Development of an Indoor Real-time Localization System Using Passive RFID Tags and

Artificial Neural Networks

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This thesis titled

Development of an Indoor Real-time Localization System Using Passive RFID Tags and Artificial Neural Networks

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ABSTRACT

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Radio frequency identification (RFID) technology is used for inventory and asset tracking because of its accuracy and speed. Currently, RFID tracking systems are being used to identify and locate tagged objects in indoor environments. In this research, received signal strength indication (RSSI) values are collected from off-the-shelf passive RFID readers and antennas to be used in conjunction with an artificial neural network (ANN) to create a localization algorithm for two-dimensional location estimation with a single tag. The aim of this research is to create a highly accurate real-time location tracking system to be used in a room with objects that create RF interference. Multiple linear regression is used as a benchmark method for comparison with artificial neural networks.

Approved: ____

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1 INTRODUCTION

1.1 Introduction to RFID

Radio Frequency Identification (RFID) was developed in the 1940's for use in military applications during World War II [1]. RFID is a form of automatic identification data capture that provides for visibility of shipped and received materials in the form of information technology. The technology was slowly developed in the 1950's and 1960's until the explosion of development in the 1970's. Los Alamos Scientific Laboratory and Northwestern University were just two of the institutions which researched the technology for commercial use in the 1970's. Studies were undertaken to investigate the potential developments of RFID in electronic toll collection, animal tracking, and factory automation [1]. While the 1970's saw the development of the intended applications of RFID, the 1980's saw the realization of the technology. The first major full-scale use of RFID was for toll collection in the transportation industry. Since the 1990's, the technology has become rooted in the manufacturing industry, the pharmaceutical industry, toll collection, animal tracking, and airline baggage tracking. Presently, RFID systems are used for a variety of applications in nearly every industry.

1.2 RFID Systems

Current uses of RFID technology are commonly implemented with a similar configuration. A typical RFID system consists of an RFID reader, an RFID transponder or tag, and one or more antennas connected to the reader. Figure 1.1 shows a typical RFID system as it is integrated with a computer system and therefore connected to the Internet.

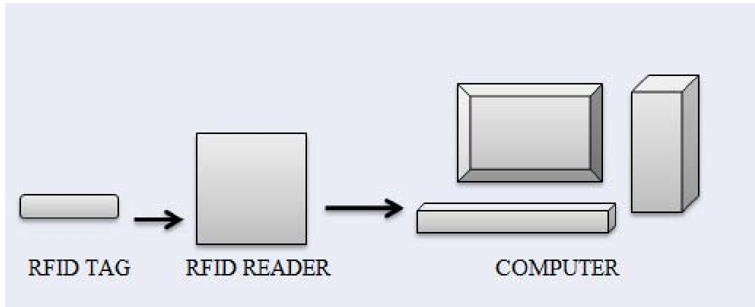

Figure 1.1: Typical RFID system

The reader's antennas transmit an RF signal. The tags emit a signal which is received by the reader's antennas. The reader then interprets the data collected from the tag usually in the form of a serial number. The tag stores a minimal amount of data (usually < 2 kilobytes) on the microchip. However, this data can relate back to a database which interprets the information. Software, known as middleware, supplies the information to a server linked to a database which has revolutionized the supply chain. RFID technology in the supply chain has enabled the internet to assist in the automation of the transfer of information about goods that are being shipped or received. Manual reads from hand-held devices or automatic reads from RFID readers stationed along dock doors or gateways can be used to read a tag in order to acquire information about the product or update the database with new information on the product. There are various types of RFID tags and RFID readers available commercially and these specific components of an RFID system are discussed in the next section.

1.3 RFID Tags and Readers

An RFID tag consists of a microchip connected to an antenna that allows the chip to transmit information to the reader in the form of a stored serial number. Data can be stored to or read from a tag multiple times or only once depending on the features of the tag. An antenna attached to the reader allows the chip on the tag to broadcast this information to an RFID reader. The reader deciphers the information received from the tag and the middleware interprets the information using a networked database. There are two major styles of tag design: active and passive. Active tags generally use battery power and possess their own transmitter to actively send out a signal which is obtained by the reader's antennas. Passive tags do not have a battery; instead, they rely on the power sent out by the reader's antennas in order to transmit. The source of power for a passive tag comes from the induction of current from the electromagnetic waves propagated by the reader's antennas. The passive tag is essentially dormant until it is activated by an RFID reader's signal.

RFID tags are manufactured in various sizes for applications experiencing normal to extreme environments, such as high humidity, high pressure, objects creating metallic interference, high temperatures, and absorption of signal due to liquids. Design considerations for tag size are constrained by the desired read range and the corresponding antenna size for that read range. A typical passive RFID tag is shown in Figure 1.2. The microchip is embedded in the center of the tag on the loop and the metallic components extending out from the chip comprise the tag's antenna.

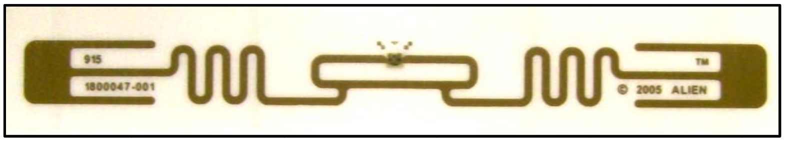

Figure 1.2: Sample passive RFID tag [2]

The cost of a tag is driven both by the intended application of the tag and the volume of the purchase order. Since active RFID tags have a battery and range from slightly expensive to very expensive depending on the size of the tag and the application, they are used for tracking valuable products and goods at longer ranges. Passive RFID tags typically cost less than 40¢ if purchased in high volume, with the lower limit being between 7 and 15¢. With the price of RFID tags reaching new levels of affordability, the tracking of goods along the supply chain can become economically feasible with both active and passive tags.

RFID readers differ in cost as well, depending greatly on the application and frequency range. The current UHF readers range from $500 to $2000 with exceptions [3]. The antennas which are connected to the reader also vary according to the manufacturer. The antennas used for this thesis cost approximately $150 per antenna. The sizes of the antennas vary from a few inches square, to 24 X 12 inches for common commercial antennas. The components of an RFID system can be used for a multitude of applications in manufacturing.

1.4 Real-Time Location Systems

Real-time location systems (RTLS) are used in manufacturing, distribution and warehouses in order to track an asset's location within the process. The location is monitored through enterprise resource planning (ERP) or warehouse management systems (WMS) software packages in order to estimate work in process (WIP) levels [4], monitor logistics operations, or provide information for supply chain management. A manufacturing system equipped with asset tracking systems can provide vital information to decision support systems or to the decision makers directly, in order to minimize inventory and remove inefficiencies in a process. These RTLS systems can be composed of RFID technology, Wireless networks, GPS systems, Infrared, barcodes, or a fusion of technologies.

1.4.1 Barcodes

A barcode label is a 2-dimensional code that is read by an optical scanning device. Barcodes are a very low cost form of tracking for high volume items inside or outside; however, they rely on a visible line-of-sight from the scanner to the barcode label. Therefore, an object has to be manually scanned or the object must be moved in front of a scanner to allow the position to be known relative to the scanner. Barcodes contain data similarly to RFID tags in that they employ a serial number to relay information to a database; however, data cannot be written to a barcode label.

1.4.2 Wireless and GPS

Wireless systems provide accurate tracking solutions in both indoor and outdoor environments using both active and passive RFID tags. Wi-Fi (Wireless Fidelity) systems consist of wireless access points and network cards. The position of the object is calculated by using the known positions of the access points to triangulate the position of the object which is tagged. Global Positioning Systems (GPS) measure the time it takes a signal to travel from a satellite to a receiver in order to calculate a 3-dimensional global position. This technology is well suited for tracking assets being transported by truck, rail, or ship due to the extremely long ranges of transportation. GPS systems are limited to outdoor environments due to the scatter of the microwaves on the roofs of a structure or building.

1.4.3 RFID

RFID is used in information technology due to its accuracy, speed, and omnipresence. It is useful for the nearly instantaneous identification of a tagged object that may or may not be in the visible line of sight of the identification system. RFID is used to identify objects much in the same way barcodes are used to identify objects with an accompanying serial number; however, the major difference lies in the proximity of the system to the object and the need for line-of-sight. The ability of an RFID system to identify an object quickly through a vision-obstructing surface gives an enormous advantage over barcode technology. With a customized RFID system, advances in the technology have allowed a location to be inferred along with the identification of the object using relative signal strength indication (RSSI) values. This feature is not possible with barcode technology. The ability to both identify and locate an object simultaneously provides increasingly useful information to those responsible for the assets.

1.5 Potential RTLS Systems

Current real-time location systems rely on pervasive wireless systems and/or active tag hybrid systems to constantly declare a location. Consequently, due to the high cost of active tags and limitations of other technologies such as GPS indoors, passive

RFID tags could potentially be used as a replacement for asset tracking solutions for low-cost assets using commercial off-the-shelf RFID equipment in an indoor environment. The location tracking system proposed in this research aims to provide an accurate low-cost adaptation to the current systems for products that are priced such that an active tag may be more expensive than the item to which it is applied. This research aims to reduce the complexity of the design of the location tracking system in order to reduce the time involved in setup, troubleshooting, and maintenance. This research also seeks to estimate the indoor position of the assets using methods other than triangulation or trilateration to further improve the predictive accuracy of the location tracking system.

1.6 Localization

A localization algorithm is a mathematical model that estimates the position of an object given input data such as signal strength, distances, or angles. Aside from the switch to passive tags, this system predicts the location of the tag based on RSSI values rather than varying the power levels of the antenna to estimate a position. In addition, there are not multiple access points to triangulate position as used in current Wi-Fi systems. Thus, the location of the tagged object is estimated based on four RSSI values extracted from the reader.

1.7 Machine Learning

Machine learning methods, specifically artificial neural networks (ANN), are used to model the data output of RSSI values from the reader. Machine learning is a form of artificial intelligence in which computer algorithms are used to optimize the parameters of a mathematical model through training with example data [5]. The mathematical model generated in this research provides an accurate estimation of the location of the tagged object using signal strength as the example data. After the system is created and tested in an empty space, it is subjected to static interference from metal and human sources in the vicinity of the tag in order to create a more realistic indoor environment. The signal strength is expected to be affected in the vicinity of the static metallic interference [6]. Thus, the model must be able to offset this interference.

1.7.1 Artificial Neural Networks

An ANN model is capable of predicting the location of the object in a test space with interference, even if one or more of the antennas are unable to read the tag at a certain location. The inherent advantage of ANNs to make predictions with non-linear data or missing values is the reason for their use rather than multiple linear regression. The ANN methodology is compared to multiple linear regression in this thesis. In addition, smoothing of the datasets with moving averages is considered in order to provide a more accurate model.

1.8 Thesis Objective

The objective of this thesis has dual purpose: the development of an accurate low-cost location tracking system and a comparison of the methods of creating the localization algorithm used in the formation of artificial neural networks and statistical models. This thesis will determine the best methodology to be followed to create a highly accurate localization algorithm. Artificial neural networks will be compared to statistical methods in order to provide a robust solution. The accuracy of the system is obviously important; however, design consideration will be given to the setup time, the cost of the equipment, and the ease of setup and maintenance. Real-world applicability is a major objective of this thesis; however, the implementation of the algorithm into software will be only briefly examined.

1.9 Thesis Organization

This research is divided into 6 sections: Section 1 introduces RFID tracking systems and artificial neural networks and details the areas of need for location tracking systems. Section 2 provides the history of current and previous RFID tracking systems and provides details of the methods used to create the localization algorithm. Section 3 illustrates the methods used in this thesis to create a location tracking system for the processes of data collection, data analysis, and construction of the predictive model. Section 4 presents the results of the construction of the model. Section 5 discusses these results and compares the results of the various methods. Section 6 offers a conclusion and provides avenues of future research.

2 LITERATURE REVIEW

This section presents the history of RFID applications, an introduction to various real-time location tracking systems and the technologies that drive them, and an introduction to localization algorithm construction techniques using statistical analysis as well as artificial neural networks.

The real-time tracking of people or objects has been an area of research for many years. As the technology has improved, the solutions have become more sophisticated. An early location-aware system was designed in 1992 to determine if a telephone receptionist was available at his or her station by means of a badge which emits a signal that is picked up by sensors [7]. Additional location systems use technologies such as Wi-Fi, Sonar, Infrared, GPS, and RFID to send and receive signals to locate the position of an object [8]. Each of these technologies has been researched in order to determine the feasibility of the technology for a location system in a certain environment. Each technology has advantages and disadvantages in the form of cost of setup and accuracy in proximity to obstacles or interference. Radio Frequency Identification (RFID) is an emerging technology used for reliable and accurate identification of tagged objects in reasonably close proximity. RFID is used for many tracking applications; however, it is more commonly used for applications such as: inventory tracking, supply chain management, asset tracking, document tracking, libraries, psychiatric patient tracking, tollbooths, livestock tracking, passports, and pet tracking [9] [10] [11] [12].

2.1 Onset of RFID

The advancement of the RFID industry occurred rapidly in recent years due in large part to governmental pressures and retailer's mandates [13]. The recent explosion of RFID implementation has been attributed to a host of factors, however, a major push in the supply chain occurred because Wal-Mart mandated its top 100 suppliers to tag all pallets and shipping crates by January 1, 2005 and the next 100 suppliers to do the same by January 1, 2006 [12]. RFID technology has been researched and developed because of the mandates adopted by both Wal-Mart and the Department of Defense in order to have all suppliers tag their products at the pallet level [14]. RFID also has roots at the Auto-ID Center at MIT, where the technology was developed to be a major contributor to the networking of the supply chain [15]. The influx of RFID use has made research with the technology possible for smaller universities and businesses as well. The increased availability of the technology in turn has made it more cost effective to use in real applications and research opportunities. The main advantage is its ability to identify an object without requiring a direct line of sight as in barcodes, while also being able to store and read data from the tag affixed to the object. While this is still the major advantage of RFID over barcodes, RFID has its own limitations in the form of RF interference [16]. Most current applications use RFID technology to simply identify an object in order to track something in terms of presence or absence in an area or to determine if an object has passed through a gateway [17]. The position of the tagged object is only known in terms of which room or area contains the tagged object. In other words, location is only known by the locale of the system, such as a dock door, storage room, conveyor system, or gateway. Lately, however, RFID systems have been used for more precise location applications like real-time location systems (RTLS) or tracking systems [8] [18] [19].

2.2 Location Tracking Systems

RTLS systems use different technologies to compute the location of a tagged object in an indoor environment. The systems can be used to track the RFID tags relative to stationary readers [19] [20], or with stationary, RFID reference tags that are read by material handling integrated automatic readers or mobile, handheld readers [18].

