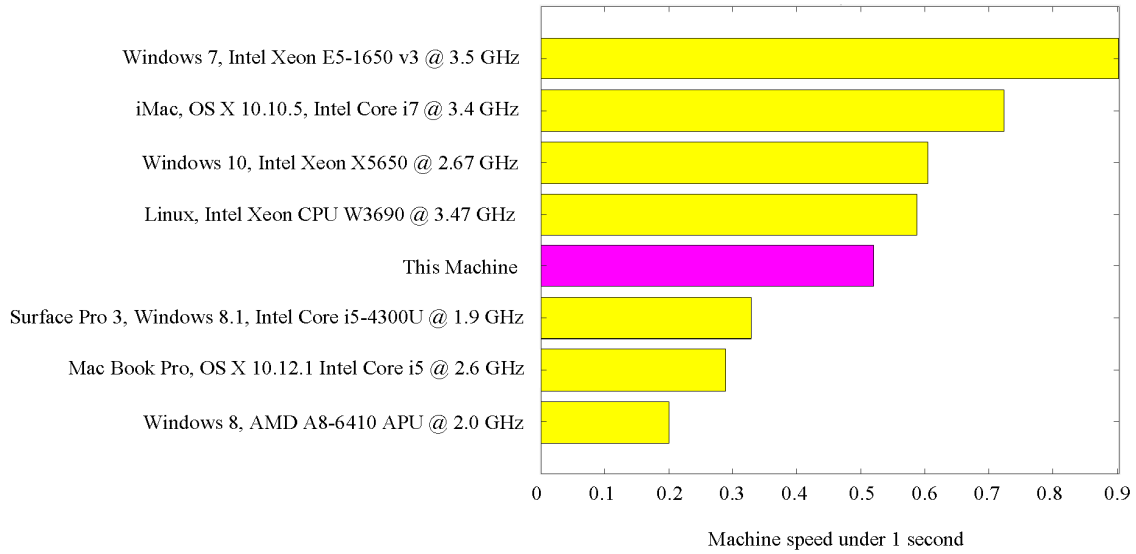


Figure 3.11. Illustration showing bar graph comparison of machine processing time using MATLAB® benchmark.

simply use the color map to force every pixel value below 30% of the frame highest intensity value to zero. This will force the zeroed pixels to be white within the image, consequently acting as a filter for each frames improving resolution. This threshold is purely for image aesthetics and is accomplished with both estimators and does not introduce bias results. Furthermore, each estimator has an internal threshold set. For Tihovnov regularization, the is a min and max thresholds are respectively set to 0.5 and 2 standard deviations from the highest intensity pixel cluster values, while the modified MLE is threshold is set to 4.4 standard deviations from the max intensity pixel cluster values.

The list below discusses the parameters used for this research. Th list includes the two estimators that are being compared as well as the calibration of each environment, y_c , and the paramters for each estimator and the weight model.

- System Model: $\mathbf{y} = \mathbf{W}\mathbf{x} + \mathbf{n}$
- Measurement Model: $\mathbf{y} = [\Delta y_1, \Delta y_2, \dots, \Delta y_M]^T$

- Calibration: $\mathbf{y}_c = [\bar{y}_{c,1}, \bar{y}_{c,2}, \dots, \bar{y}_{c,M}]^T$
- Weight Model: $\mathbf{W}_{i,j}^{Ellipse} = \frac{1}{\sqrt{d_i}} \begin{cases} 1, & \text{if } d_{i,j}(1) + d_{i,j}(2) < d_l + \lambda \\ 0, & \text{otherwise} \end{cases},$
- λ : 0.33ft
- Modified MLE Estimator: $\hat{\mathbf{x}}_{r(new)} = \left(\frac{\sum_{m=1}^M (\mathbf{y}_m \mathbf{W}_{m,r})}{\sum_{m=1}^M \left(\sum_{n=1}^N \mathbf{W}_{m,n} \hat{\mathbf{x}}_{r(old)} \right) \cdot \mathbf{W}_{m,r}} \right) \cdot \hat{\mathbf{x}}_{r(old)}$
- Tikhonov Estimator: $\hat{\mathbf{x}}_{TIK} = \underset{\mathbf{x}}{\operatorname{argmin}} \left(\frac{1}{2} \|\mathbf{W}\mathbf{x} - \mathbf{y}\|_2^2 + \alpha \|\mathbf{Q}\mathbf{x}\|_2^2 \right)$
- Tikhonov Matrix: $\mathbf{Q} = \mathbf{D}_H^T \mathbf{D}_H + \mathbf{D}_V^T \mathbf{D}_V$
- α : 32.8 ft²
- Pixel Size: 1 ft $\times$ 1 ft

3.5 Assumptions

The following assumptions are made in this research [23]:

1. $\mathbf{n} \sim \mathcal{N}(\mathbf{0}, \sigma_n^2 \mathbf{I}_M)$.
2. $\mathbf{y}|\mathbf{x} \sim \mathcal{N}(\mathbf{W}\mathbf{x}, \sigma_n^2 \mathbf{I}_M)$.
3. Transmitted power and static losses are constant and are canceled out when computing the change in RSS.
4. Weather conditions did not affect WSN and transceiver performance.
5. Battery life did not affect mote performance and RSS.
6. There is at least one target within the network.
7. Target is big and tall enough to obstruct the LOS of transceivers.

8. All transceivers are designed and manufactured exactly the same.
9. Transceivers transmit in sequential order instead of simultaneously and, therefore, there is a linear relationship between the number of transceivers and time required for all transceivers to transmit their RF signal.
10. For simulations, the *BaseStation* transceiver is always within range of the transceivers in the WSN and there are never any dropped RSS packets.

3.6 Metrics

For this research, two estimators used to compute the $\hat{x}$ value will be compared, the Tikhonov Regularization method and the modified MLE. These estimators are used in order to calculate the changes in RSS values on a particular pixel, which aid in image reconstruction and resolution. In order to compare the two techniques, each environment has three data sets that were analyzed. The three data sets from each environment are then processed by both estimators for image reconstruction. The data sets are comprised of a single static object set, a double static object set, and a data set containing one static object and one moving object. The remainder of this section will discuss the metrics by which the data will be analyzed. It is very important to highlight that the focus of this research does not include position estimation accuracy. Even though resolution and accuracy are related for object detection, this research uses a technique that creates better resolution around the highest intensity pixel also known as the pixel with the highest RSS attenuation, and not the estimated location of the aforementioned pixel.

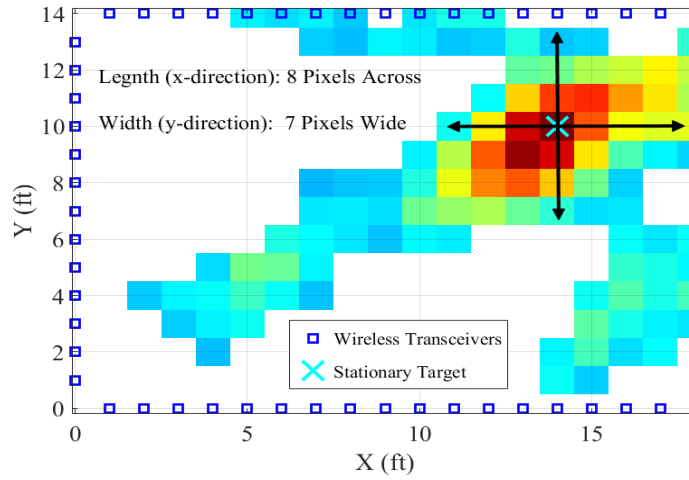


Figure 3.12. Illustration showing pixel cluster resolution. The true position of the target is located at [14,10] and the cluster size is $(8 \times 7) \text{ ft}^2$

3.6.1 Resolution.

For this research, resolution will be measured by calculating the pixel cluster(s)' length and width, which represents the size of the desired target(s), across the true position of the target. Figure 3.12 shows how the resolution of the cluster is measured. The measurement across the true position stops at the first null/white pixel. In other words, the resolution of the pixel cluster is defined by counting the amount of pixels across the vertical and horizontal axis of documented "true position" of the target(s).

3.6.2 Static Objects Data Sets.

For the data sets containing one or two static objects, twenty frames are used to take the mean and standard deviations of the pixel cluster's length and width which represents the size of the desired target(s) within the WSN. This is accomplished by counting the amount of pixels across the vertical and horizontal axis of documented "true position" of target. Also, we can visually compare the size and dimensions of the pixel cluster for each estimator's results. Furthermore, the true position that is measured by the experimenter is then compared to the reconstructed images for accuracy even

though position estimation is not the focus of this research. Furthermore, the processing time which includes the transmission time for each mote, calculating the weight matrix and drawing the reconstructed image, for each estimator will be assessed by taking the mean and standard deviation of the processing time over each data set.

3.6.3 Moving Object Data Sets.

Since there are no truth coordinates available for the moving object data sets, and the object is moving in between frames, the mean and standard deviation cannot be derived from these sets. Alternatively, the path of the moving object can be visually estimated. Furthermore, the frames of the moving object can be overlaid to show the resolution path. To reiterate, even though the focus of this research is not localization accuracy but resolution, the object location error is slightly related to resolution.

3.7 Data Analysis

3.7.1 Experimental Challenges.

With any experiment, unforeseen challenges may arise and must be overcome. Occasionally, during data collection, the transceivers fail to create a proper link. Consequently, this will return a NaN reading for links within the $\mathbf{y}$ data vector. It is important to correct this issue in order to have a successful image reconstruction. Furthermore, there can be a possibility of negative values in the $\mathbf{y}$ data. The following sections will explain how to resolve these issues.

3.7.2 NaN Solution.

The average percentage for NaN occurrences within a particular frame was less than 7 percent of the frame value. To provide usable $\hat{\mathbf{x}}$ vector data from the measured data $\mathbf{y}$, it is imperative to not include the NaN values. This is accomplished by removing

the values from both the $\mathbf{y}$ data vectors and its corresponding weight matrix multiplicative, $\mathbf{W}_{Ellipse}$, seen in Equation (2.19).

3.7.3 Negative Pixel Density.

The novel portion of this research is to exploit a property of the MLE that forces the solution of $\hat{\mathbf{x}}$ to always be positive, as long as the $\mathbf{y}$ data vector contains all positive numbers. However, since the desired signal is coupled with noise and the mean of the entire collected signal is close to zero; the noise can cause some of the $\mathbf{y}$ data values to be negative. Consequently, this will cause the $\hat{\mathbf{x}}$ solution to contain negative pixel density values. With the understanding that all of the calculated signals must be positive due to the manipulated MLE equation proposed in Chapter IV, any negative value contained in the $\mathbf{y}$ data vector is caused by the noise and not the actual signal. Exploiting this notion, all negative values can be simply set to zero at the end of every iteration without the possibility of lost information.