2.2.1 Wireless Systems

Current real-time location systems, such as Wi-Fi systems, pervasively emit a signal that is picked up by access points. A Wi-Fi location system has a multitude of environmental factors that can negatively affect the accuracy, such as humidity, metal objects, and people in the RF field as well as the need to conduct a lengthy site survey to calibrate the system [21]. The site survey consists of teaching the system by traversing the tagged object throughout the areas where the tag is read by the system, in order to define the boundaries of the space. Wireless systems are effective for location tracking systems and provide good accuracy, however, the cost and energy consumption can be considered a limitation. One proposed wireless system uses a wireless local area network (WLAN) and discriminant-adaptive neural networks to approximate position with received signal strength values to achieve great accuracy [22]. The need to retrain the system could arise if the environment changed significantly. Therefore, this system would not work well for a dynamic application with sources of interference constantly being moved around because of the need to perform the extensive site survey periodically. While the accuracy of a wireless system is sufficiently accurate in a static environment, the limitations in terms of the interference can be overcome by using a system that combines the benefits of multiple technologies.

2.2.2 Hybrid Systems

Hybrid systems can combine technologies to both create a concurrent system and overcome the deficiencies of each individual technology. One such hybrid, location-aware system integrates Wi-Fi, Infrared (IR), and RFID technologies to interact with mobile devices (PDA) to communicate the physical location of an object using both passive and active RFID tags. The system uses mobile, hand-held readers for identification rather than mobile tags to predict location [23]. Another hybrid system alters the prediction of the location of the object using regression analysis in order to apply an offset to the prediction when there are modifications to the indoor environment [24]. Therefore, these hybrid systems have combined technologies to improve the prediction when the object is located near a source of interference. The major limitation with the hybrid systems is the increased expense of the extra technologies, as well as the cost of integration and maintenance.

2.2.3 Active RFID Systems

RFID location systems can be implemented in a more cost-effective way than the hybrid systems; however, the RFID systems may not be as well equipped to contend with the interference in the indoor environment. RFID technology has limited effectiveness in the vicinity of metal and liquids due to interference and absorption of the RF signal [6]

[25]. The LANDMARC system attenuates the power level to create distinct ranges of distances with active tags [26]; however, the issue with this system is the time it takes to cycle through the power levels. Hospitals have attempted to track medical devices using active RFID tags with positive results depending on the equipment tested [27]. The research alludes to the cost of the tag as the determining factor as to whether a passive or active tag is suitable. The study concludes that passive tags are better served for use with more inexpensive items, while the active tags are reserved for more expensive items that require a wider read range.

Aside from the different methodologies to judge distance in the current RFID location tracking systems, there are also differences in the tags. Active and passive RFID tags differ in the method by which the signal is transmitted and received. Active RFID tags contain a battery that emits a signal, while passive RFID tags are activated by the reader's antennas and therefore does not require a battery.

2.2.4 Passive RFID Systems

Since passive tags do not need batteries, manufacturers are able to make them smaller and with reduced cost to the consumer. Using passive RFID tags is an alternative to the more expensive active tag location system. Passive RFID tags do not contain a battery and therefore are cheaper to use for such an application because they are more expendable. One RFID-based location system uses passive RFID tags for construction projects in order to locate non-metallic items accurately that are hidden beneath the ground [28]. An additional method proposes the use of passive RFID tags embedded along the walkways in a building to act as a guide to people with a visual impairment in order to navigate large buildings such as airports or offices [29]. The current active RFID systems provide good solutions for location; however, the performance of these systems can likely be improved with the use of passive RFID tags in terms of cost and received signal strength indication (RSSI) values in terms of time.

2.3 Localization Algorithm

Location tracking systems use varying methods of prediction regardless of the technology used to collect the data. The potential for RFID systems to predict the location of an object depends on the method of inferring distance, which varies among the existing location systems. One way to estimate signal strength with RFID tags is to *attenuate* or lower the power level of the antennas in order to find at which power levels the tag can be read in order to estimate a perceived distance [30]. An additional paper suggests the use of mobile readers and passive reference tags that rely on random sampling to provide the algorithm for the prediction [31]. Artificial neural networks (ANNs) are used with the current location tracking systems in order to create a model that approximates the position of the object. ANNs are considered to perform as well as regression with consideration to the limitations and benefits under certain circumstances [32] [33]. Since the signal strength outputs in this project are expected to be non-linear in the proximity of the sources of interference, the application of ANNs provide better potential to model this data output. RSSI values have been used in location systems to predict location [34]; however, most of them use other means of prediction than ANNs such as triangulation or trilateration which is based on time difference of arrival or time of flight calculations [35] [36]. A new functionality in the Alien® RFID Developer's kit provides an RSSI value that does not estimate power levels as the previous methods used. This new feature paired with the ability of artificial neural networks to model noisy data has potential for an RFID location tracking system that takes the RSSI values from the antennas as the input space and predicts an output that is the location. Predictions can be formulated using statistical methods, machine learning, expert knowledge, or heuristic methods.

2.3.1 Regression

Multiple linear regression estimates a line to minimize the sum of the squared error using multiple inputs to produce a single output [37]. Regression approximation models are used to estimate an output with a linear function. The linear function minimizes the error between the sample data and the regression line. The capability of multiple linear regression to fit a line to a set of data is the central reason for its use in localization algorithms. In this thesis, the RSSI values are not linearly proportional to the distance. For this reason, artificial neural networks are proposed to predict the location of the tagged object.

2.3.2 Artificial Neural Networks

The disciplines employing artificial neural networks to make predictions and generalize relationships include but are not limited to: geology [38], sports [39], pharmaceuticals [40], and aircraft engines [41]. An ANN is an adaptive network of inter-connected weights consisting of processing elements or neurons that generalize or classify patterns and relationships between inputs and outputs through a process known as training [42]. ANN learning is intended to emulate the functions of neural processing in the brain using sample data in order to learn the relationships between the attributes and the outputs. ANNs modify the set of weights of a discriminant function in order to minimize the mean square error of the response during training iterations. The number of processing elements in the network determines the dimensions of the discriminant function as well as the number of inter-connected weights of the network. A sample artificial neural network is shown in Figure 2.1.

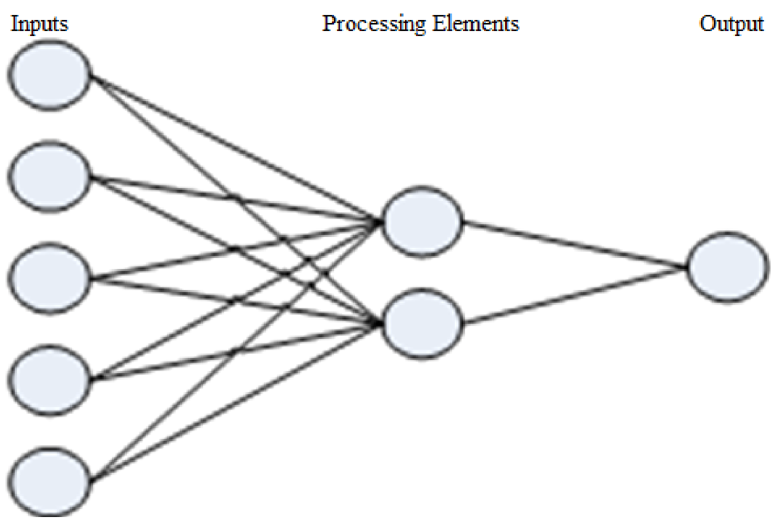

Figure 2.1: Sample artificial neural network structure

Figure 2.1 shows an ANN with five inputs and two processing elements contained within a single hidden layer. The training algorithm of the network determines which of the nodes of the network are connected and which error criterion is used [43]. Each line represents a weight that is associated with the corresponding connection in the network. A single iteration through the training algorithm is known as an epoch. The training set is a subset of the data which the ANN uses to learn the relationships between input and output response. The data can be further divided into a testing and *cross-validation* subset. The testing set is a portion of the data saved for the purpose of testing a trained model. The instances have not been learned by the network; therefore, they constitute a blind sample capable of determining the predictive power of the model. In order to prevent the network from merely memorizing the set of instances and the corresponding outputs in the training sample, a cross-validation data subset is also set aside in order to prevent *overfitting* of the model. Essentially, training the model without cross-validation yields a model which accurately predicts the data the network has previously seen without interpolation or extrapolation. Cross-validation acts as a constant check of the capability of the network to predict an output that has not been seen by the model [44]. If the model is not validated by training with the cross-validation set; then, the results would resemble the upper curve shown in the graph in Figure 2.2.

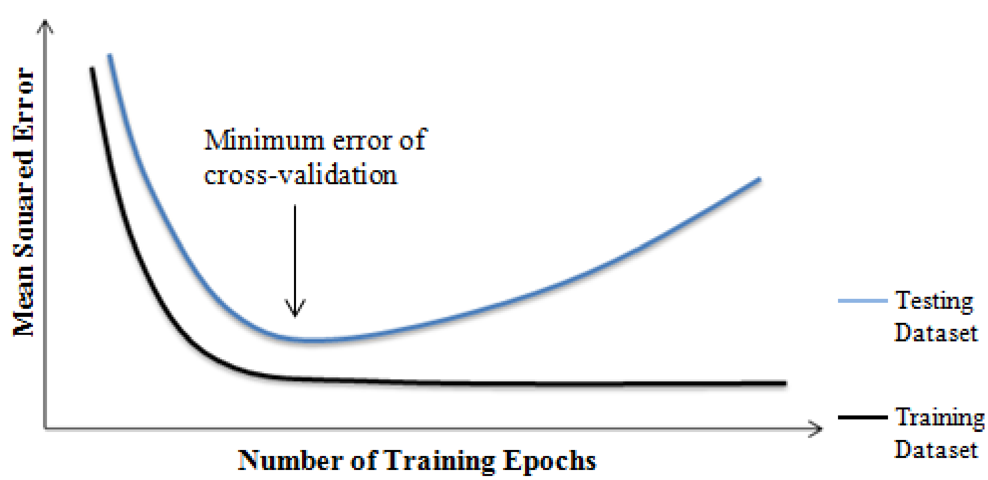

Figure 2.2: Cross-validation & training versus only training set [42]

The training set if left unchecked will worsen the model's capability to generalize the test dataset after a certain number of training iterations. With a cross-validation training dataset, the result continues to improve the model's capability to predict the testing dataset when there are more training iterations. The best network is determined by assembling the network with the weights from the point at which the cross-validation has reached a minimum error. This point corresponds to the culmination of the model truly learning the data rather than memorizing the outputs for the given samples. At this point the model is no longer permitted to train in order to prevent overfitting and encourage generalization.

2.3.2.1 ANN Topologies

Despite many ANN methodologies, this thesis focuses primarily on the multilayer perceptron (MLP) classifier networks. The multilayer perceptron is a feed-forward network that utilizes back-propagation to execute training across multiple layers [42] [43]. The models in this thesis employ the conjugate gradient learning rules. The learning rule was developed in the 1950's in order to find a solution for a sufficiently large system of simultaneous equations [45]. The rule starts with an arbitrary solution and iteratively improves the result by seeking to reduce the error. There are countless methods of error reduction used for ANN training; however, this thesis is restricted to the conjugate gradient.

2.3.2.2 Knowledge Extraction

Parameters, such as number of processing elements, hidden layers, training length (epochs), transfer functions, and learning rules can all be varied as well as network structures and inter-connections in the network in order to create ANN models for datasets of varying size and dimensionality. The patterns found by the ANN can be used for knowledge extraction in the form of weights used to create a discriminant function that satisfies the relationships distinguished by the training iterations. The relationship between the algorithm and the human knowledge of the system may not be comprehensible or transparent, but the hidden layers of the network are capable of producing a model with high accuracy. The lack of transparency is an acknowledged limitation of artificial neural network models, often referred to as *black box* models [46]. This distinction is made because of the lack of transparency in the calculations made within the model. It is also critically important that the integrity of the network not be compromised when the model is extracted to a simpler function, or else the accuracy of the network is irrelevant.

2.4 Summary

RFID technology is well-suited for an application in location tracking since it has been utilized with this main function for many years. The issues with RFID around interference can be overcome using machine learning methods. Since artificial neural networks can be used to generalize relationships and find patterns in datasets, RSSI values are used due to the simple methods of collection from the RFID reader. In addition, the location of the object can be predicted using the algorithm extracted from the ANN model. Table 2.1 summarizes the advantages and disadvantages of the current location systems. The hybrid systems include Infrared, Wi-Fi, and RFID.

Table 2.1: Limitations and benefits of current RFID location systems

RFID Location System	Benefits	Limitations
Active RFID	Great accuracy, good read rates, good range	Expensive tags, issues with interference
Hybrid(Infrared, Wireless, RFID, Handheld readers)	Technologies mesh to overcome obstacles, good accuracy	Can be very complex to integrate technologies, expensive to implement and maintain each of the technologies
Wireless	Good accuracy, Dual purpose technology	Expensive to implement and maintain, issues with interference
Passive RFID	Great accuracy, minimal cost for tags, good read rates	Unproven, issues with interference

Table 2.1 shows that each technology is capable of producing accurate results for a location tracking system; however, certain technologies are better suited for applications with interference. Passive tags are better suited for tracking items with high volume, low cost, short shelf life, or objects which the tag becomes part of the finished product such as an embedded tag due to the low cost of the tags. A passive RFID tag system is explored in this research due to the inexpensive nature of the tags and the potential for increased use near interference in the future.

3 METHODOLOGY

The following section outlines the methodology of the creation of a passive RFID location tracking system. The system aims to predict the location of a tagged object in a normal sized room with local, static interference. The development of the system requires the completion of an initial site survey to collect data with a tagged object located in various spots in a room. The collected data consists of a relative signal strength value from each of four antennas and the x-y coordinates of the measured location within the room where the tag was located. This data is subsequently partitioned into training, cross-validation, and testing data subsets for the creation of an artificial neural network. RF interference, due to absorption and reflection from human and metallic sources, is introduced to the system, resulting in four total arrangements. Ultimately, a localization algorithm is extracted from the network weights in order to give an accurate x-y prediction of the location of the object for the various arrangements. The following sections detail the equipment used in this system, the procedure of data collection, the arrangements during the data collection, and the creation of the predictive models for the different arrangements.

3.1 Equipment

The proposed system consists of an Alien 9900 915 MHz RFID reader, four circular Alien antennas, and an Alien squiggle tag, which is a Class 1, Generation 2 tag as shown in Figure 3.1.

Figure 3.1: Equipment used for this system provided by Ohio University's Automatic Identification and Data Capture Laboratory [47]

Additionally, in order to perform the data collection, a laptop, tape measure, and tripods are necessary if the antennas are not intended to be mounted permanently. Ohio University's Automatic Identification and Data Capture Laboratory provided the RFID equipment used in the data collection for this research. Because of the functionality and features of the Alien 9900 and the simplicity desired for this system, four antennas suffice to provide enough RSSI values to create an accurate model in a normal sized room.

3.2 Test Space

This system has been developed for a typical room with square sides approximately 16-20 ft. on each side due to the constraining length of the coaxial cord and the read range for most passive tags. For a room of this size, the standard issue wire connectors for the Alien antennas are capable of creating up to a 20 ft. square without stretching the wire connectors excessively. For larger applications such as a large office building or warehouse, the system would either have to be duplicated adjacently or altered in some way to add more antennas as shown in Figure 3.2.

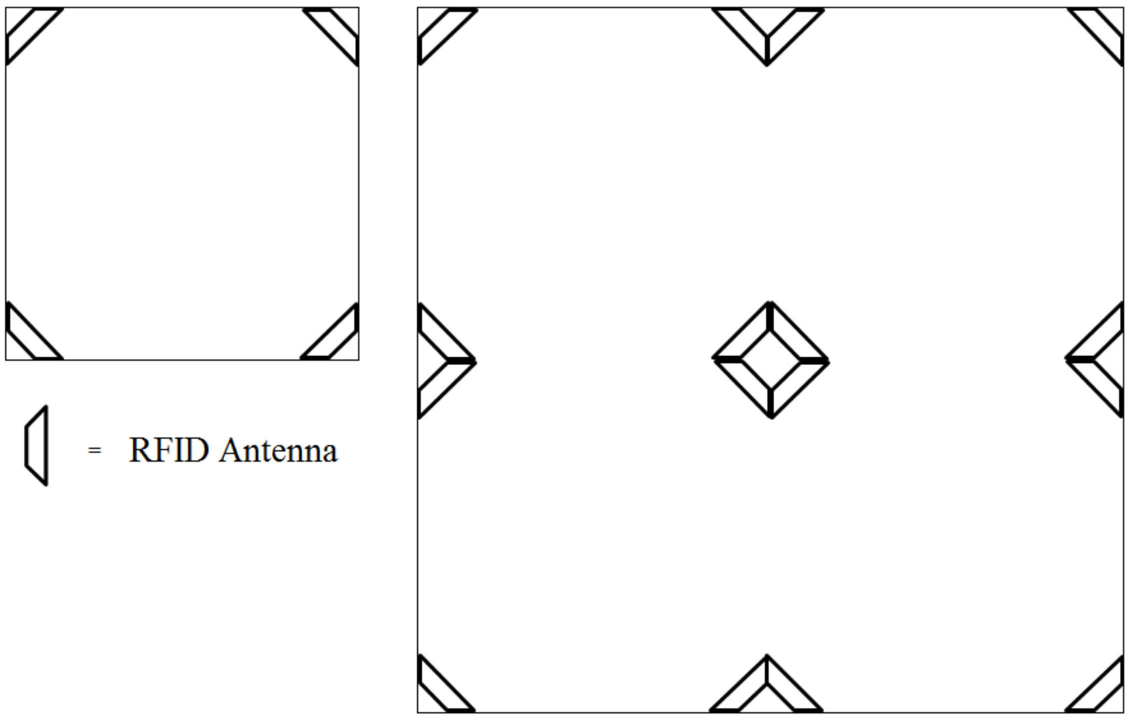

Figure 3.2: Small room versus large room with replicated system

A square space with no obstacles initially provides both a good benchmark for data collection and an opportunity to examine the most promising arrangements of the antennas, the best-performing tags, and the most consistent antennas in order to achieve good read rates and consistent read strengths at similar locations. The arrangement of the antennas, type of tag, and selection of antennas has been determined by testing which is included in the results section of this paper. The following section outlines the methods used in order to collect the data for this system.

3.3 Data Collection Methods

The data collection is the major task involved with the development of the procedure to create an RFID location tracking system. Numerous trials were undertaken in order to tune the process of collecting data efficiently and accurately. An initial, planning phase data collection showed proof of concept and allowed for the creation of models to test the accuracy of the RSSI value predictions.

3.3.1 Proof of Concept Phase Data Collection

Initially, the system was developed for a 12’ by 12’ room in order to provide feedback for subsequent system improvement. The setup of the antennas is shown below in Figure 3.3 with the antenna’s location shown in the corners of the space. The four antennas are placed in the corners of the space, pointed at its center. The black rectangle represents the tagged object in the grid being read by the reader for the empty test space. The shades of colors of the RF field generated by each antenna are varied in order to show that each antenna is independently and simultaneously reading the tag in the space.

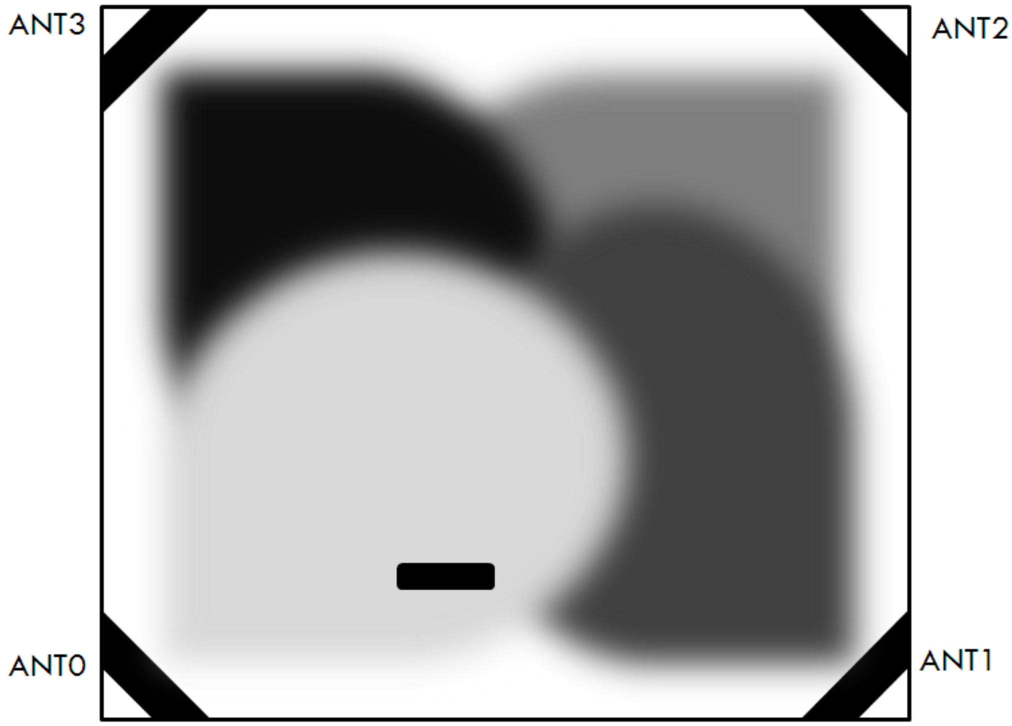

Figure 3.3: Layout for the collection of training data for proof of concept phase

The orientation of the tag, relative to the antennas, was consistently facing the same direction. In addition, the tag was consistently suspended above the ground on a PVC stand at approximately the same height as the antennas to ensure that the tag is along the same plane. In order to maintain accuracy of measurements, a gymnasium with 12 inch tiles provided an accurate grid without the need for time-consuming measurement between readings. In order to allow for an accurate prediction, RSSI values are collected evenly across the test space.

3.3.2 Data Collection

A random generated list was used to determine the locations in terms of x and y that were tested within the test space. The list of positions tested for each of the arrangements is shown below in Table 3.1. Throughout this thesis, the origin (0,0) is referring to the lower left corner of the test space.

Table 3.1: Random locations tested for data collection

X (ft.)	Y (ft.)	X (ft.)	Y (ft.)
17	0	1	11
12	0	20	11
2	1	8	13
2	2	6	14
15	3	9	14
2	4	12	15
4	4	11	15
5	5	4	16
14	5	16	16
1	5	4	16
18	7	5	16
0	9	6	17
18	9	2	18
14	9	16	19

The random locations serve to define boundaries of the test space for the predictive models. The number of locations to be tested was chosen based on the amount of time needed to perform the data collection. The intention was to limit the time needed to collect the data. Figure 3.4 shows the distributions of the locations in which the tag was tested in order to collect the data for the initial model without interference. The shapes in the space represent the locations tested in the grid.

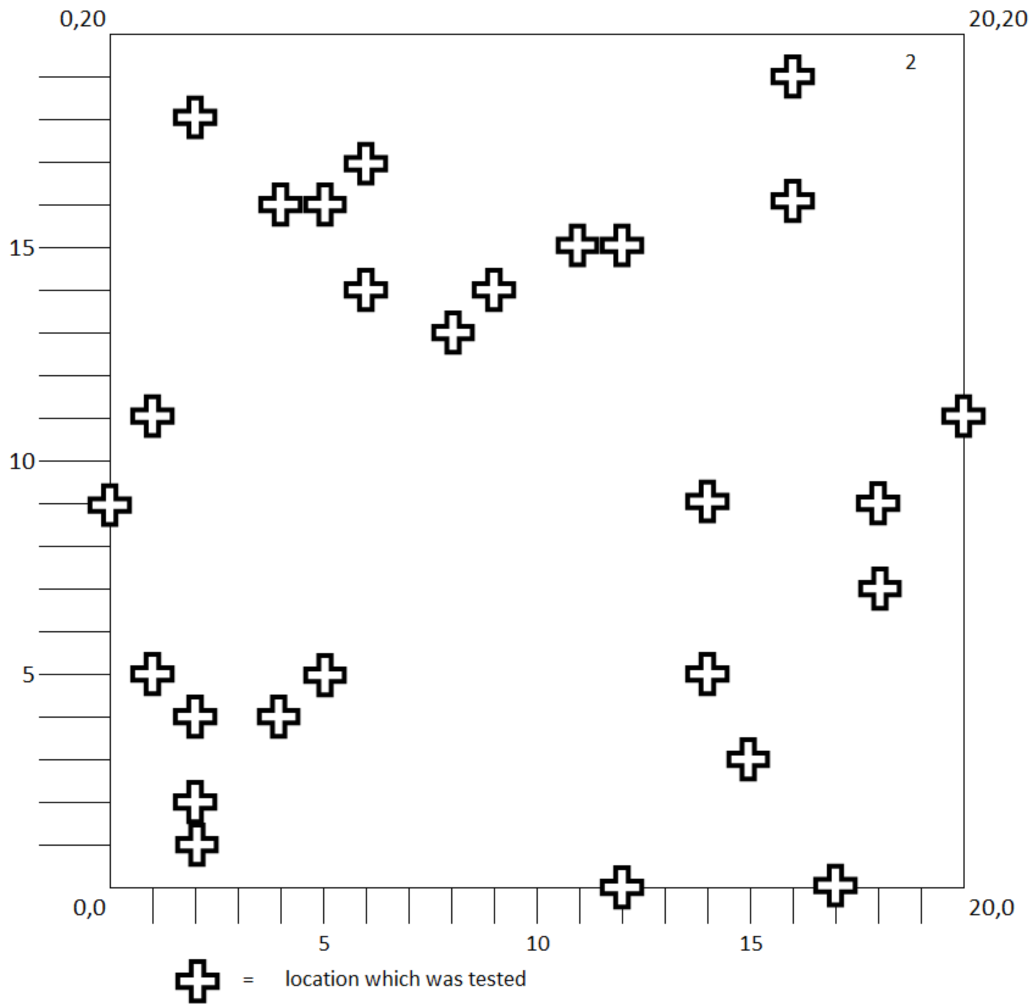

Figure 3.4: Orientation of antennas and placement of tags for the collection of data in an empty room

The initial data that was collected during the proof of concept phase from the 12’ by 12’ empty space provided improvements and validation of methodology before the second wave of data collection. The changes were implemented throughout the remainder of the data collection. The data was wholly collected using custom software that logs a received signal strength indication value (RSSI) value from each antenna and links it to the measured location of the tag in the grid in terms of an x and y coordinate.

The tag is manually moved to a new location, the location is noted in the software and then the program is started. The software collects an RSSI value from each antenna for a selected number of cycles. Subsequently, the values are tabulated with their measured location into a text file. The antennas, while identical in model and type, do not necessarily have the same maximum RSSI value for a tag placed directly in front of them. This concern is not significant, however, since the model normalizes the data, essentially removing any effect that dissimilar antennas could have on the prediction. Additionally, at certain locations in the grid, such as along the edge of the test space, the tag simply cannot be read by one or more antennas. Whether it was the tag being outside of the angle or direction of one of the antennas or the orientation of the tag relative to an antenna in its field, the missing value in the tabulated data was represented by a zero for the model, since essentially there was no signal strength.

3.3.3 Data Collection with Interference

The data was subsequently collected with metal interference in the same 20’ by 20’ testing space. Figure 3.5 shows the placement of the tags and the location of the metal interference in the same test space.

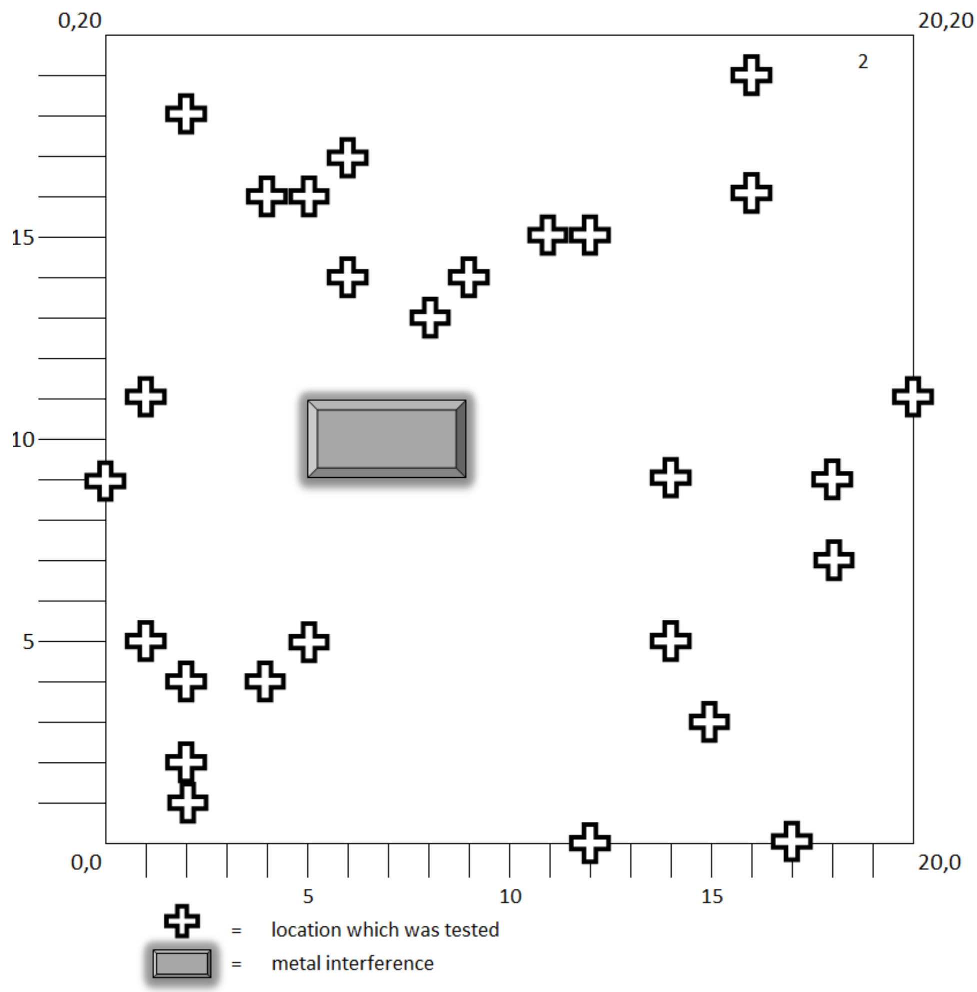

Figure 3.5: Placement of tags for the collection of training data with metal interference

The metallic interference consisted of a 12’ high metallic ladder covering a 4’ by 2’ area and 12’ tall. The values were collected at the same random spots as the empty grid for the sake of later comparison among spots and to compare like models. Data was collected at the same locations for the setup which consisted of human interference in the same location where the metal was placed. The similar placement, again, provides the possibility for the comparison of the effects of the type of interference on the nearby predictions. This scenario is shown in Figure 3.6.