IV. Maximum Likelihood Estimation

The following chapter walks through the derivation that allows for improved image resolution for Radio Tomographic Imaging (RTI) using a slightly modified form of the classic Maximum Likelihood Estimate (MLE) derivation to solve for x_p from Equation (2.2). Recall Equation (2.2) from Chapter II, the x -value x_l is embedded in the extracted data collection Δy_l along with $W_{l,p}$ being the weight for each link, l and pixel p . It is important to be able to obtain an accurate estimate for the x -value in order to reconstruct the image. Additionally, if the x -values are negative, it can cause the reconstruction to have incorrect results. The proposed mathematical derivation below highlights the process taken to force the solution to be positive which should ultimately produce better imaging results [24].

The MLE is used to estimate a parameter value of a statistical model that maximizes the likelihood of that value with the given observation values. Equation (4.1) is the definition of the MLE, where $\hat{x}$ is the parameter value that is being maximized from a vector $\mathbf{x}^{N \times 1}$ observations of a Probability Density Function (PDF).

$$\hat{\mathbf{x}}_{ML}(\mathbf{y}) = \underset{\mathbf{x}}{\operatorname{argmax}} P(\mathbf{y}; \mathbf{x}) \quad (4.1)$$

Section 2.3.7 explains how the signal can be characterized as a Gaussian distribution. For this research, the Gaussian PDF equation is tailored by substituting in $\sum_{p=1}^P W_{l,p} x_p$, where $W_{l,p}$ is the weight matrix value and x_p is the embedded x -value.

$$P(y_l | \mathbf{x}) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{-(y_l - \sum_{p=1}^P W_{l,p} x_p)^2}{2\sigma^2}\right) \quad (4.2)$$

Next, since there are multiple observations, the product of the distributions are calcu-

lated.

$$P(\mathbf{y}|\mathbf{x}) = \prod_{l=1}^L \left(\frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{-(y_l - \sum_{p=1}^P W_{l,p} x_p)^2}{2\sigma^2}\right) \right) \quad (4.3)$$

Furthermore, since the argmax of an observation is the max location value along the PDF and not actual max value, the log can be taken in order aid in computational convenience, while having no affect on the solution. This is known as log-likelihood function and is denoted by the character $\mathcal{L}$.

$$\mathcal{L} = \ln \left(\prod_{l=1}^L \left(\frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{-(y_l - \sum_{p=1}^P W_{l,p} x_p)^2}{2\sigma^2}\right) \right) \right) \quad (4.4)$$

$$= -M \ln(\sqrt{2\pi}\sigma) - \frac{1}{2\sigma^2} \sum_{l=1}^L \left(y_l - \sum_{p=1}^P W_{l,p} x_p \right)^2 \quad (4.5)$$

The MLE process can now be used to maximize the log-likelihood function by choice of θ . Since the log-likelihood is a quadratic with respect to θ , the MLE can be found by taking the derivative and setting it equal to zero. However, in this case, the derivative is taken with respect to a single random x -value denoted as, x_r where $r \in 1, 2 \dots N$.

$$\frac{\delta \mathcal{L}}{\delta x_r} = 0 - \frac{1}{2\sigma^2} \sum_{l=1}^L 2 \left(y_l - \sum_{p=1}^P W_{l,p} x_p \right) \cdot W_{l,r} \quad (4.6)$$

$$0 = 0 - \frac{1}{2\sigma^2} \sum_{l=1}^L 2 \left(y_l - \sum_{p=1}^N W_{l,p} x_p \right) \cdot W_{l,r} \quad (4.7)$$

$$0 = \sum_{l=1}^L \left(y_l - \sum_{p=1}^P W_{l,p} x_p \right) \cdot W_{l,r} \quad (4.8)$$

$$0 = \sum_{l=1}^L (y_l W_{l,r}) - \sum_{l=1}^L \left(\sum_{p=1}^P W_{l,p} x_l \right) \cdot W_{l,r} \quad (4.9)$$

Traditionally, the next step would involve isolating the parameter value that maximizes the PDF. However, the desired parameter value, x_r , is nested in a summation. The next step is important to show how this issue becomes moot while still forcing the solution to be positive and accurate. By simply adding the negative gradient term to both sides of the equation and then dividing both sides by that same term; a positive ratio is created that is equal to 1 when a maximum in the likelihood function is achieved. Furthermore, we can use this ratio by multiplying the original x_r value, denoted as $\hat{x}_{r(old)}$, to provide a new $\hat{x}_r$ value that is closer to the desired argmax value, denoted as $\hat{x}_{r(new)}$. This technique was used in [24] for data acquired from a Charge-Coupled-Device (CCD) camera which was used for image recovery using the Poisson distribution.

$$\sum_{l=1}^L (y_l W_{l,r}) = \sum_{l=1}^L \left(\sum_{p=1}^P W_{l,p} x_p \right) \cdot W_{l,r} \quad (4.10)$$

$$1 = \frac{\sum_{l=1}^L (y_l W_{l,r})}{\sum_{l=1}^L \left(\sum_{p=1}^P W_{l,p} x_p \right) \cdot W_{l,r}} \quad (4.11)$$

$$\hat{x}_{r(new)} = \left(\frac{\sum_{l=1}^L (y_l W_{l,r})}{\sum_{l=1}^L \left(\sum_{p=1}^P W_{l,p} \hat{x}_{r(old)} \right) \cdot W_{l,r}} \right) \cdot \hat{x}_{r(old)} \quad (4.12)$$

Where

$$\Delta = \left(\frac{\sum_{l=1}^L (y_l W_{l,r})}{\sum_{l=1}^L \left(\sum_{p=1}^P W_{l,p} \hat{x}_{r(old)} \right) \cdot W_{l,r}} \right). \quad (4.13)$$

Essentially, the derivation can be described as

$$\hat{x}_{r(new)} = \Delta \cdot \hat{x}_{r(old)}, \quad (4.14)$$

$$\Delta = \begin{cases} = 1, & \text{if } \hat{x}_r \text{ is correct} \\ < 1, & \text{if } \hat{x}_r \text{ is too big} \\ > 1, & \text{if } \hat{x}_r \text{ is too small} \end{cases}, \quad (4.15)$$

where the updated $\hat{x}_r$ -value is always being “pushed” in the correct direction. Generally, $\hat{x}_{r(old)}$ is initialized with a value of one for every image element in the field and then updated via Equation (4.11) to get a new updated value. For each iteration $\hat{x}_{r(old)}$

is chosen to be $\hat{x}_{r(new)}$ from the last iteration and a new $\hat{x}_{r(new)}$ value is computed. The number of iterations are set by the user depending on processing time and desired image resolution.

V. Analysis of Results

This chapter contains the results acquired from data collections and experiments conducted as described in Chapter III. Stationary localization for single and dual targets as well as tracking moving targets were conducted in environments which had both obstructed and unobstructed objects within their respective Wireless Sensor Network (WSN). Additionally, there was signal interference caused by Wireless Fidelity (Wi-Fi) from the residential neighborhood environment. The focus of the different environmental data collections is to prove the robustness in image reconstruction for the modified Maximum Likelihood Estimate (MLE) estimator in comparison to the Tikhonov regularization method. Furthermore, additional comparisons are made from image reconstruction time, also known as frame rate. The results discuss how the image resolution using the modified MLE out performs the traditionally used Tikhonov regularization method by more than 7 times. Additionally, while processing the data, it was discovered that the modified MLE's processing time can compete with, if not perform better than, the Tikhonov method; even though the MLE is a gradient decent method and is expected to have a longer processing time over the Least Squares (LS) method. Again, For all data collections, foot (ft) will be used as the metric for distance and all position and tracking coordinate estimation will be characterized by an (x, y) coordinate in feet.

Each environment has a single target, double target and moving target data set. From the data sets, a frame with the best and the worst resolution was chosen for comparison of both estimators. These frames were arbitrarily chosen from their respective data sets to be a representative of how well both estimators can perform. Due to time constraints, the metric for choosing the frames was determined by performing a visual analysis that incorporated the length and width of the pixel cluster, as well as pixel intensity. Additionally, the targets are humans and the average width of an adult human

is approximately 17 in. In theory, this means that a human target should only highlight a pixel that is $1 \times 1 \text{ ft}^2$ within a WSN.

Processing Time. As mentioned in Section 2.2.2, the processing time, which also includes the the frame rate ($1/T$), is the time it takes all the transceivers in a WSN to transmit one time and process and plot the information, creating one frame of data. This time will vary depending on numerous factors, mainly the amount of transceivers used in a WSN. For this experiment, a total of 60 transceivers were used to make up the WSN. Tables 5.1, 5.2 and 5.3 show the processing time for each environment's respective data sets. It is important to note that the processing time, which includes the frame rate, for the modified MLE was averaged over all experiment data and proved to be 1.81 times faster then the traditional Tikhonov Regularization method. This experiment proves that the modified MLE is more than capable of keeping up with the processing requirements for near real-time Radio Tomographic Imaging (RTI) for real-world applications.

Table 5.1. Process Time for Open Field.

Estimator	Target(s) Data Set	Avg Process Time (s)	Standard Deviation (s)	Max Process Time (s)	Min Process Time (s)	Amount of Frames
Tik	<i>Single</i>	0.91	0.03	0.967	0.858	20
Tik	<i>Double</i>	0.91	0.06	1.045	0.78	20
Tik	<i>Moving</i>	0.9	0.04	0.936	0.905	3
MLE	<i>Single</i>	0.51	0.03	0.5629	0.4274	20
MLE	<i>Double</i>	0.52	0.06	0.7424	0.4463	20
MLE	<i>Moving</i>	0.6	0.23	0.9346	0.4548	3

Table 5.2. Process Time for Wooded Area.

Estimator	Target(s) Data Set	Avg Process Time (s)	Standard Deviation (s)	Max Process Time (s)	Min Process Time (frame/sec)	Amount of Frames
Tik	<i>Single</i>	1.02	0.23	1.965	0.873	20
Tik	<i>Double</i>	0.96	0.04	1.06	0.89	20
Tik	<i>Moving</i>	0.996	0.08	1.123	0.811	9
MLE	<i>Single</i>	0.5	0.1	0.9024	0.4131	20
MLE	<i>Double</i>	0.47	0.03	0.5989	0.4293	20
MLE	<i>Moving</i>	0.58	0.16	0.8138	0.4824	9

Table 5.3. Process Time for Residential Playground.