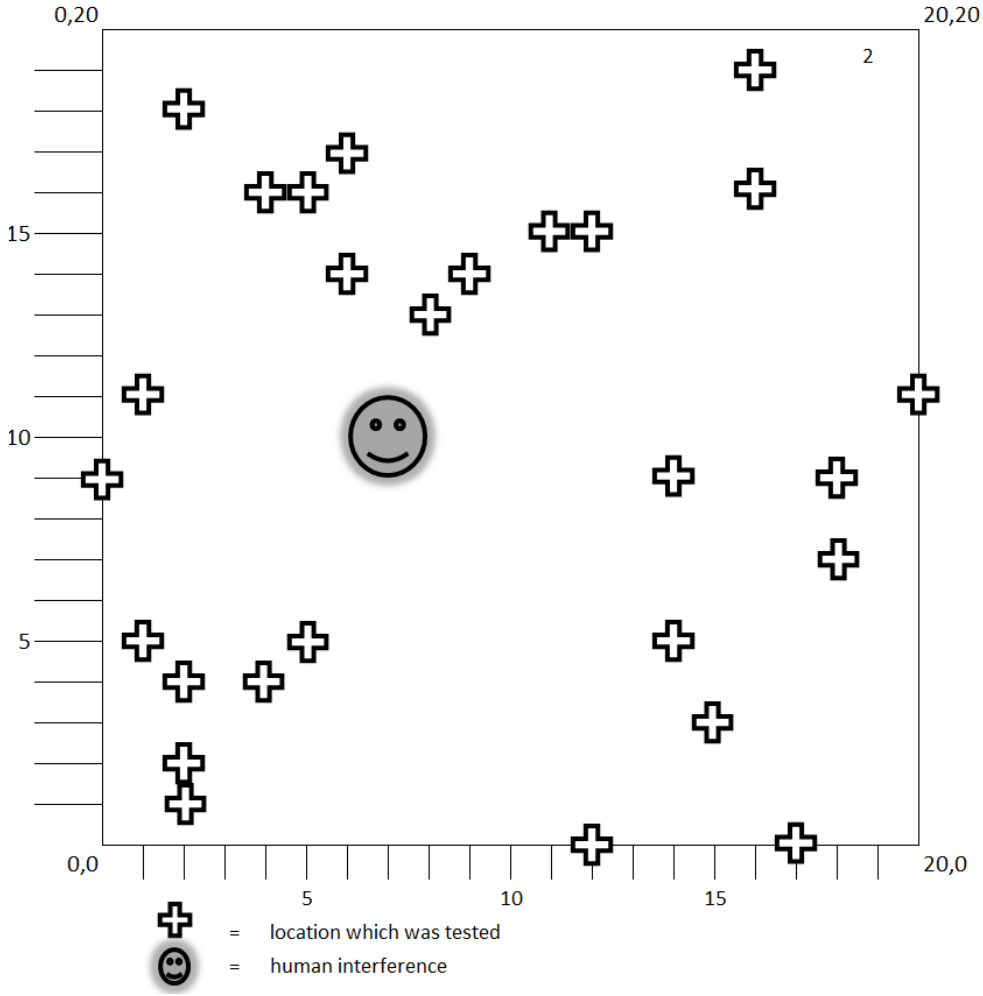

Figure 3.6: Placement of tags for the collection of training data with human interference

The human interference was located at the same spot as the metal interference for the sake of comparison between each of the scenarios as well as the empty test grid. The final scenario that was tested consisted of both human and metal interference. The metallic ladder was placed at the same spot, however; the human interference was located at (16,12). The scenario is shown below in Figure 3.7.

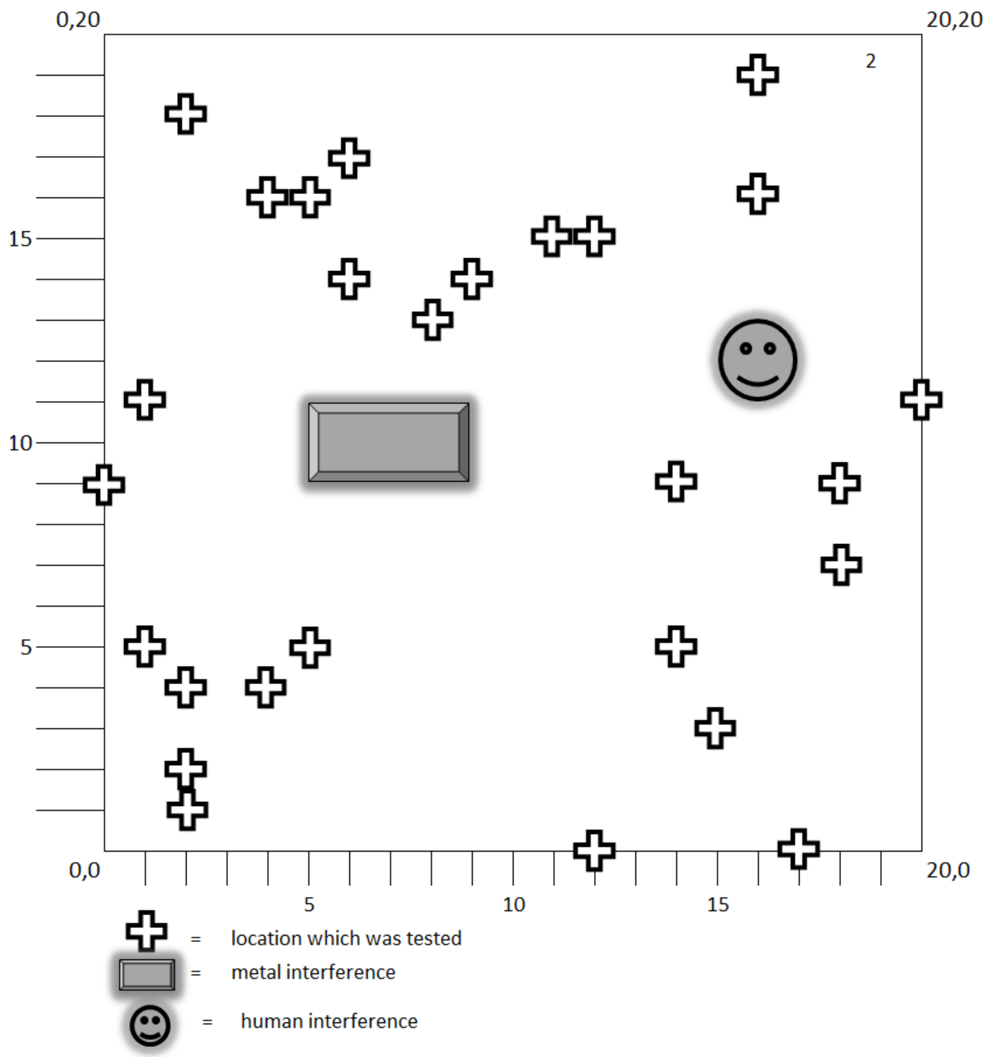

Figure 3.7: Placement of tags for the collection of training data with human and metal interference

The metal interference in this arrangement can be compared evenly with the arrangement with only metallic interference. The data collected for this thesis was completed in four hours for the process of tag selection, antenna selection, empty test space, human interference, metal interference, and human and metal interference. With four complete datasets, the creation of the mathematical models begins with data analysis.

3.4 Creation of ANN Model

3.4.1 Data Preprocessing

The procedure of pre-processing the data was minimal for the data collected for this system. The major concern with the data was the absence of the tag being read showing up as an empty space in the dataset. The replacement of the entry with a zero is adequate to fix this setback. Although the system is designed to predict the two-dimensional x-y coordinate that describes the location of the tagged object, the feasibility of dividing the room into small sections and changing the prediction to a classification model was considered. Ultimately, this method was ruled out because the x-y result is more favorable to give the model transparency and usability. As Figure 3.8 shows, classification may give better accuracy in terms of the prediction to a zone, but the practical use of this information is significantly better with the regression model result.

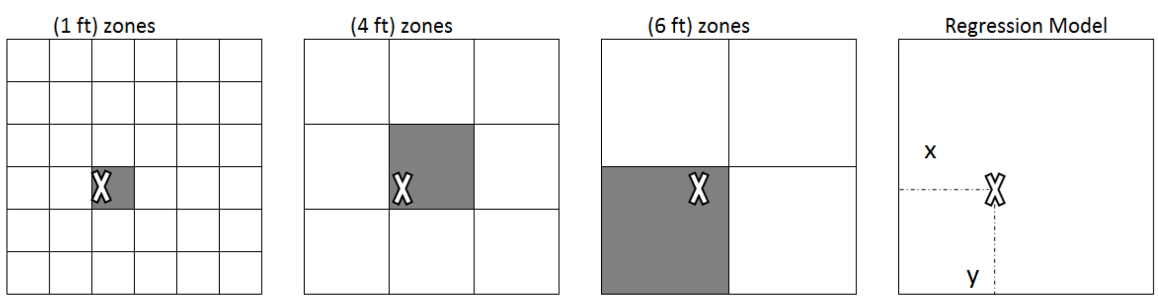

Figure 3.8: Tradeoff between the transparency of regression model vs. accuracy of classification model

Figure 3.8 shows four models with an accurate prediction of the tag's location. In order to give the model transparency and usability, the regression model gives the best result. In addition to the characteristics of the model, there are further differences in this system. Instead of attenuating the power sent to the antennas and determining distance by the mere identification of a tag at a certain power level as previous systems, this system estimates the location of the tag based on relative RSSI values extracted from the reader's software.

Traditionally, methods such as triangulation, time difference of arrival, or trilateration are used in positioning systems, such as global positioning systems (GPS), to calculate a position. However, this system uses machine learning methods to deal with the noisy, non-linear data output of RSSI values from the reader. An artificial neural network (ANN) is used to create a predictive model that generates a robust solution. The chosen ANN architecture was selected because of the model testing in the proof of concept phase with the 12' by 12' empty grid.

3.4.2 ANN Construction

A multilayer perceptron architecture was used in order to create a model that can be constructed quickly without sacrificing accuracy. By varying the number of processing elements from 2 to 24, hidden layers from 2 to 3, and learning rules (conjugate gradient or momentum); the best permutation has been assembled to satisfy the accuracy, time, and simplicity constraints of the system. The chosen ANN architecture is shown in Figure 3.9.

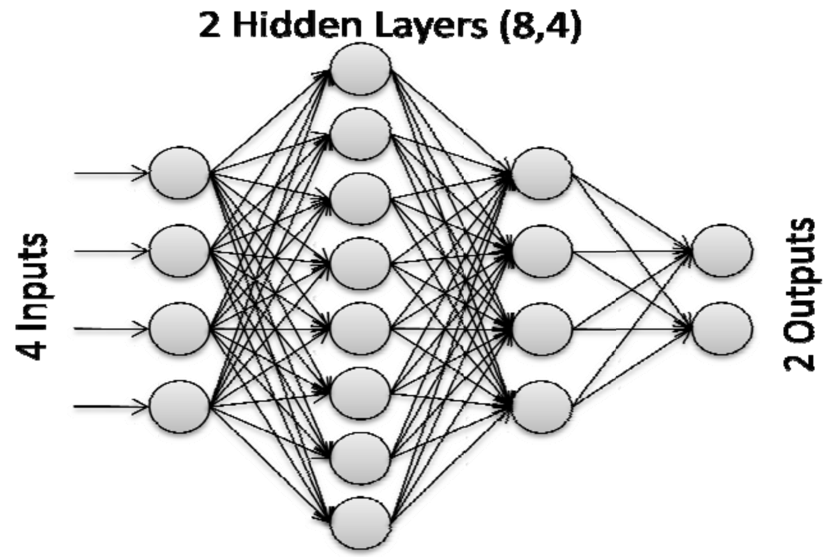

Figure 3.9: ANN architecture for the four models

Each of the models created in this thesis use a multilayer perceptron with a conjugate gradient transfer function. The network has two hidden layers with eight and four processing elements, respectively and uses a hypertangent activation function. Since the collected data was gathered in accordance with Table 3.1, each of the datasets was ordered by location. In order to train the model appropriately, the order of the data samples was randomized. With the randomized dataset, the first 60 percent of the instances were designated as training data, the next 15 percent as cross-validation, and the remaining 25 percent as testing data. The randomization is essential in order to create a mixture of locations within each partition and to prevent the model from training on a portion of the data and testing on another set of instances. Figure 3.10 shows the representation of the data as it was partitioned in each of the models.

Figure 3.10: Breakdown of the partitions of the datasets

The model was then trained over 30 iterations of 10000 epochs with the training being terminated if there were more than 400 epochs trained without improvement. After the 30 iterations of training, the model was tested for accuracy by generating a prediction of the testing dataset. From the ANN model, a localization algorithm is extracted and prepared for implementation in software to provide a visual representation of the room and its contents. A linear regression model is used as a benchmark method to compare with the ANN methodology. A model with good accuracy is imperative but the time required to build the model is also measured when choosing the final model. Ideally, this system will allow for quick calibration and training with an initial site survey.

3.4.3 Dataset Smoothing

The data was smoothed in order to generate datasets of a moving average of the collected RSSI values. The data was separated into averages and medians of 100, 50, 25, 10, and 5 instances separately in order to compare the median of instances and the average of instances. The averages and medians have a smoothing effect to further reduce the variation in the data. The method effectively reduced the collected dataset into an average or median of varying numbers of instances. For example, of the 100 instances at each of the 28 locations tested, the first 10 instances at the first location were averaged to create a new instance. This process was repeated until the data set was reduced from 2800 instances at 28 locations to 280 instances at 28 locations. Figure 3.11 gives a visual representation of the reduction of the dataset into the average of 5 instances.

RSSI value0	RSSI value1	RSSI value2	RSSI value3	X loc	Y loc	RSSI value0	RSSI value1	RSSI value2	RSSI value3	X loc	Y loc
646	1881	0	0	17	0	738.4	1937	467.8	0	17	0
635	1917	0	0	17	0						
792	1972	741	0	17	0						
745	1937	802	0	17	0						
874	1978	796	0	17	0						
584	1882	480	0	17	0	702	2076	614.8	0	17	0
545	1869	689	0	17	0						
797	2279	662	0	17	0						
738	2228	641	0	17	0						
846	2122	602	0	17	0						
488	2050	596	0	17	0	713.6	2096	602	0	17	0
924	2169	654	0	17	0						
777	2178	674	0	17	0						
882	2151	518	0	17	0						
497	1932	568	0	17	0						

Figure 3.11: Sample calculation of the reduction of the dataset into the average of 5 instances

Since the datasets were partitioned to training, cross-validation, and test datasets at the same proportion throughout all the models, the size of the datasets used to train the ANN were effectively reduced. For example, the model which considered the average of 100 instances used only 28 total instances for training, cross-validation, and testing. The test dataset itself contained only 7 instances, therefore the robustness of this model would likely be insufficient. Without collecting large amounts of data, it remains difficult to compare the model constructed with 100 average instances or more with one constructed from only 10 instances.

The models constructed with 100 and 50 instances were included in this thesis mainly to determine if the ANN could train on such a small amount of data and yield an accurate result. Since the data can be collected quickly (22-24 seconds to collect 100 instances), the prediction can be made using the average of a given number of instances. Therefore, the software solution would gather the given number of instances and make the prediction with the average of instances model.

3.4.4 Test Methods

The models in this thesis are compared using the coefficient of determination (R^2) to show the amount of variation that is explained by the model as well as the actual predicted error. The actual predicted error represents the distance the prediction was from the measured location in inches. Figure 3.12 shows the visualization of the predicted error that is used throughout this thesis.

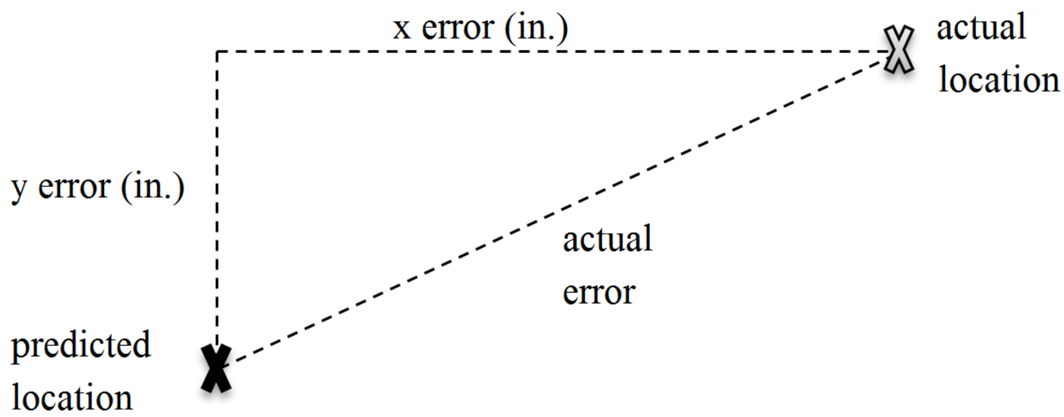

Figure 3.12: Calculation of actual error

This error was calculated by finding the error in the x coordinate and the y coordinate separately and then using the Pythagorean Theorem to find a radial error as shown in Table 3.2. Finally, the error measured in feet is converted to inches.

Table 3.2: Error calculation sample for the proof of concept phase model

X(ft.)	Y(ft.)	X_{pred}	Y_{pred}	$X-X_{pred}$	$Y-Y_{pred}$	sqrt{[X-X_{pred}]^2 +[Y-Y_{pred}]^2} (ft.)	Error(in.)
3	9	2.99829	8.89372	0.00170	0.10628	0.10629	1.276
9	3	8.97028	2.95718	0.02972	0.04282	0.05212	0.626
6	3	6.02409	2.92883	0.02409	0.07117	0.07514	0.902
6	9	5.85095	8.19217	0.14904	0.80783	0.82146	9.858
9	6	8.89959	6.11795	0.10040	0.11795	0.15489	1.859
…	…	…	…	…	…	…	…
						Average:	3.646 (in.)

4 RESULTS

This section provides the accuracy results of the system with each of the arrangements of interference and the results of the analysis used for the selection of antennas, RFID tags, and network parameter selection.

4.1 Evaluating Equipment for System Parameters

Prior to providing the results of the system performance, it is imperative to show the selection process for the equipment used for this system in terms of the available antennas and the numerous types of passive RFID tags. It is not sufficient to assume that the tags or antennas perform consistently without testing. The next section details the analysis used to determine the tag type and antennas that were selected for use in this system.

4.1.1 Antenna Selection

In order to evaluate the antennas, a test was conducted to determine which of the available seven circular antennas produce the most consistent results in terms of standard deviation. This test was conducted by placing the tag in the center of the 20’ X 20’ grid (10’ X 10’) with the four antennas in place in the corners of the space. Thus, the tag was placed at a comparable diagonal distance (14.14 feet) from each antenna in order to have an equivalent comparison of the four antennas being tested. Once the data was collected the remaining antennas were checked with the same scenario. The results of this test are shown in Table 4.1.

Table 4.1: Standard deviation of RSSI values for antenna selection

Antenna	Standard Deviation
#11	110.1
#21	138.6
#20	153.7
#10	178.9
#15	185.0
#5	196.9
#9	335.1

The table shows the four antennas with the lowest standard deviation: #11, #21, #20, and #10. These four antennas were used throughout the data collection process for all four arrangements. The available antennas used for this research vary in age and wear. The significant gap in the standard deviation is likely due to signal loss in a loose connector on the antenna.

4.1.2 Tag Selection

With the best four antennas in place, the available tags were tested with the same environment. Since RFID tags are designed for different applications and are tuned for different ranges, certain tags perform more favorably for a grid of a larger size. For this reason, the best antennas were used to determine the best tag for the environment. The passive tags were all placed in the center of the grid (x=10 ft., y=10ft.) one at a time in order to compare the RSSI values of the tags in terms of the standard deviation. The results of this analysis are shown in Table 4.2.

Table 4.2: Results of standard deviation values for tag selection

Tag Number	Standard Deviation
ABDD33B2DCA9021025050011	249.9
300833B2DDD7134135051111	207.3
100533A2BCC9015732056375	172.2
ABCD00000000000000030002	110.8

As Table 4.2 shows, the best performing tag clearly provided the most consistent result among all the tested tags. Although the selections for the tag and antenna are tailored to this system, the analysis conducted for this research could be repeated in order to compare available equipment. The models created in the next sections, with the exception of the proof of concept phase model, used the best performing tag and antennas found by this analysis during the data collection phase.

4.2 Proof of Concept Phase Model Performance

During the proof of concept phase, the data collection was conducted in much the same way as the latter stages. The major difference was the smaller grid (12’ X 12’) in comparison to the later grid (20’ X 20’). The results of the model created for the 12’ by 12’ empty space are given in this section. The ANN model was created with the proof-of-concept data in order to determine the optimum network parameters. The best ANN model for the proof of concept phase was a multilayer perceptron with two hidden layers of eight and four processing elements, respectively, utilizing a conjugate gradient learning rule and hypertangent transfer function. The model has good accuracy with an average prediction of 3.65 inches from the actual location for the 12’ X 12’ test space. Table 4.3 shows the results of the model parameter selection.

Table 4.3: Comparison of network architectures

Multilayer Perceptron - Learning Rule	# of layers / Processing Elements per layer	Error (in.)	Combined R2
Momentum	4-2	8.89	0.920
	8-4	4.54	0.964
	12-6	4.25	0.969
	24-12	4.08	0.970
	8-4-2	4.60	0.962
	24-12-6	3.79	0.969
Conjugate Gradient	4-2	8.82	0.924
	8-4	3.65	0.970
	12-6	4.07	0.968
	24-12	4.55	0.960
	8-4-2	6.71	0.955
	24-12-6	4.06	0.964

The construction of the model required approximately 20 minutes, including training with a conjugate gradient transfer function. The results of the network parameter selection for the initial data validate the use of the conjugate gradient learning rule with two hidden layers. The results of the proof of concept model were highly accurate; however, the larger space (20' X 20'), used for the four arrangements in the data collection required more analysis to provide an accurate estimate.

4.3 Model Performance for Different Arrangements

This section gives the results of the models created for all four arrangements. In the interest of space, several graphs and figures are given in the appendix. The four arrangements of interference are referred to as: Empty, Metal, Metal & Human, and Human. The 20' X 20' test space did not perform as accurately as the smaller grid, which was expected. However, considering the increased scale, the accuracy is proportionally similar. The results of the four arrangements are shown in Table 4.4.

Table 4.4: Model performance for the four arrangements of interference

Coefficient of determination	R^2	Empty	Metal@7X10	Metal@7X10, Human@16X12	Human@7X10
Full Dataset	X loc.	0.868	0.841	0.910	0.852
	Y loc.	0.928	0.908	0.938	0.916
	Avg R^2	0.898	0.874	0.924	0.884

Figure 4.1 shows the results of the model for the empty test space for a 20' X 20' square room using the full dataset for training. The distance between the points and the line represent the error for the prediction of the x and y components of the location.

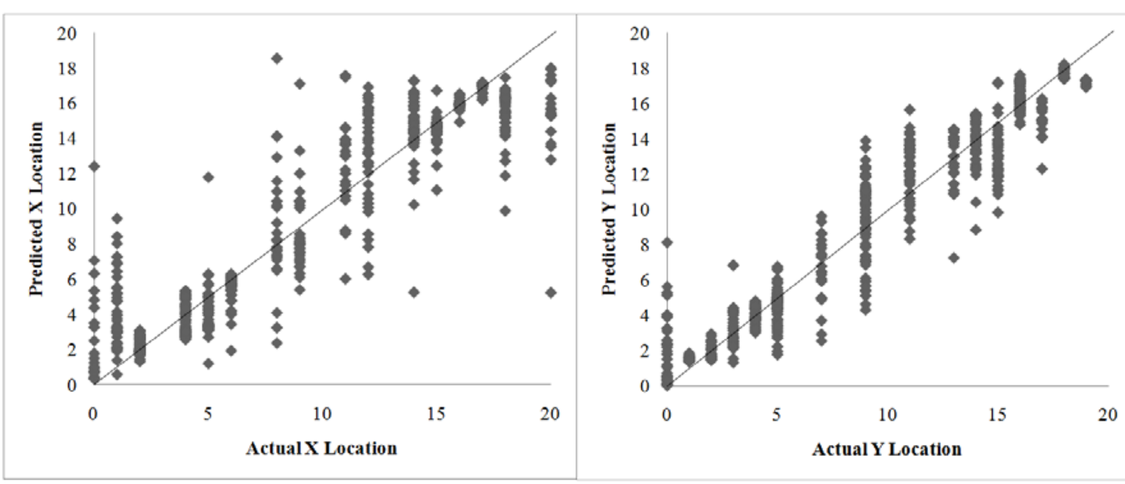

Figure 4.1: Predicted location vs. actual location for empty test grid (20' X 20')

The corresponding figures for the other three arrangements are provided in the appendix. Figure 4.1 shows significant variation for the empty test space. Therefore, the accuracy of the empty test space can be significantly improved by reducing the dataset into averaged instances.

4.4 Smoothing with Average Values

A simple method to improve the accuracy of the model was used with good results as described in the methodology section. The method involved reducing the collected dataset into an average of varying numbers of data samples. Table 4.5 summarizes the results of the models that were trained and tested using average instances.

Table 4.5: Summary of coefficient of determination for each of the models

R^2	Empty	Metal@7X10	Metal@7X10, Human@16X12	Human@7X10	Average
Full Dataset	0.898	0.874	0.924	0.884	0.888
Average 5	0.942	0.952	0.973	0.926	0.948
Average 10	0.948	0.972	0.979	0.954	0.963
Average 25	0.973	0.940	0.966	0.961	0.960
Average 50	0.931	0.949	0.961	0.878	0.930
Average 100	0.869	0.911	0.821	0.789	0.847

The results show that the models are increasingly accurate for an increasing number of averaged instances up to a limit for all levels of interference. The positive effect of the smoothing begins to decline after an average of 25 instances, due to the lack of a large sample size. At each location, 100 RSSI values were collected from each of the four antennas. Therefore, the average of 100 instances creates only one new instance to be in the reduced dataset. Since the reduced dataset only contained 28 instances, with the partitioning of the data, there are only 7 instances in the test set, 4 instances in the cross-validation set, and 17 instances in the training set as shown in Figure 4.2.

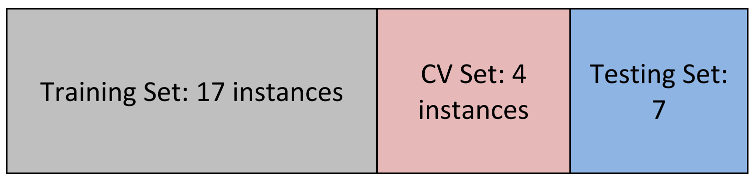

Figure 4.2: Reduced dataset partitions for the average of 100 instances

Understandably, there is not sufficient data to train an accurate model with a robust solution from such limited data. The average of 50 and 100 instances were included in these results in order to examine the potential of the model to be trained on the smallest amount of training data. The overall trend should indicate an improvement in accuracy for an increasing number of averaged instances. This trend is disrupted by the lack of sufficient training data with the reduced datasets for the averages of 50 and 100 instances. Increasing the amount of data collected at each test location in the room; however, would greatly raise the setup time with only a slight upgrade in the accuracy. An average of between 10 – 25 values provided an accurate prediction for this system for all types of interference. Figure 4.3 examines the expected effect on the accuracy of the model with reduced datasets compared to datasets with large amounts of data.