Estimator	Target(s) Data Set	Avg Process Time (s)	Standard Deviation (s)	Max Process Time (s)	Min Frame Rate (s)	Amount of Frames
Tik	<i>Single</i>	0.91	0.03	0.967	0.858	20
Tik	<i>Double</i>	0.91	0.06	1.045	0.78	20
Tik	<i>Moving</i>	0.9	0.04	0.936	0.905	4
MLE	<i>Single</i>	0.49	0.044	0.5444	0.3655	20
MLE	<i>Double</i>	0.49	0.04	0.5995	0.4137	20
MLE	<i>Moving</i>	0.48	0.22	0.5001	0.4601	4

5.1 Open Field

This section presents the results from processing the data in an open field environment with the least amount of interference possible in an outside setting. Table 5.4 contains the calculations for the image resolution for both the modified MLE and the Tikhonov Regularization method for each data set at its corresponding target location. Table 5.4 provides the mean and standard deviation for the pixel cluster's length and width [L×W] across the “true” target location for each data set. Furthermore, Fig. 5.5 will cover how well each estimator performed with image reconstruction for motion

tracking.

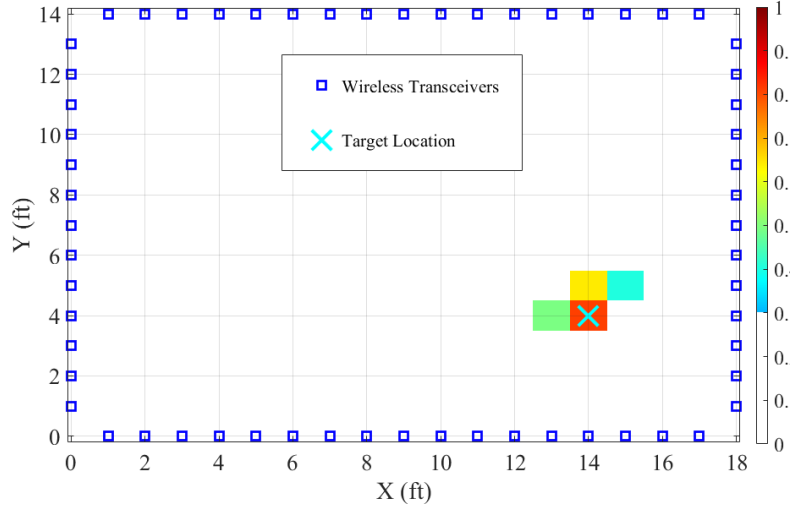
5.1.1 One Stationary Target.

Figures 5.1 and 5.2 respectively show the worst and best data frame for this particular data set. Fig. 5.1, shows the worst resolution frames for a target located at x-y coordinates (14,4). Notice that the modified MLE's image resolution is far superior than the traditionally used Tikhonov regularization method in both Figs 5.1 and 5.2. The pixel cluster's length and width, which should directly correspond to the size of the actual target, across the "true" target position for the modified MLE estimator is $2 \times 2 \text{ ft}^2$, while the Tikhonov dimensions are $8 \times 4 \text{ ft}^2$. The image reconstructed by the Tikhonov method shows that the area of the target is 32 ft^2 while the area of the target for the MLE is 4 ft^2 . This single frame from the data set shows that the modified MLE has 8 times improved resolution in comparison to the Tikhonov image.

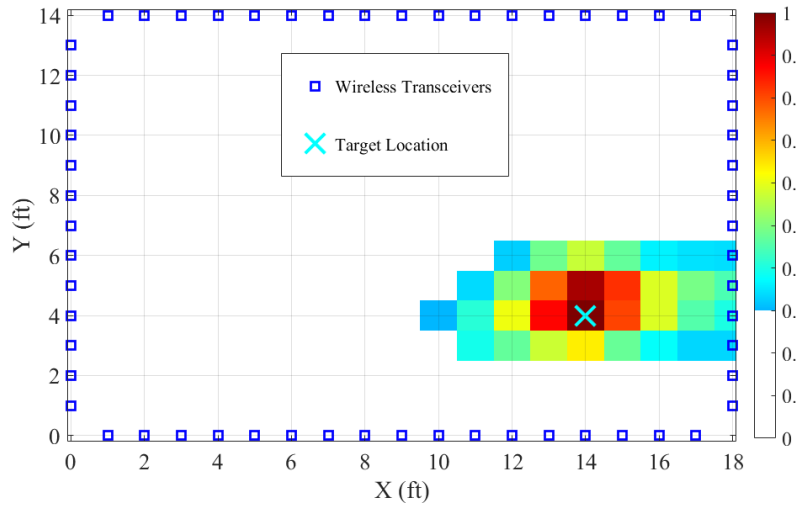
Figure 5.2 shows the frames with the best resolution from the data set. For these images, Fig. 5.2a shows the MLE resolution is $2 \times 1 \text{ ft}^2$ and the Tikhonov is $7 \times 4 \text{ ft}^2$. The image reconstructed by the Tikhonov method shows that the area of the target as 28 ft^2 while the area of the target for the MLE is 2 ft^2 , resulting in an improved image resolution that is 14 times better than the Tikhonov method.

5.1.2 Two Stationary Targets.

Having two targets introduced into an Area of Interest (AoI) is important in order to see how image resolution is affected. It is suspected that the target closest to the sides of the WSN will draw a higher signal attenuation than the target that is farthest, resulting in the target with the lowest Received Signal Strength (RSS) value to have less pixel intensity. Consequently, this could make it difficult to detect the lesser RSS value targets and ultimately affect image resolution.

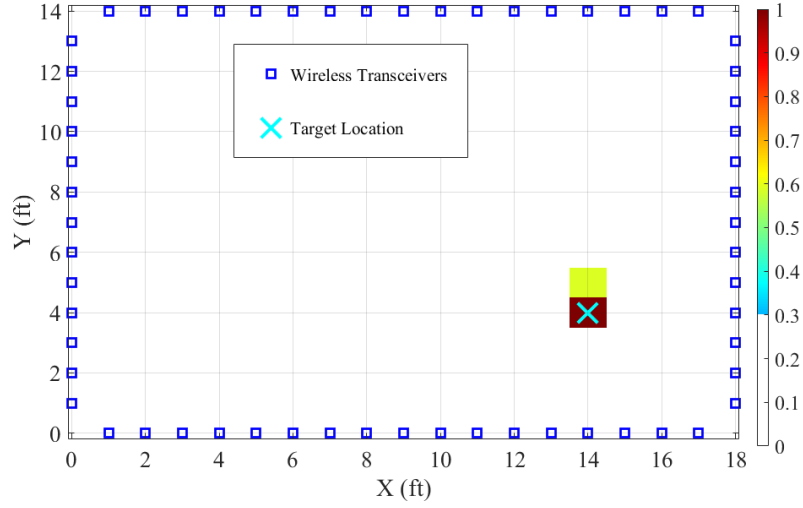


(a) Modified MLE.

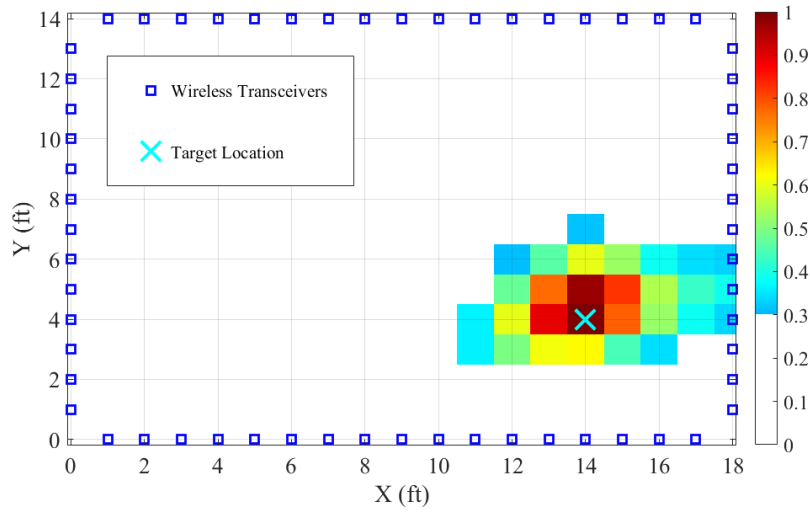


(b) Tikhonov Regularization.

Figure 5.1. **Open field** environment illustration showing frames with the **worst** resolution within the data set for both estimators with **one target**. Target location is (14,4). Modified MLE pixel resolution across target location for this frame is $2 \times 2 \text{ ft}^2$ and Tikhonov resolution is $8 \times 4 \text{ ft}^2$.

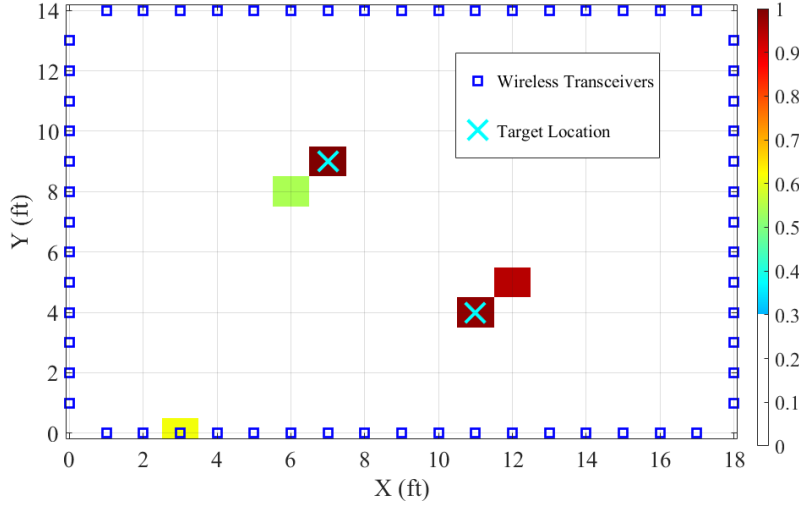


(a) Modified MLE.

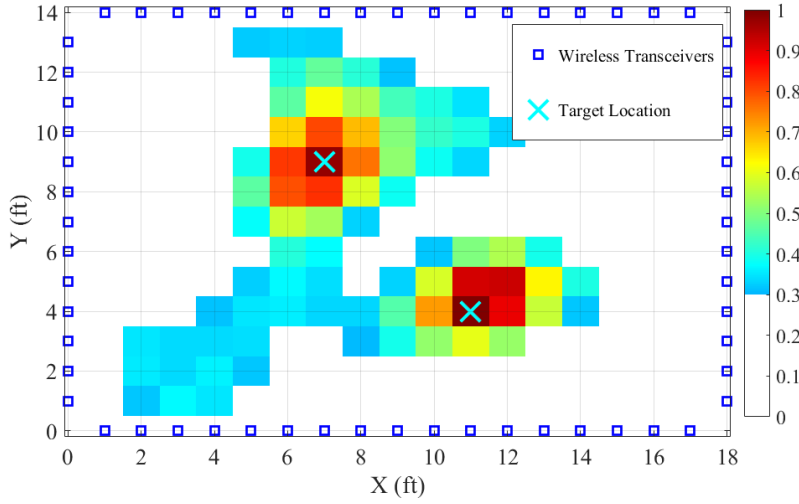


(b) Tikhonov Regularization.

Figure 5.2. **Open field** environment illustration showing frames with the **best** resolution within the data set for both estimators with **one target**. Target location is (14,4). Modified MLE pixel resolution across target location for this frame is $2 \times 1 \text{ ft}^2$ and Tikhonov resolution is $7 \times 5 \text{ ft}^2$.

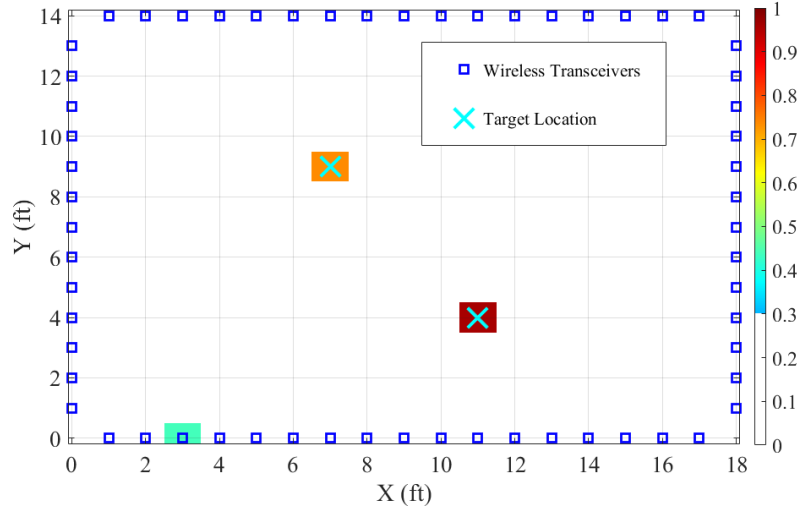


(a) Modified MLE.

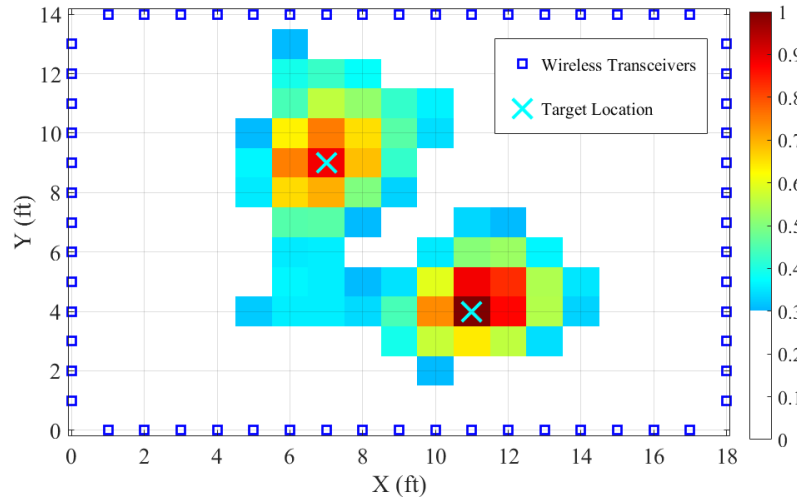


(b) Tikhonov Regularization.

Figure 5.3. **Open field** environment illustration showing frames with the **worst** resolution within the data set for both estimators with **two target**. Target locations are (7,9) and (11,4). Modified MLE pixel resolution across target location for both targets is $1 \times 1 \text{ ft}^2$ and Tikhonov resolution is $7 \times 10 \text{ ft}^2$ and $11 \times 4 \text{ ft}^2$, respectively.



(a) Modified MLE.



(b) Tikhonov Regularization.

Figure 5.4. **Open field** environment illustration showing frames with the **best** resolution within the data set for both estimators with **two targets**. Target locations are (7,9) and (11,4). Modified MLE pixel resolution across target location for both targets is $1 \times 1 \text{ ft}^2$ and Tikhonov resolution is $5 \times 9 \text{ ft}^2$ and $10 \times 5 \text{ ft}^2$, respectively.

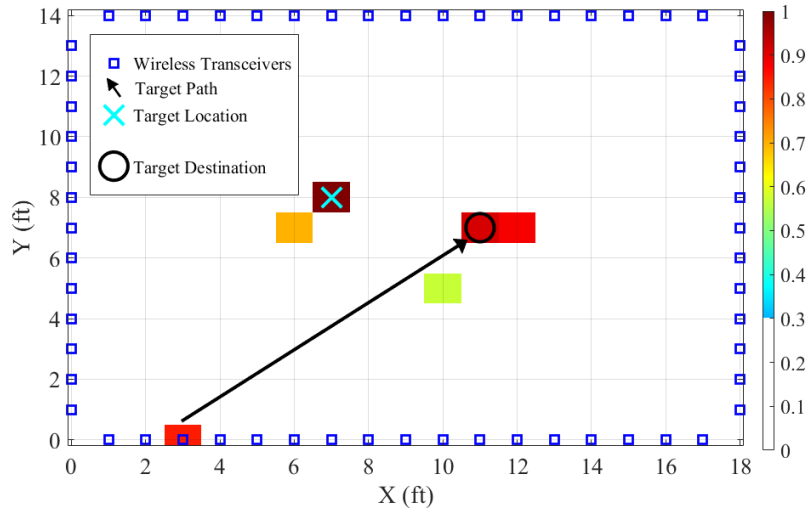
Table 5.4. Image Resolution for Open Field.

Estimator	Target(s) Data Set	Avg Target Resolution [L×W] (ft ²)	Standard Deviation [L×W] (ft ²)	Max Pixel Cluster [L×W] (ft ²)	Min Pixel Cluster [L×W] (ft ²)	Target Location (x,y)
Tik	<i>Single</i>	7.1×4.5	0.31×0.51	8×5	7×4	(14,10)
Tik	<i>Double</i>	6.95×9.25	1.43×1.45	10×12	5×6	(7,8)
Tik	<i>Double</i>	10.1×5.45	1.17×1.76	12×9	8×4	(10,7)
MLE	<i>Single</i>	1.65×2	0.49×0	2×2	1×2	(14,10)
MLE	<i>Double</i>	1×1	0×0	1×1	1×1	(7,8)
MLE	<i>Double</i>	1×1	0×0	1×1	1×1	(10,7)

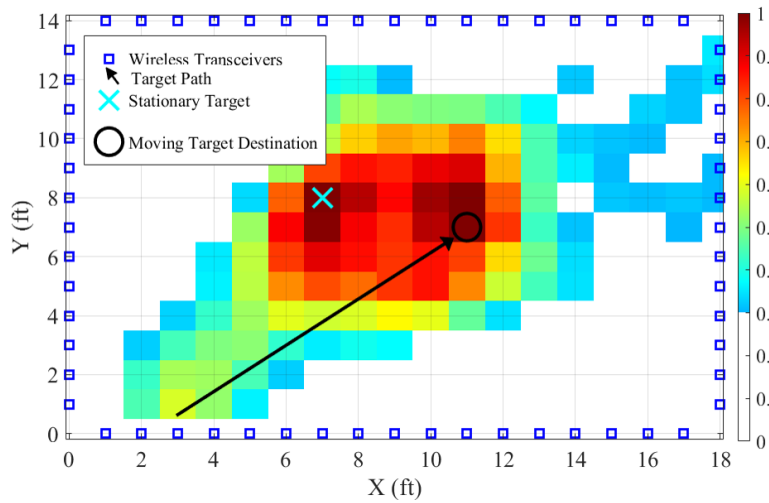
Similar to the single target Figs. 5.1 and 5.2, Figs. 5.3 and 5.4 comparatively show the differences in resolution when two targets are introduced into the AoI at positions (7,9) and (11,4). Notice that the pixel clusters begin to merge in the Tikhonov estimator reconstruction images, Figs. 5.3b and 5.4b. Distributing the intensities across two targets possibly affected the calculation of the $\hat{x}$ -values and could have made caused the pixel clusters to spread. Conversely, for the MLE images, Figs. 5.1b and ?? pixel dimensions are both 1×1 ft². Even though Fig. 5.1b shows artifact pixels diagonally adjacent to the “true” position pixel, the introduction of a second target has improved resolution. This could be caused by the second target decreasing the overall intensity values for both targets in the WSN, in comparison to having one single target where the single pixel intensity is so high that it affects the adjacent pixel.

5.1.3 One Stationary Target, One Moving Target.

In order for RTI to be useful in real-world the system has to be able to track moving targets. Unfortunately, when the data was collected, the emphasis was focused on stationary targets and there was not as many data sets collected with moving targets. Figure 5.5 is the overlay of 3 frames, all of which include a target in motion. There is a



(a) Modified MLE.



(b) Tikhonov Regularization.

Figure 5.5. Open field environment illustration is an overlay of 3 frames with one stationary target located at (7,8), and a moving target entering the WSN at (3,0) with a destination location of (11,7). An arrow shows the target's path.

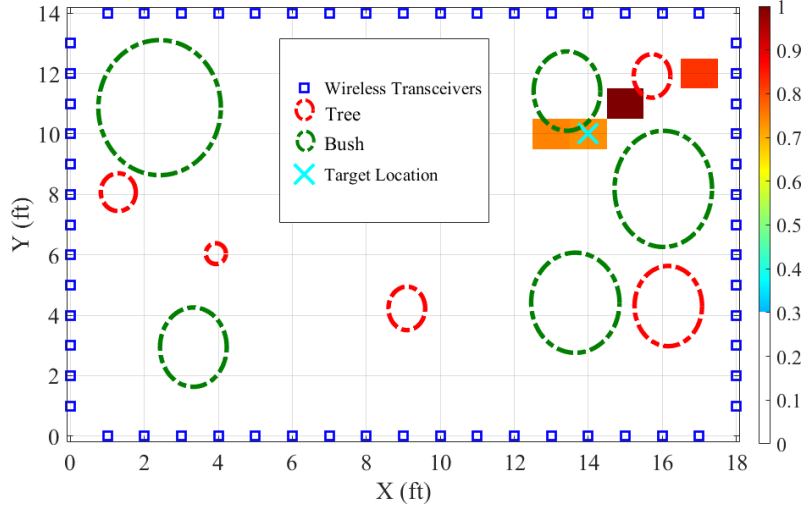
stationary target at position (7,8), an arrow that shows the path of the moving object entering the WSN at (3,0) and a black circle depicting the moving target's destination at location (11,7). Even though, the MLE image has better resolution, it performs poorly for tracking the target's motion. This could be caused by the speed at which the target was moving. If the target was moving faster than 1 foot per second, which is the processing speed for each frame, tracking the object can be challenging. The Tikhonov estimator proves to be worst which shows as a huge cluster of pixels that makes it difficult to distinguish between multiple targets in the WSN.