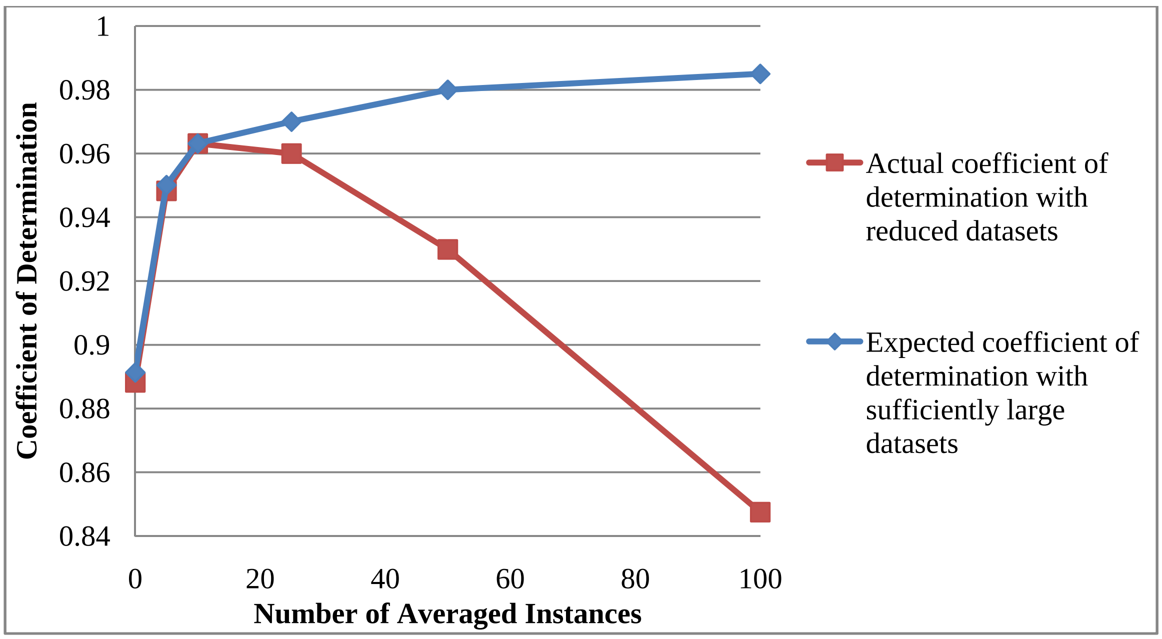

Figure 4.3: Expected R^2 vs. actual R^2 for reduced datasets and sufficiently large datasets

In order to provide another metric of accuracy and to provide a solution with more visible accuracy, Table 4.6 compares the prediction of the models with average values in terms of the actual distance the prediction was from the measured location in inches.

Table 4.6: Comparison of models using average values in terms of distance away from actual location

Error (inches)	Empty	Metal@7X10	Metal@7X10, Human@16X12	Human@7X10
Full Dataset	24.497	23.653	21.127	24.648
Average 5	19.446	18.502	13.265	20.124
Average 10	17.740	14.220	11.993	17.975
Average 25	12.615	21.433	15.709	17.623
Average 50	23.446	22.248	21.753	38.789
Average 100	26.235	31.286	49.396	38.237

The result, shown graphically in Figure 4.4, demonstrates the optimum number of instances to be reduced down to averages, in order to maximize the accuracy for a dataset starting with 100 data samples recorded per location.

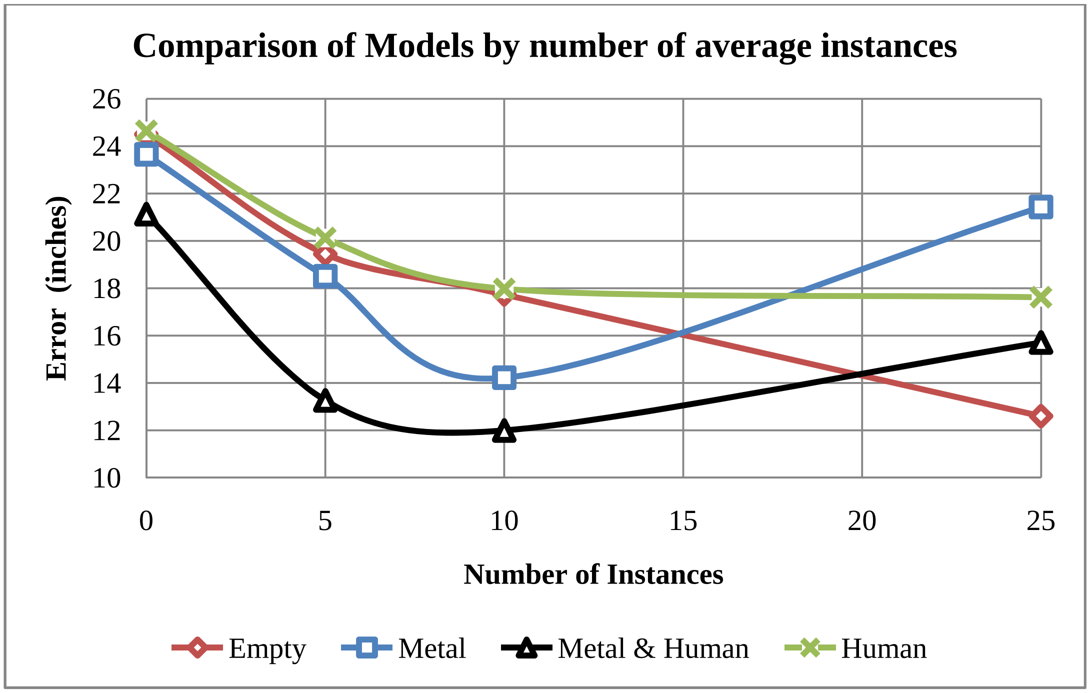

Figure 4.4: The comparison of models based on the number of instances with error measured in inches

The usage of average instances certainly enhanced the accuracy of the model without sacrificing abundant amounts of time in the data collection or model creation process. Figure 4.4 suggests that reducing the data down to 10 instances per location has approached a minimum error. The next section presents the results of smoothing the models with a median of instances rather than the average.

4.5 Smoothing with Median Values

The median of a varied number of instances provides another method to smooth the output of the model. A median of 10 values has the unique ability to eliminate an outlier from skewing the average. Table 4.7 provides the results of the models which consider the median of instances in order to smooth the outputs.

Table 4.7: Performance of models using the median of various numbers of instances from the dataset

	Empty	Metal@7X10	Metal@7X10, Human@16X12	Human@7X10	AVG
Full Dataset	0.898	0.874	0.924	0.884	0.895
Median 5	0.902	0.933	0.949	0.943	0.932
Median 10	0.928	0.964	0.971	0.955	0.955
Median 25	0.951	0.937	0.960	0.971	0.955
Median 50	0.916	0.946	0.974	0.895	0.933
Median 100	0.779	0.960	0.833	0.758	0.833

As with the smoothing by way of average instances, the median of instances increasingly improves the accuracy of the model. Table 4.7 shows that the median values increase the accuracy of the model effectively when given a sufficient amount of data with which to train. The accuracy for the median of 10 instances produces the best model as shown by the average R^2 and as shown by the average of instances. The actual predicted error in inches is provided for further comparison of the median and average smoothing models. Table 4.8 provides a comparison of the actual predicted error in inches from the measured location for the models constructed from median values.

Table 4.8: Comparison of the predictions in terms of the distance away from the actual location (in.)

error (inches)	Empty	Metal@7X10	Metal@7X10, Human@16X12	Human@7X10
Full Dataset	24.50	23.65	21.13	24.65
Median 5	24.27	19.20	17.29	19.99
Median 10	18.89	15.57	14.80	15.65
Median 25	17.71	23.75	16.19	13.94
Median 50	19.97	18.70	13.76	41.72
Median 100	51.53	25.23	43.48	54.76

The predicted error is slightly better on average for the median of 10 instances compared to 25. In order to determine the best method to construct the model for this system, the error rates are compared with the coefficient of determination and the predicted error in inches. The difference between the median models and the average models, in terms of coefficient of determination (R^2), are shown in Table 4.9.

Table 4.9: Comparison of models constructed from average or median values in R^2

		Average values	Median values
Full dataset		0.8951	0.8951
5 values		0.9483	0.9320
10 values		0.9631	0.9546
25 values		0.96	0.9546
50 values		0.9299	0.933
100 values		0.8475	0.8326
	Total	0.9240	0.9170

The results show that sampling using average values and median values increased the accuracy of the model. The difference between the median and average models is slight; however, the models constructed with average values give a minor improvement over the models constructed from median values. This result is confirmed by Figure 4.5, which shows that the predicted error is smaller with the models constructed with average values rather than median values.

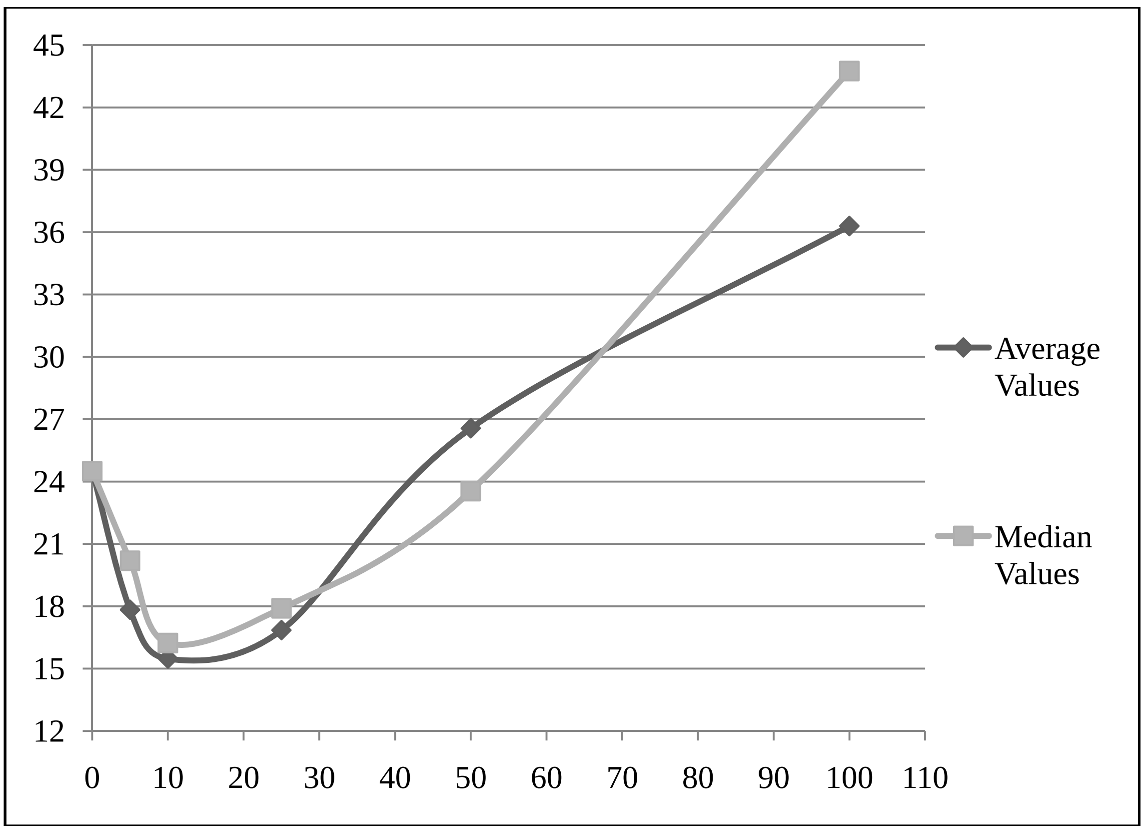

Figure 4.5: Comparison of models constructed from average & median values in terms of predicted error

The results show that both predicted error and coefficient of determination are improved with a model constructed from an increasing number of average or median values. These results show that reducing the dataset into averages of 10 instances has improved the accuracy of the model. The time needed to collect 10 samples of RSSI values from the four antennas for use with implementation software is approximately 2.4 seconds for this system. Thus, the accuracy of the system is improved by approximately 9 inches with the addition of the average values model while; the speed of the system is only slightly reduced. The software would need no more than 2.4 seconds to gather an adequate amount of data to generate a prediction of the location of the tagged object with minimal latency. The system is capable of adequate accuracy using a model that considers the average of 10 instances, but the model has to be more accurate than a multiple linear regression or the time needed to construct this model would be unnecessary.

4.6 Artificial Neural Networks vs. Multiple Linear Regression

This section provides a comparison of the ANN models and the multiple linear regression models. The regression models are created from the same partitions of the datasets used to construct the ANN models. Using the same data ensures that the models are being tested with the same input set. The cross-validation and training datasets were used to create the multiple linear regression models in this thesis. Table 4.10 shows the comparison of the regression models with the ANN models.

Table 4.10: Comparison of regression models and ANN models

Error (inches)	Empty		Metal@7X10		Metal@7X10, Human@16X12		Human@7X10	
	ANN	Reg.	ANN	Reg.	ANN	Reg.	ANN	Reg.
Full Dataset	24.50	52.10	23.65	44.41	21.13	46.90	24.65	50.22
Average 5	19.45	43.62	18.50	38.28	13.26	41.04	20.12	40.54
Average 10	17.74	42.40	14.22	34.20	11.99	40.15	17.98	43.67
Average 25	12.61	34.52	21.43	38.83	15.71	39.35	17.62	40.55

The ANN models surpassed the regression models independent of the number of instances averaged or the type of interference present in the test space. As has been proven in other research studies [33] [48], ANNs generally perform at least as well as linear regression when using linear or non-linear data, if the model is trained sufficiently. In this research, the artificial neural network provided an accurate solution compared to the multiple linear regression method used. While this research does not include multiple types of regression, this addition was meant to illustrate the comparison of the ANNs to a familiar method.

5 DISCUSSION

The models created from the average of 10 instances were accurate within 12-18 inches for each of the arrangements of interference. Additionally, a model can be created for a 20’X20’ room in 20-30 minutes after a site survey and data collection that takes approximately one hour. Thus, this system could be operational rather quickly and inexpensively to provide highly accurate asset tracking indoors.

5.1 System Accuracy

The mathematical models, created in this thesis, predicted the location of the tagged object an average of 23.4 inches closer than a multiple linear regression method. The actual effects of metal and human interference were less than expected for this system; however, the justification of the use of ANNs is derived from the increased accuracy. Additionally, the smoothing of the data with averaged samples provided a boost to the accuracy without requiring a significant amount of analysis. The best result involved attaining the average of 10 samples to create a new reduced dataset. Further smoothing had a negative result due to the lack of data samples to train the model. This result was expected but was not overcome because of the desire to limit the amount of data collection needed to provide enough training data to produce an accurate model. The smoothing of the data with median values produced better results as well; however, the averaged samples performed slightly better. The major limitation of this system is its inflexibility to an ever-changing environment.

5.2 Interference

The accuracy of the models created for this system did not deteriorate when the interferences were added to the test space as much as expected; however, the average difference in error from an empty room to interference was less than 6 inches. Perhaps, the metallic object was not as disruptive as in other environments or not large enough to greatly affect the results. The intention of this research was not to vary the interference from extreme to none but rather to illustrate a working system with different types of interference. A more extensive study could examine the effects of larger amounts of interference, such as a metallic object placed directly in front of an antenna.

Additionally, if the system did not require accuracy within 12-18 inches or there was little or no RF interference, then another method such as multiple linear regression would be sufficient because of the benefit from the decrease in computation cost. Since the RSSI values would be affected by extremely strong interference of the RF signal, the samples from each point would have more variation which can reduce the accuracy of the system.

5.3 Implementation of the System

In order to provide a real indoor environment in which to test the system, it was constructed at the 2009 RFID Journal Live Conference in Orlando, FL. The system was constrained by the 6' by 8' booth that consisted of a metallic table placed at the back of the space and one or two people standing or sitting in the space. Additional challenges were discovered at the conference such as the need to filter the reader from reading unwanted tags. The model was created for the booth prior to the conference to validate its ability to be applied to a different environment while maintaining the same RFID tags and antennas. The weights of the model were extracted into a software solution which showed a picture representing the predicted location of the tagged object. The models were accurate for the small space; however, a person standing directly in front of an antenna in the small space severely decreased the accuracy. Implementation of the system was a goal for this thesis; however, it was not explored in this research beyond the scope of validating the system as functional.