5.2 Wooded Area

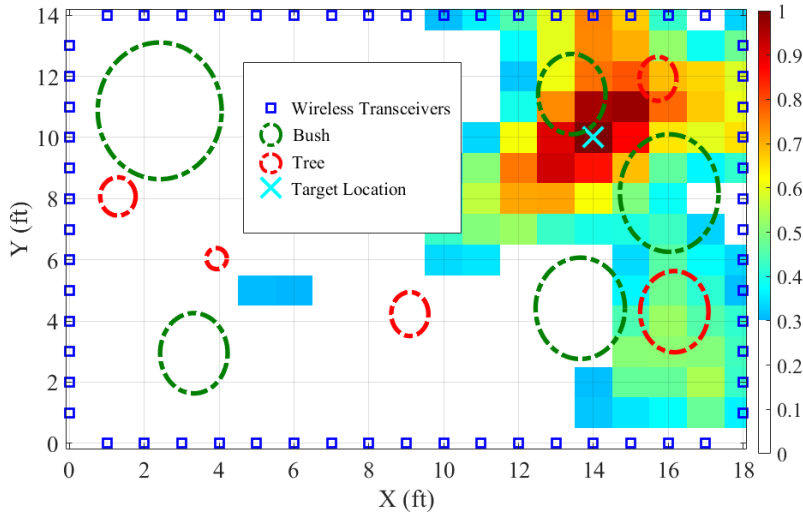
This section presents the results from processing the data in a wooded environment with interference within the WSN caused by trees, leaves and bushes. Table 5.5 contains the calculations for the image resolution for both the modified MLE and the Tikhonov Regularization method for each data set at its corresponding target location. The table provides the mean and standard deviation for the pixel cluster's length and width $[L \times W]$ across the "true" target location for each data set. Fig. 5.10 will cover how well each estimator performed with image reconstruction for motion tracking in the densely wooded area.

5.2.1 One Stationary Target.

Out of all three environments, the wooded area seemed to pose a challenge for RTI. Even though accuracy is not the scope of this research, the estimators mildly struggled with identifying the true position of the target, located at (14,10). As seen in Fig. 5.6b, the Tikhonov estimator had multiple high intensity pixels that span almost the entire side of the reconstructed image. Even the MLE had issues with pixel intensity. Shown in Fig. 5.6a, you can see that the highest intensity pixels are not on the true location.

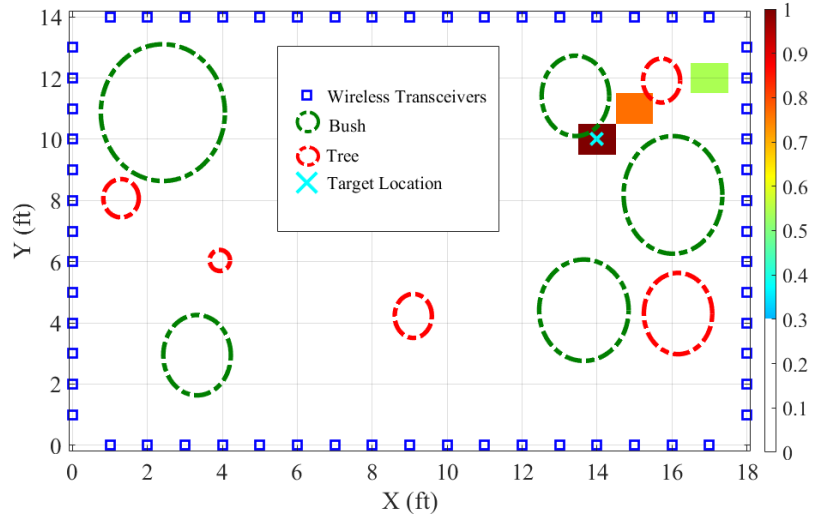


(a) Modified MLE.

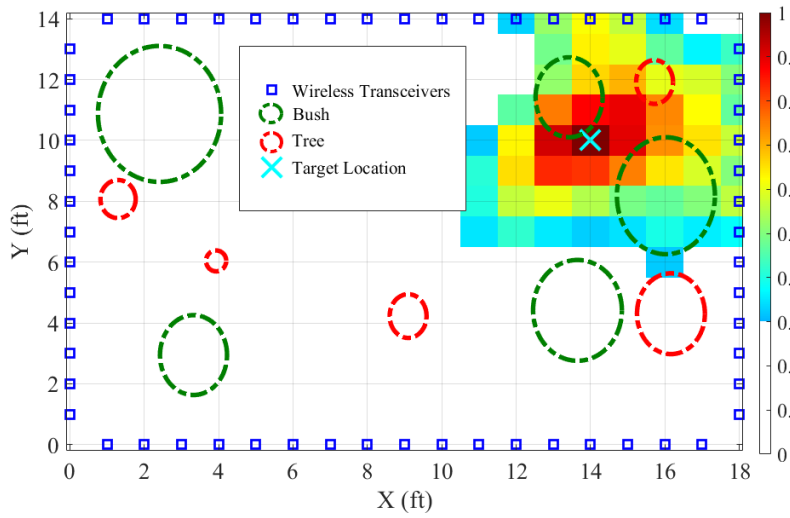


(b) Tikhonov Regularization.

Figure 5.6. **Woods** environment illustration showing frames with the **worst** resolution within the data set for both estimators with **one target**. Target location is (14,10). Modified MLE pixel resolution across target location for this frame is $2 \times 1 \text{ ft}^2$ and Tikhonov resolution is $8 \times 7 \text{ ft}^2$.



(a) Modified MLE.



(b) Tikhonov Regularization.

Figure 5.7. **Woods** environment illustration showing frames with the **best** resolution within the data set for both estimators with **one target**. Target location is (14,10). Modified MLE pixel resolution across target location for this frame is $1 \times 1 \text{ ft}^2$ and Tikhonov resolution is $7 \times 7 \text{ ft}^2$.

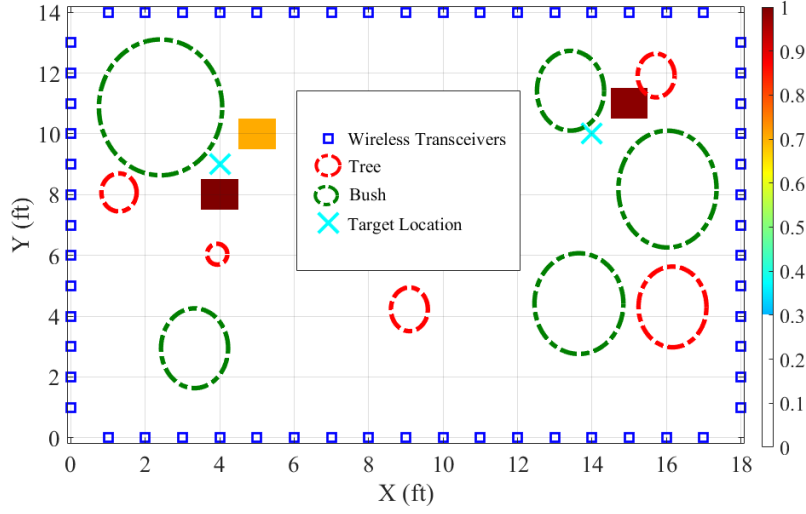
Table 5.5. Image Resolution for Wooded Area.

Estimator	Target(s) Data Set	Avg Target Resolu- tion [L×W] (ft²)	Standard Deviation [L×W] (ft²)	Max Pixel Cluster [L×W] (ft²)	Min Pixel Cluster [L×W] (ft²)	Target Location (x,y)
Tik	<i>Single</i>	7×7	0×0	7×7	7×7	(14,10)
Tik	<i>Double</i>	6.2×9.5	0.41×1.4	7×11	6×6	(14,10)
Tik	<i>Double</i>	6.05×9.45	0.22×0.61	7×8	6×6	(4,10)
MLE	<i>Single</i>	1.42×1	0.5×0	2×1	1×1	(14,10)
MLE	<i>Double</i>	1×1	0×0	1×1	1×1	(14,10)
MLE	<i>Double</i>	1×1	0×0	1×1	1×1	(4,10)

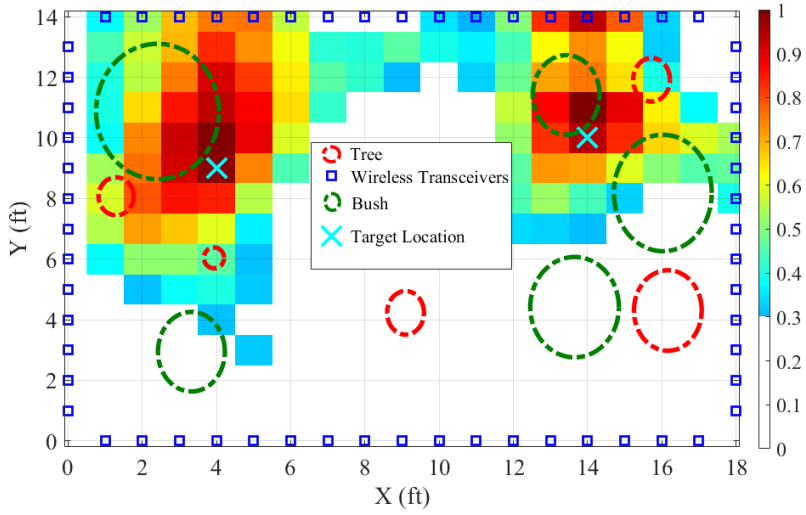
However, the image resolution in Fig. 5.6a had a 2×1 ft² pixel cluster, still proves to be far superior than the Tikhonov method in the wooded single target data set. For the best frames of the estimators, shown in Fig. 5.7a, there was little improvement with multiple high intensity pixels showing up near the true target's position in the reconstructed image.

5.2.2 Two Stationary Targets.

The locations for the double targets in the wooded area is (4,9) and (14,10). Again, even though accuracy is not the focus of this research, accuracy slightly relates to image resolution. Knowing the true position of the target aids in improving resolution for a specific location. Figure 5.9a shows that the modified MLE still had great resolution for its worst frame but both target's pixels were not highlighted. The pixels adjacent to them at (4,8) and (15,11) were highlighted. In the wooded data sets there were many prevalent location inaccuracies. Albeit being inaccurate, the image resolution was excellent with both targets having 1×1 ft² resolution in both Figs. 5.8a and Figs. 5.9a. The Tikhonov showed most of the target's size to be massive with each target being a quarter of the WSN size, shown in Figs. 5.8b and Figs. 5.9b.