5.4 Design Review

Return on Investment (ROI) is always a major concern when implementing any type of RFID solution. However, with a commercial off-the-shelf (COTS) passive-tag indoor location tracking system, an RFID reader and four antennas can be purchased for approximately $3000, representing a relatively small cost per room to have the benefit of real-time tracking in the supply chain or in the warehouse. With the high cost of active tags and the expenses of a pervasive wireless system, a passive RFID tag location system can be used as a low-cost location tracking solution using cost-effective RFID readers and antennas. The implementation of this system would be a low energy solution with minimal complexity and less maintenance than other systems. The model created for this system is highly accurate for the test space described, however, the data pre-processing and model construction would create some cost in the form of setup time. Since, the setup time of the equipment and model creation would represent less time than the current systems, the usability of the system increases.

6 CONCLUSION

This thesis demonstrates a methodology to construct an accurate location system using RFID technology in conjunction with artificial neural network mathematical models. The objective of this thesis was to determine the best parameters used in order to create a highly accurate localization algorithm. Artificial neural networks provided a robust solution that favorably compares to multiple linear regression. The accuracy of the system is obviously important; however, the setup time was reasonable, the cost of the equipment was competitive, and the ease of setup and maintenance is one of the best features of the system. Additionally real-world applicability was a major goal of this thesis. The accuracy of the system is not exceptional (<6 inches) with local interference; but, the added benefit of tracking objects in terms of the room in which it is located along with a good(12-18 inches) prediction of location within the room would still provide more information than merely presence or absence.

6.1 Future Research

The accuracy of the proposed system in this research depends on the antennas to remain stationary because the locations of the antennas affect the prediction. To prevent this dilemma, a software solution could update the training set and recalculate the weights of the ANN at intervals throughout the day to ensure that the system is responsive to its environmental changes. The performance of the system would greatly depend on its ability to contend with real-world RF interferences as well, such as metal objects, people in the RF field, and certain liquids. In future research, factors such as dynamic interference, scalability, and the use of reference tags could be introduced in order to make the system more applicable to real-world applications and contend with a dynamic environment with RF obstacles. A reference tag could be added to the system in order to provide a known location at all times. This known location could be used to discern an offset factor to adjust the prediction. Ultimately, the ability of the system to adapt to its surroundings will be the indicator of its success.

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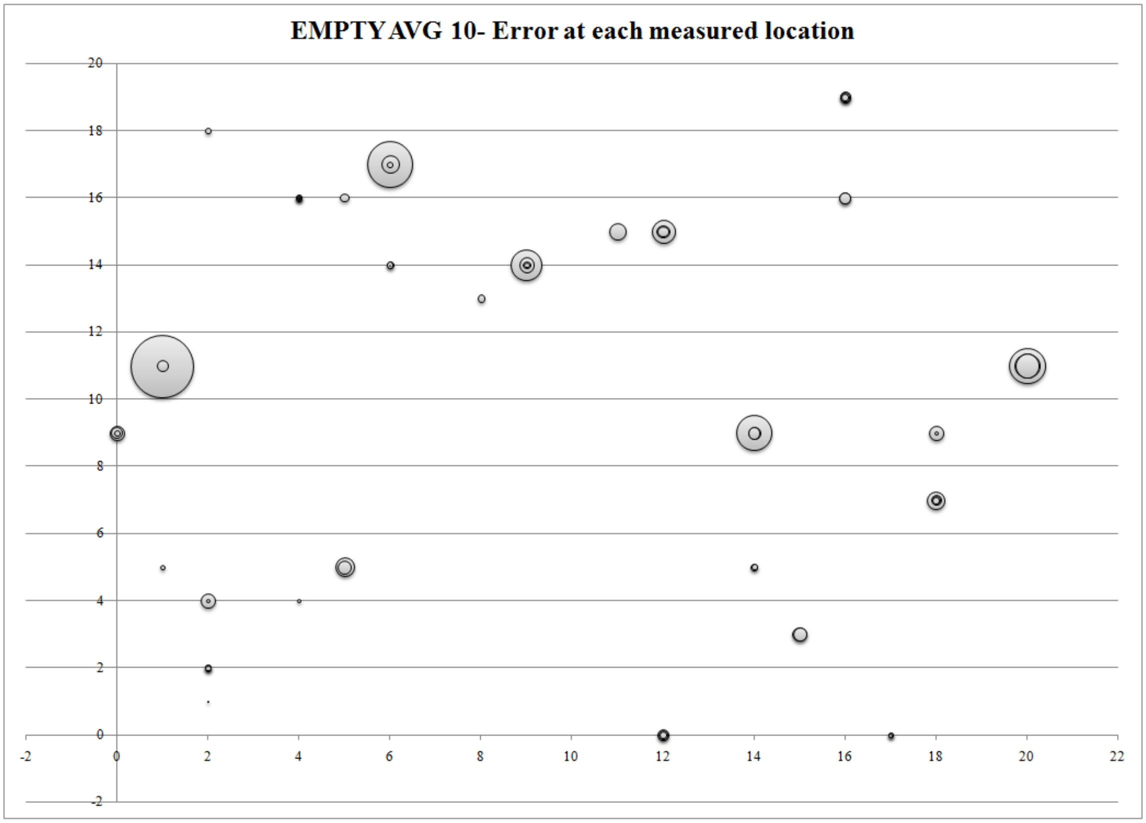
8 APPENDIX A

Coefficient of determination	R^2	Empty	Metal@7X10	Metal@7X10, Human@16X12	Human@7X10
Full Dataset	x loc	0.868	0.841	0.910	0.852
	y loc	0.928	0.908	0.938	0.916
	avg R^2	0.898	0.874	0.924	0.884
Average 5	x loc	0.938	0.936	0.970	0.887
	y loc	0.946	0.969	0.975	0.965
	avg R^2	0.942	0.952	0.973	0.926
Average 10	x loc	0.937	0.965	0.977	0.934
	y loc	0.960	0.979	0.981	0.973
	avg R^2	0.948	0.972	0.979	0.954
Average 25	x loc	0.964	0.900	0.965	0.944
	y loc	0.982	0.980	0.967	0.979
	avg R^2	0.973	0.940	0.966	0.961
Average 50	x loc	0.881	0.962	0.965	0.789
	y loc	0.981	0.936	0.958	0.968
	avg R^2	0.931	0.949	0.961	0.878
Average 100	x loc	0.804	0.937	0.670	0.640
	y loc	0.934	0.885	0.972	0.938
	avg R^2	0.869	0.911	0.821	0.789

Coefficient of determination	R^2	Empty	Metal@7X10	Metal@7X10, Human@16X12	Human@7X10
Full Dataset	x loc	0.868	0.841	0.910	0.852
	y loc	0.928	0.908	0.938	0.916
	avg R^2	0.898	0.874	0.924	0.884
Median 5	x loc	0.896	0.906	0.948	0.935
	y loc	0.908	0.960	0.951	0.951
	avg R^2	0.902	0.933	0.949	0.943
Median 10	x loc	0.908	0.956	0.971	0.941
	y loc	0.949	0.972	0.971	0.969
	avg R^2	0.928	0.964	0.971	0.955
Median 25	x loc	0.916	0.894	0.960	0.974
	y loc	0.987	0.980	0.960	0.967
	avg R^2	0.951	0.937	0.960	0.971
Median 50	x loc	0.869	0.941	0.984	0.861
	y loc	0.964	0.950	0.965	0.930
	avg R^2	0.916	0.946	0.974	0.895
Median 100	x loc	0.811	0.938	0.869	0.582
	y loc	0.748	0.981	0.797	0.935
	avg R^2	0.779	0.960	0.833	0.758

Error (inches)	Average Values	Median Values
0	24.5	24.5
5	17.83	20.19
10	15.48	16.23
25	16.85	17.9
50	26.56	23.54
100	36.29	43.75
Total	22.91	24.35

The following figures show the four layouts with the tested locations represented by circles. The size of the circle denotes the maximum predicted error at the measured location. A small circle or dot represents the model's ability to correctly predict the location of the tag at the measured location while a large circle signifies poor ability to predict the location at that spot. Inner circles represent more accurate predictions at the same measured location. The first four figures show the models created with the dataset consisting of the average of 10 instances. The next four figures show the models created with the full datasets.