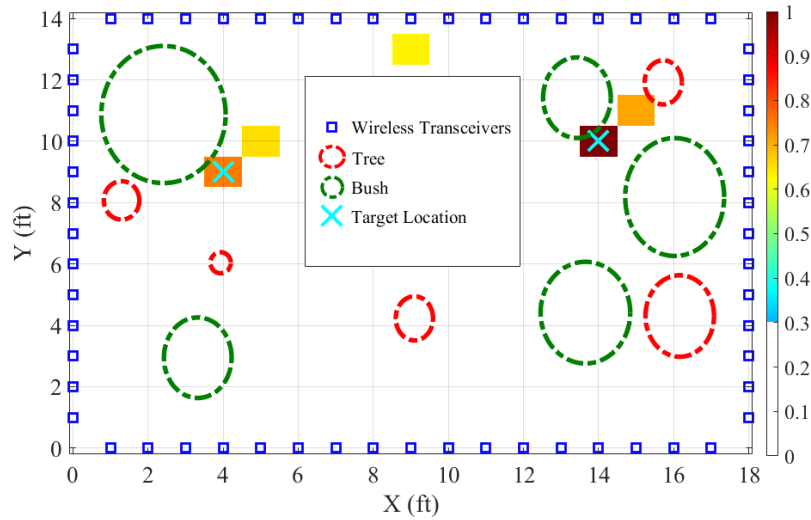


(a) Modified MLE.

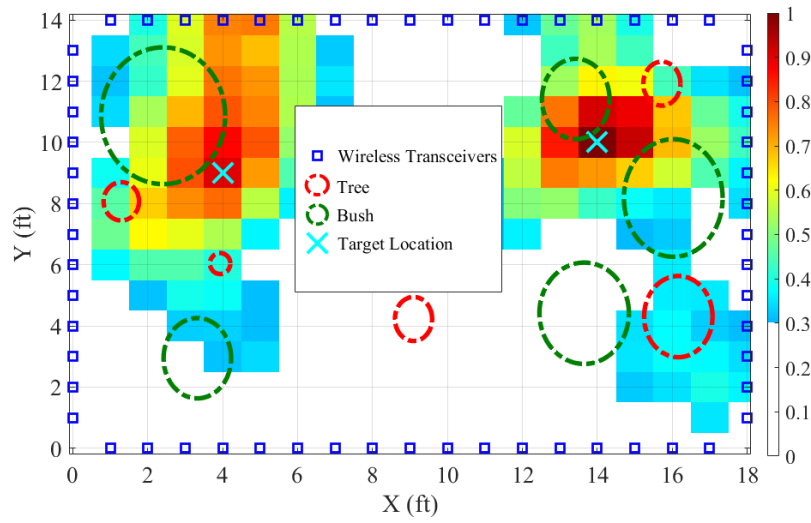


(b) Tikhonov Regularization.

Figure 5.8. **Woods** environment illustration showing frames with the **worst** resolution within the data set for both estimators with **two targets**. Target locations are (4,9) and (14,10). Modified MLE pixel resolution across target location for both targets is 1×1 ft² and Tikhonov resolution is 7×10 ft² and 11×4 ft², respectively. Note Fig. 5.8a shows the highest intensity pixels are not on the target location but the resolution for adjacent high intensity pixels are still good.

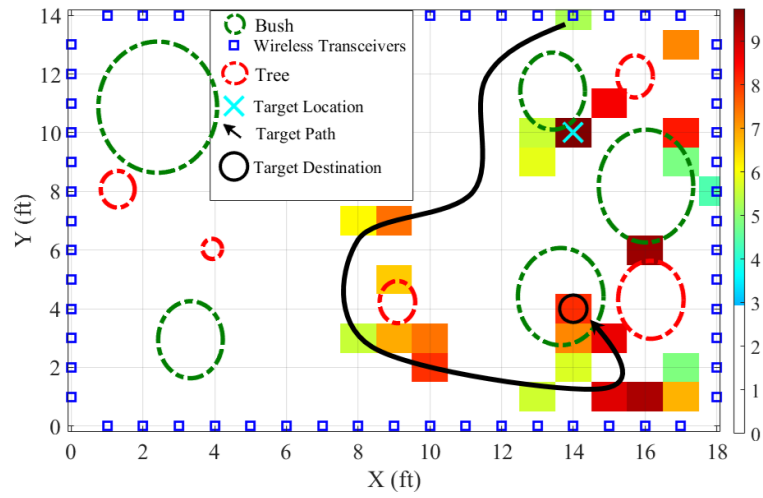


(a) Modified MLE.

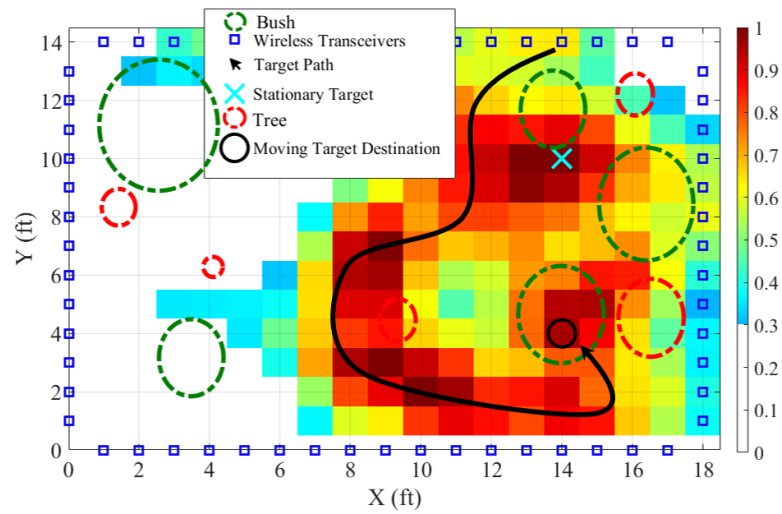


(b) Tikhonov Regularization.

Figure 5.9. **Woods** environment illustration showing frames with the **best** resolution within the data set for both estimators with **two targets**. Target locations are (4,9) and (14,10). Modified MLE pixel resolution across target location for both targets is $1 \times 1 \text{ ft}^2$ and Tikhonov resolution is $7 \times 11 \text{ ft}^2$ and $7 \times 6 \text{ ft}^2$, respectively.



(a) Modified MLE.



(b) Tikhonov Regularization.

Figure 5.10. Woods environment illustration is an overlay of 3 frames with one stationary target located at (14,10), and a moving target entering the WSN at (14,14) with a destination location of (14,4). An arrow shows the target's path.

5.2.3 One Stationary Target, One Moving Target.

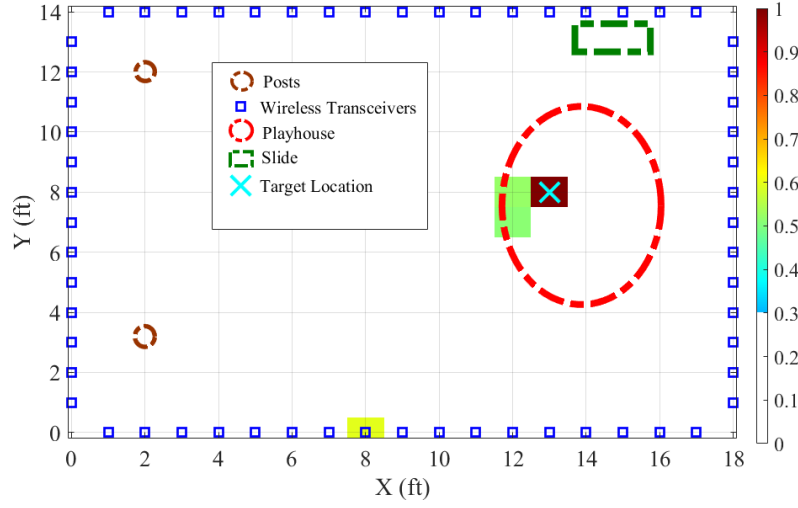
The moving data for the wooded area has 9 frames of data that was overlaid in order to show target tracking and motion. There is a stationary target at position (14,10), an arrow that shows the path of the moving object entering the WSN at (14,14) and a black circle depicting the moving target's destination at location (14,4). Again, Fig. 5.10a shows that the MLE image has better resolution, it performs poorly for tracking the target's motion because of the unknown speed of the target. However, it is possible to see a slight path. In Fig. 5.10b there is a huge cluster of highlighted pixels that fill up most of the WSN. However, if you follow the pixels of highest intensity, a path can be distinguished but the number of objects within the path cannot be.

5.3 Residential Playground

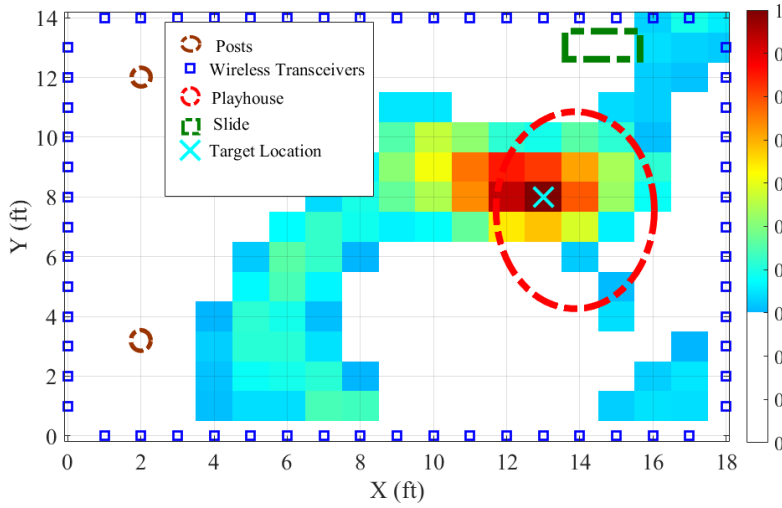
Table 5.6. Image Resolution for Residential Playground.