EMPTY AVG 10- Error at each measured location
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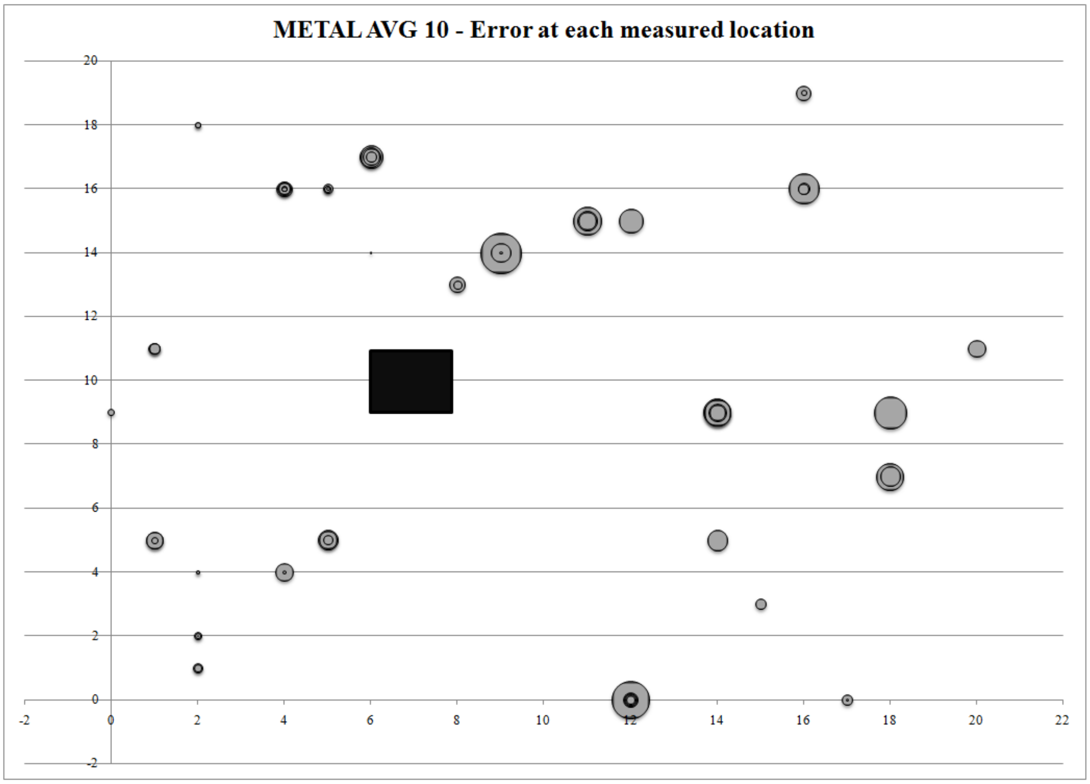
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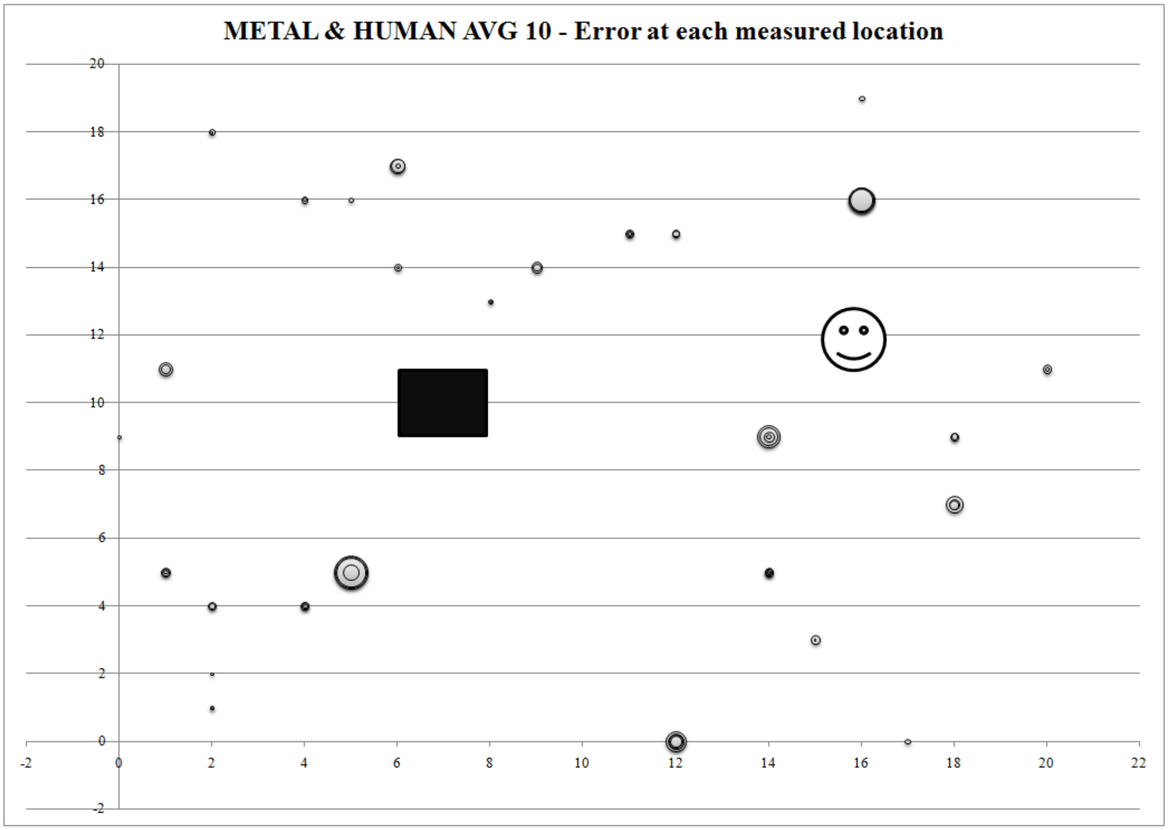
METAL & HUMAN AVG 10 - Error at each measured location
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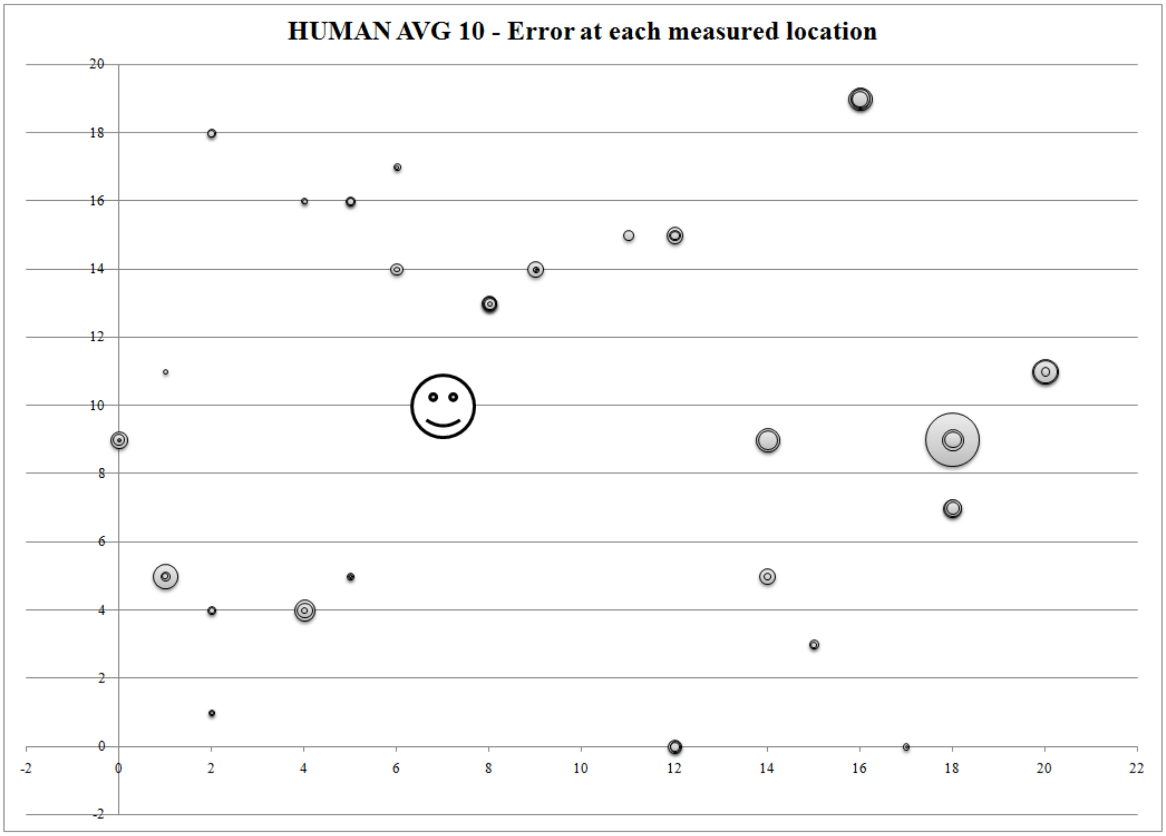
HUMAN AVG 10 - Error at each measured location
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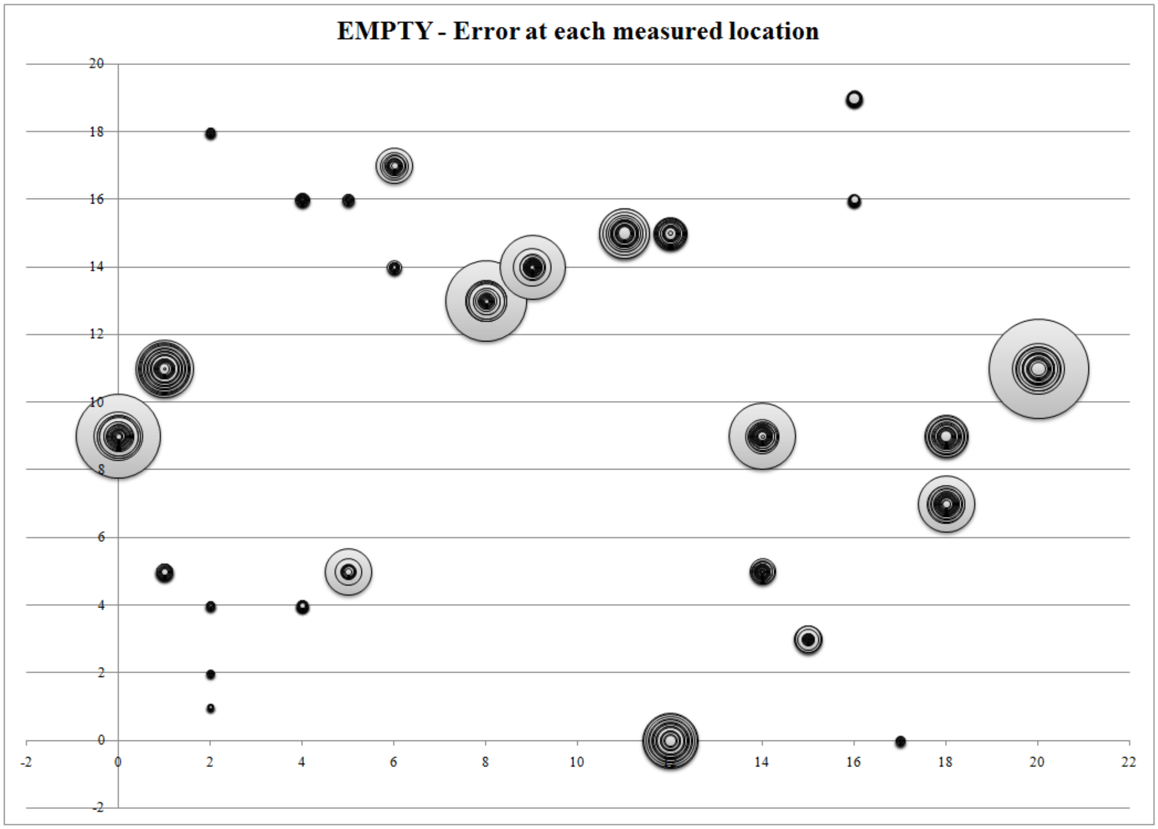
EMPTY - Error at each measured location
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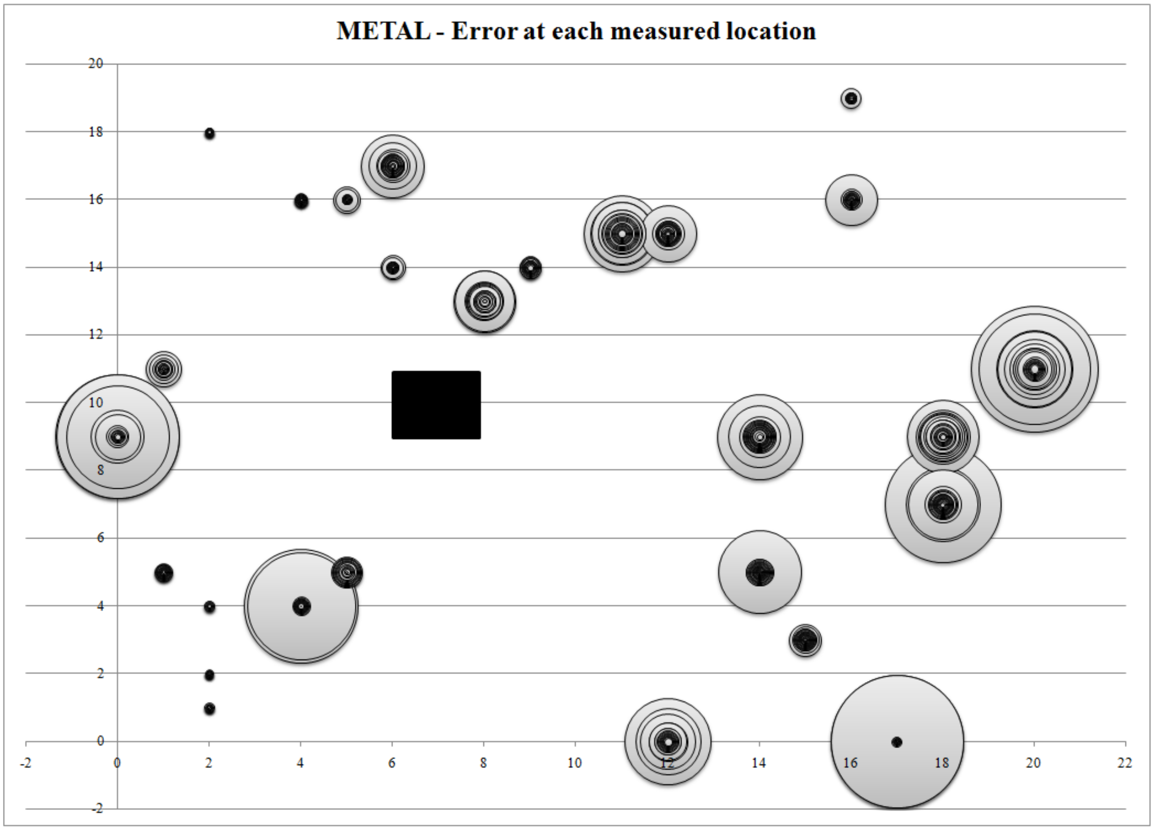
METAL - Error at each measured location
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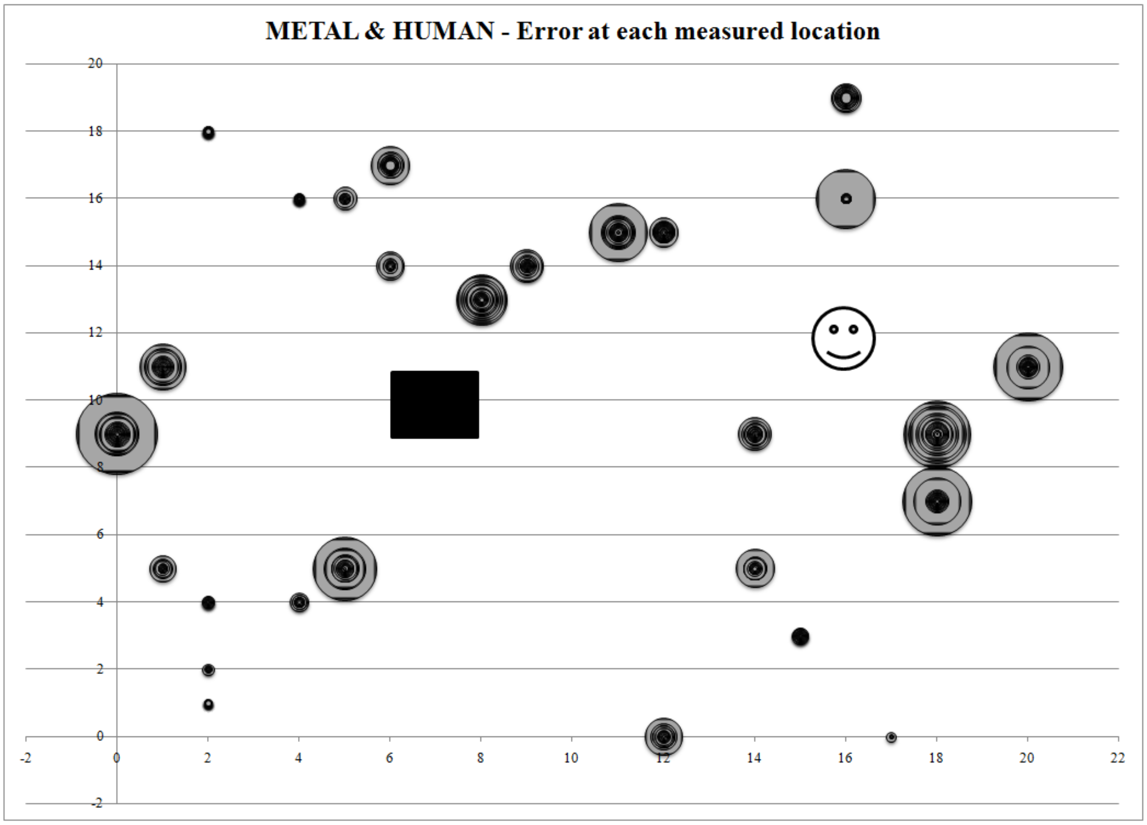
METAL & HUMAN - Error at each measured location
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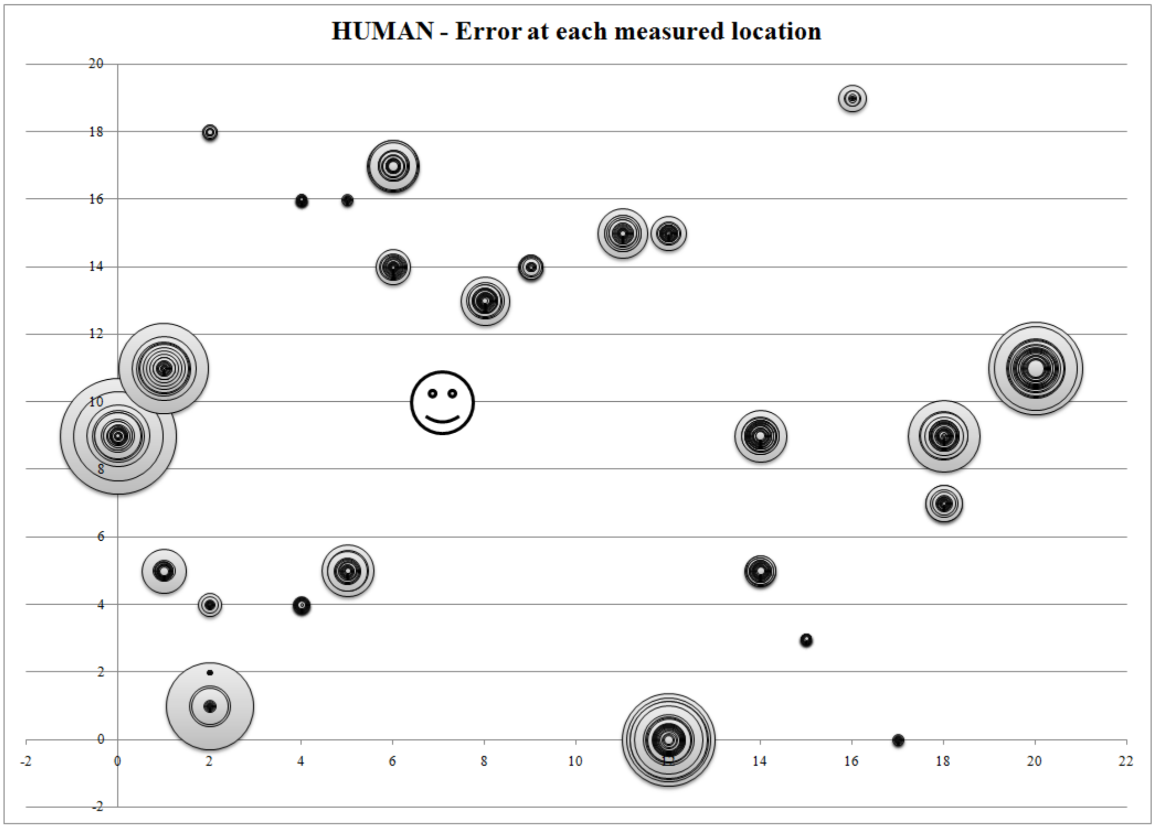
HUMAN - Error at each measured location
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