Estimator	Target(s) Data Set	Avg Target Resolu- tion [L×W] (ft ²)	Standard Deviation [L×W] (ft ²)	Max Pixel Cluster [L×W] (ft ²)	Min Pixel Cluster [L×W] (ft ²)	Target Location (x,y)
Tik	<i>Single</i>	6.85×4.05	1.18×0.51	10×6	5×4	(13,8)
Tik	<i>Double</i>	5.95×5.95	0.69×0.22	8×6	5×5	(12,8)
Tik	<i>Double</i>	6.6×4.55	0.68×0.89	8×6	5×3	(3,4)
MLE	<i>Single</i>	1.61×1	0.5×0	2×1	1×1	(13,8)
MLE	<i>Double</i>	1.6×1.35	0.5×0.49	2×2	1×1	(12,8)
MLE	<i>Double</i>	1.2×1	0.41×0	2×1	1×1	(3,4)

This section presents the results from processing the data in an outdoor environment with internal interference caused by a playground and external interference caused by various residential Wi-Fi signals. Table 5.6 contains the calculations for the image resolution for both the modified MLE and the Tikhonov Regularization method for



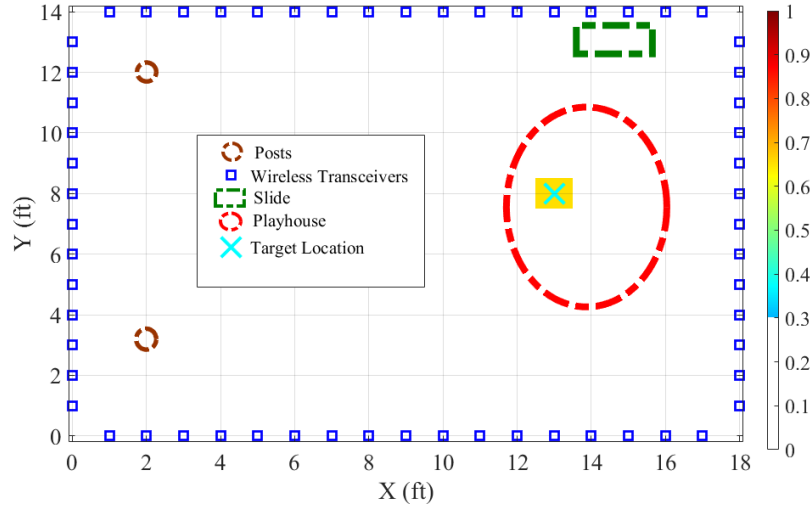
(a) Modified MLE.



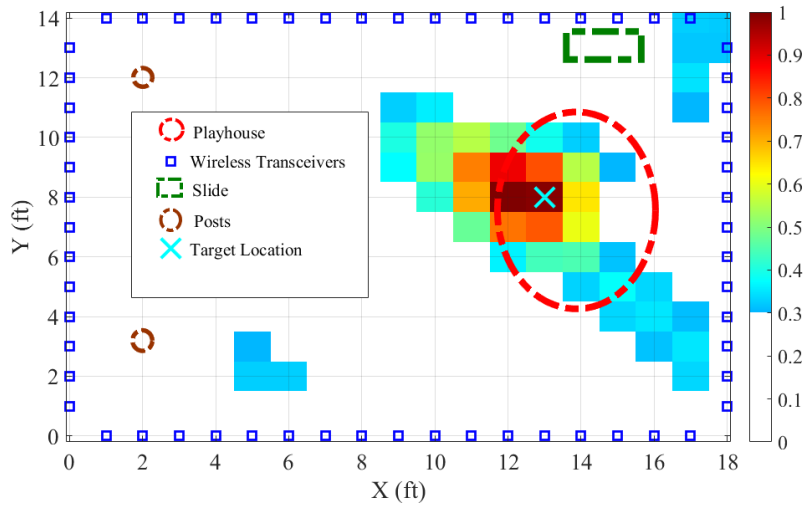
(b) Tikhonov Regularization.

Figure 5.11. **Residential playground** environment illustration showing frames with the **worst** resolution within the data set for both estimators with **one target**. Target location is (13,8). Modified MLE pixel resolution across target location for this frame is $2 \times 1 \text{ ft}^2$ and Tikhonov resolution is $10 \times 4 \text{ ft}^2$.

each data set at its corresponding target location(s). The Table 5.6 provides the mean and standard deviation for the pixel cluster's length and width $[L \times W]$ across the "true" target location for each data set. Fig. 5.15 will cover how well each estimator performed with image reconstruction for motion tracking in the residential playground setting.



(a) Modified MLE.



(b) Tikhonov Regularization.

Figure 5.12. **Residential playground** environment illustration showing frames with the **best** resolution within the data set for both estimators with **one target**. Target location is (13,8). Modified MLE pixel resolution across target location for this frame is $1 \times 1 \text{ ft}^2$ and Tikhonov resolution is $5 \times 5 \text{ ft}^2$.

5.3.1 One Stationary Target.

The residential playground setting proved to have slightly better results than the wooded environment. However, the Tikhonov reconstructed images, shown in Figs. 5.11b and 5.12b, still contained large artifact clusters with their respective dimensions across the target location being $10 \times 4 \text{ ft}^2$ and $5 \times 5 \text{ ft}^2$. The modified MLE performed well with a

pixel resolution of $2 \times 1 \text{ ft}^2$ for the worst frame, shown in Fig. 5.11a and a pixel resolution of $1 \times 1 \text{ ft}^2$ in the best resolution frame, shown in Fig. 5.12a.

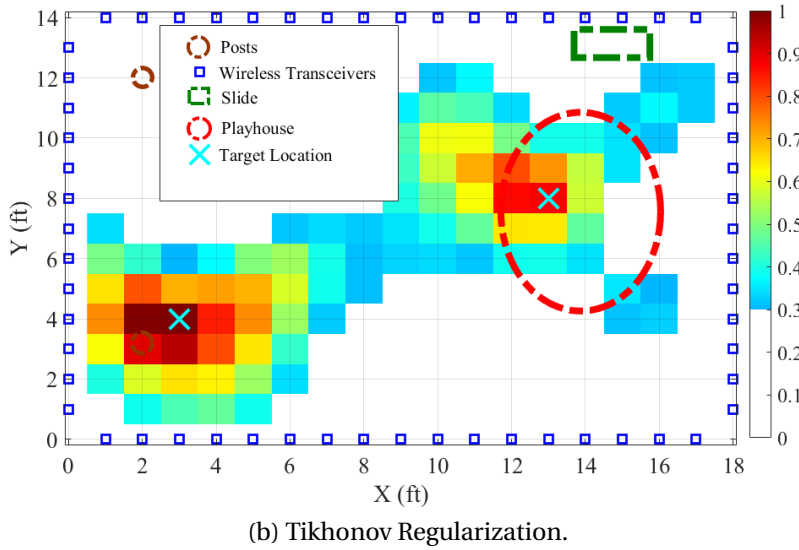
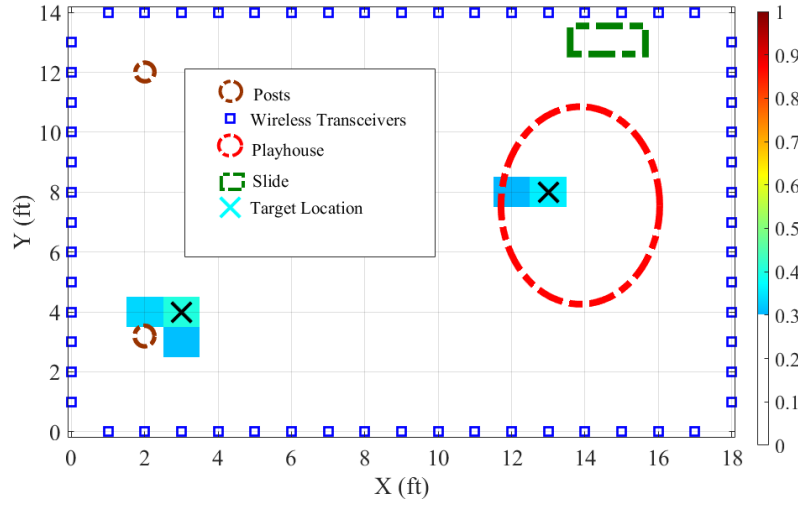
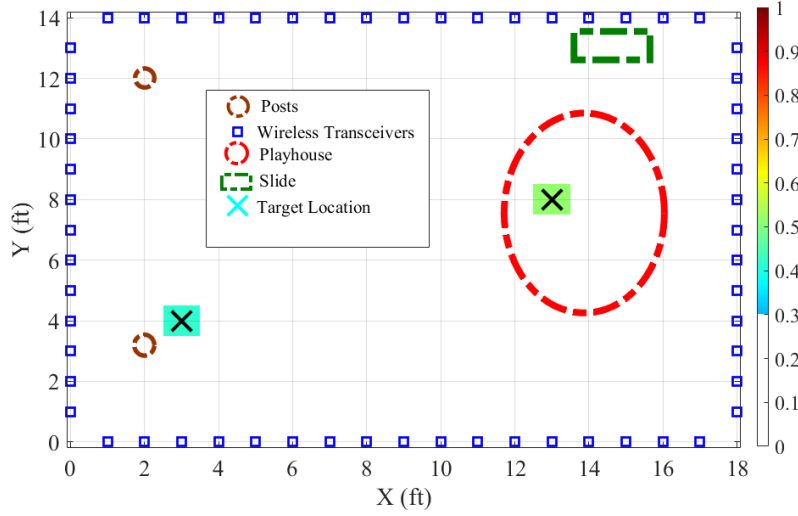
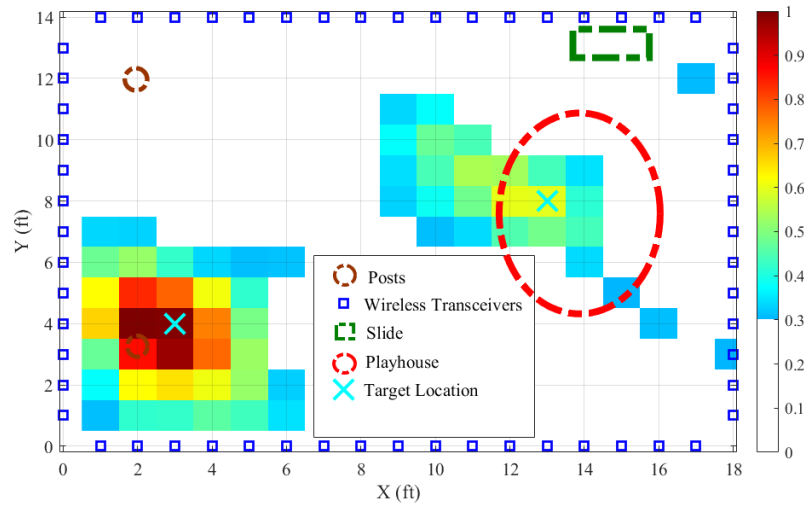


Figure 5.13. **Residential playground** environment illustration showing frames with the worst resolution within the data set for both estimators with **two targets**. Target locations are (13,8) and (3,4). Modified MLE pixel resolution across target location for both targets is $2 \times 2 \text{ ft}^2$ and $2 \times 1 \text{ ft}^2$, receptively. The Tikhonov resolution is $6 \times 5 \text{ ft}^2$ and $7 \times 6 \text{ ft}^2$, respectively.



(a) Modified MLE.



(b) Tikhonov Regularization.

Figure 5.14. **Residential playground** environment illustration showing frames with the best resolution within the data set for both estimators with **two targets**. Target locations are (13,8) and (3,4). Modified MLE pixel resolution across target location for both targets is $1 \times 1 \text{ ft}^2$ and Tikhonov resolution is $5 \times 6 \text{ ft}^2$ and $6 \times 3 \text{ ft}^2$, respectively.

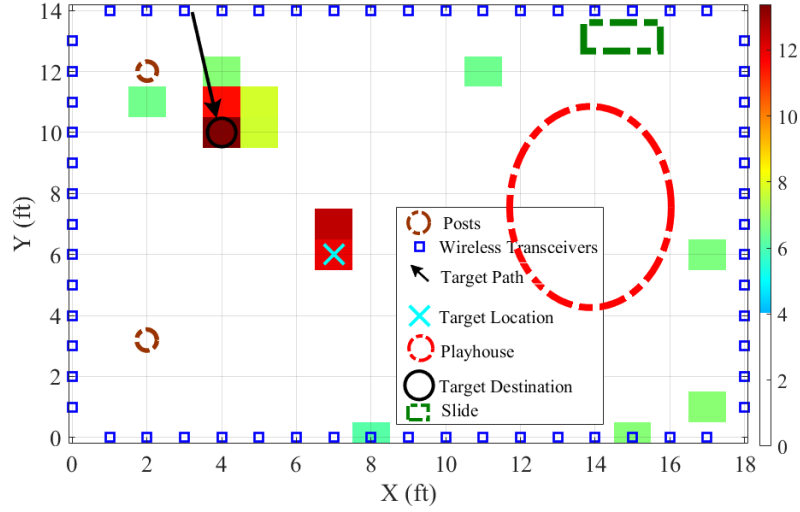
5.3.2 Two Stationary Targets.

Having two targets introduced into an AoI for this environment yielded interesting results. For the MLE reconstructed images, Figs. 5.13a and 5.14a, the intensity of the target pixels were not high. When the second target was introduced the intensities

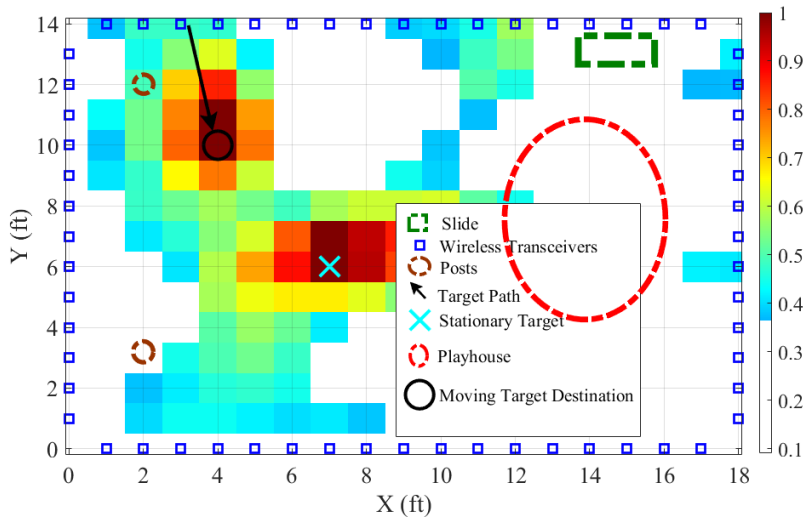
drastically declined. Furthermore, in Fig. 5.14a the target inside the playhouse at location (13,8) has a higher intensity pixel than the target that is closer to the side WSN, outside of the playhouse located at position (3,4). The suspected outcome for the intensities should be the opposite. However, the resolution was still excellent at $1 \times 1 \text{ ft}^2$ for both targets and $2 \times 2 \text{ ft}^2$ and $2 \times 1 \text{ ft}^2$ for the targets in Fig. 5.13a at locations (3,4) and (13,8), respectively. The Tikhonov reconstructed images' target intensities behaved as expected with the intensity of the target at position (3,4) than that of the target inside the playhouse at location (13,8). The dimensions for the pixel cluster for Fig. 5.13b is $7 \times 6 \text{ ft}^2$ for position (3,4) and $6 \times 5 \text{ ft}^2$ for position (14,8). The dimensions for the pixel cluster for Fig. 5.14b is $6 \times 6 \text{ ft}^2$ for position (3,4) and $6 \times 3 \text{ ft}^2$ for position (14,8).

5.3.3 One Stationary Target, One Moving Target.

The moving data for the residential playground setting has 4 frames of data that was overlaid in order to show target tracking and motion. There is a stationary target at position (7,6), an arrow that shows the path of the moving object entering the WSN at (3,14) and a black circle depicting the moving target's destination at location (4,10). Figure 5.15 shows that the MLE image overlay has better resolution, but tracking the target's motion is still poor. Figure 5.15b image reconstruction looks like a normal Tikhonov image reconstruction. A path is indistinguishable and the image looks as if there is simply two static targets in the WSN. This is because the travel distance is so short that the path is overshadowed by the pixel intensity when the target becomes stationary.



(a) Modified MLE.



(b) Tikhonov Regularization.

Figure 5.15. Residential playground environment illustration is an overlay of 4 frames with one stationary target located at (7,6), and a moving target entering the WSN at (3,14) with a destination location of (4,10). An arrow shows the target's path.

VI. Conclusion and Future Work

This chapter summarizes the methodology, results and conclusions made from the research. Furthermore, this chapter covers some of the recommendations for future work and expansion. With the interest in Radio Tomographic Imaging (RTI) growing for multiple applications such as military target tracking and location, as well as civil law enforcement and emergency first responders, there is a growing need for improved image resolution for the reconstructed image to aid in accurately locating objects.

The goal of this research was to explore a new estimating technique for improving image resolution in RTI reconstruction, in comparison to the commonly used Tikhonov approach. Chapter II presented related work on regularization methods for image reconstruction. Notably, the most popular regularization method is the Tikhonov approach. Chapter II also covered the basic concepts of RTI, the use of Received Signal Strength (RSS), weight models, and shadowing effects to reconstruct an image for a Wireless Sensor Network (WSN) setup.

This research implemented a modified Maximum Likelihood Estimate (MLE) model to address the ill-posed problem resulting from the inversion of a non-invertible matrix. The proposed modified MLE technique utilizes a gradient decent method that guarantees the reconstructed image estimate is always positive. This concept was used for image recovery using a Poisson distribution in [24]. This constraint helps produce a solution with superior resolution. Chapter IV shows the derivation of the modified MLE and how the solution is always forced to be positive. For this research, a WSN was set up using 60 wireless transceivers spaced 1 foot (ft) apart with a total network perimeter of $18 \times 14 \times 4$ [L $\times$ W $\times$ H] ft^3 . Chapter III covers the methodology and metrics used to collect and process the data. The aforementioned WSN was set up in three different environments to test the robustness of the estimators for image reconstruction. The first environment was an open field with no obstructions; the second

environment was a densely wooded area containing various trees and bushes within the WSN; the third environment was in a residential neighborhood with the WSN set up around a playground made of dense plastic and metal. Performance was evaluated in all environments using three data sets. The data sets included 1) data with one single stationary target, 2) data set with two stationary targets and 3) data that consisted of one stationary target and one moving target. Furthermore, the processing time was calculated for each estimator.

The experimental results show that for a network with 60 transceivers using the traditional Tikhonov estimator, the average processing time, which included image reconstruction, was 0.94 s and was averaged over all three environments. The average processing time using the modified MLE process was 0.52 s. This shows that image updates for using the modified MLE can occur 1.81 times faster than the Tikhonov regularization estimator. Using the modified MLE allows the detector to process more frames per second to provide better target tracking capabilities within a given Area of Interest (AoI).

The main focus for this research was on improved image resolution and the modified MLE proved to be a far superior estimator for image reconstruction than the traditionally favored Tikhonov regularization method. Resolution is defined as the size of the pixel cluster calculated by the number of pixels across the $L \times W$ of the target's true position. In all three environments, the poorest resolution for a target produced by the modified MLE was $2 \times 2 \text{ ft}^2$ within an area of 4 ft^2 while the best resolution for a target using the Tikhonov estimator was $6 \times 3 \text{ ft}^2$ within an area of 18 ft^2 . In comparing these calculations of the poorest MLE image resolution for one target to the best target resolution using the Tikhonov, the modified MLE is still possess a target resolution that is 4.5 times better than the Tikhonov estimator. Overall, the modified MLE estimator's resolution was 7-8 times better than the widely used Tikhonov regularization

method. Introducing a second target caused the pixel intensities to decline, but the average image resolution was still preserved.

Different environments did have an effect on image resolution with the wooded area data sets having the poorest image resolution. Instead of having a target with one pixel of high intensity, the setting which contained a large amount of foliage in the WSN caused the RSS values to be distributed across multiple pixels and some of the pixels around the true position of the target to have higher intensities than the actual target's location. Having more obstruction in a WSN definitely decreases resolution and accuracy, especially when using the Tikhonov estimator. However, the modified MLE still had excellent resolution albeit location inaccuracies.

For moving targets, both estimators did poorly and it was difficult to track objects in all three environments. However, this could have been attributed to the lack of frames having moving objects in data sets. There wasn't enough frames to comparatively exploit characteristics for image resolution for the moving targets.

6.1 Future Work

Multiple and Moving Targets. Even though some experimenting on moving targets was accomplished in this research, having a larger data set with a moving target that included a known target path and speed of the target would aid in characterizing the capabilities of the estimator for moving targets would be beneficial. Furthermore, the experiments showed that introducing a second target reduced pixel intensity. Adding more targets to the WSN can test the MLE estimator limitations as the pixel intensity decreases due to multiple targets.

Adaptive Filtering. As seen in the wooded environment, more obstructions can cause artifacts and poorer image resolution for the reconstructed image. Advanced

adaptive filters such as the Kalman filter could minimize the effects of observation noise. Consequently, these filters could potentially improve target location accuracy and resolution [25].

Automatic Target Recognition. For this research the number of targets was known. When applying RTI for real-world applications the number of targets is likely to be unknown. Additionally, there may not be an observer available to visually analyze each frame. Implementing a program that estimates the number of targets within a frame would be hugely beneficial in both target location accuracy as well as computational cost [25].

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