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FACILITY RFID LOCALIZATION SYSTEM BASED ON ARTIFICIAL NEURAL NETWORKS

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Radio frequency identification (RFID) technology is used for asset tracking due to its accuracy and speed. RFID tracking systems are being used to locate tagged objects in indoor environments, however; reliability is low due to interferences. To overcome this limitation, artificial neural networks (ANNs) can be used to determining a device's location in the proximity of interference. This research presents a proof of concept to an industrial application of using ANNs as an RFID localization algorithm when objects are subjected to metallic and human interference. To prove this concept, random samples are collected using the received signal strength indication (RSSI) values from passive RFID readers and antennas. The test results show that ANNs can determine the location of a passive RFID tag accurately in the presence of noise and shows that data preprocessing techniques can improve the predictive capabilities of the ANN-RFID localization algorithm.

Significance: Research shows that passive tags are better suited for tracking items that are high volume, low cost, or have a short shelf life. A passive RFID tag system is explored in this research due to the inexpensive nature of the tags. Thus, there is a great potential for many industrial applications if advancements are made to increase the reliability of determining a tag's location. Constructing an ANN-RFID localization algorithm is significant because ANNs are capable of predicting non-linear, noisy, or incomplete readings that are obtain from RFID antennas. These models can ultimately decrease the setup time needed to implement and increase the accuracy of a location system in the presence of noise.

Keywords: Radio frequency identification, Inventory location systems, Artificial neural networks, Interference

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1. INTRODUCTION

Real-time location systems (RTLS) can be used for a variety of applications in manufacturing. For example, these systems can be used when material is being handled. The ability to tack an item's location can ultimately give decision makers a way to control or to improve upon existing manufacturing systems (Zhou, Ling, & Peng, 2007). For example, the location of an object can monitored for enterprise resource planning (ERP) or warehouse management systems (WMS) in order to estimate work in process (WIP) levels, monitor logistical operations, provide information for supply chain management, or even to optimize inventory levels (Huang, Zhang, & Jiang, 2008). RTLS can be composed of various locations technologies that include radio frequency identification (RFID), global position systems (GPS), wireless fidelity (Wi-Fi), and barcodes (Ding, Chen, Chen, & Yuan, 2008). Current real-time location systems rely on pervasive wireless systems and/or active tags to determine a location of a tagged item. Consequently, due to the high cost of active tags and limitations of other technologies, such as the limited functionality of using GPS indoors, passive RFID tags can be used as a potential replacement for asset tracking since they are relatively low in cost for a manufacturing facility to implement into their current practice.

RFID is a form of information technology and is used because of its accuracy, speed, and omnipresence. RFID was initially developed in the 1940's for military applications during World War II (Landt, 2001). Over the years, RFID applications have become more prominent due to the decrease in cost, and the increase of reliability. Today, RFID is being used in many applications that are both small and large in scale. For example, RFID is being used in manufacturing (Landt, 2001), health care (Huang, Chung, Tsai, Yang, & Hsu, 2008), parcel retrieval and delivery (Faber, 2002), security (Lockton & Rosenberg, 2005), and even farming (Chen, Chen, Chen, & Chang, 2007). As history shows, as RFID technology improves and becomes more reliable and affordable, the applications have become increasingly abundant.

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 of a tagged object to the reader or receiver. Thus, RFID can identify a tagged object almost instantaneously when the object near a visible line of sight of the identification system. 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. The ability to identify and locate an object simultaneously provides increasingly useful information to those responsible for managing an asset's location.

Being able to identify an object without requiring a direct line of sight provides information that can be monitored continuously. However, while this is still the major advantage over barcodes, RFID has its own limitations (Nikitin & Rao, 9-14 July 2006). For example, most current applications using RFID technology determine if an object has passed through a specific gateways located about a manufacturing facility (Park, Choi, & Nam, Aug. 31 2006-Sept. 1 2006). This is used to determine the general location of the tagged object, but not the precise location of the object. In other words, location is only known in a general sense in relation to the series of gateways that are placed around the manufacturing environment (Song, Haas, & Caldas, 2007). This is because determining the precise location of a RFID-tagged item is difficult when there are interferences, which limits the accuracy of the RFID receiver. In order to overcome these limitations, the research presented in this paper utilizes a machine learning technique called artificial neural networks (ANNs) in order to determine a tagged item's location in the presence of interference.

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 its applied. Thus, 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, the system proposed in this research estimates the location of the tag based on relative RSSI values extracted from the reader's software. Finally, as the research will show, the proposed system it reduces the complexity of the design of the location tracking system by reducing the time involved in setup, troubleshoot, and maintenance in order to track an item's location more precisely in the presence of noises.

2. ACTIVE AND PASSIVE RFID SYSTEMS

There are two main tag types found in RFID location systems. These tags types are either active or passive, which differ in the method by which the signal is transmitted to the received. In general, active RFID tags contain a battery that emits a signal that is are activated by the reader's antennas, which is unlike passive tags that do not require a power source. The majority of the research found in literature address when passive or active tag are suitable for a certain applications. In other words, this work is dedicated to determine when a certain tag-type should be used based on evaluating the cost effectiveness of tracking assets. In general, these studies conclude that passive tags are more cost efficient for tagged items that are relatively inexpensive and that active tags are more efficient when dealing with assets that are relatively expensive in comparison to the cost of the tag. Active tags have a major advantage over passive tags in that they can be tracked over a much larger range than passive tags. However, these devices are often very costly and require a dedicated power supply, which can limit the functionality of the tag. Therefore, passive tags, which are often smaller, are attractive for a manufacturing facility to purchase an implement because they do not require a recurring cost.

Though active tags provide a good solution for problems dealing with obstruction or interference, they are cost productive for most applications. Since passive RFID tags are expendable, they have made their way into a variety of nontraditional applications. For example, certain construction projects have used a passive-location system to locate non-metallic items that are hidden beneath the ground (Dziadak, Sommerville, & Kumar, 2008). In addition, passive RFID systems have also been used to aid visually impaired pedestrians in order to navigate through larger buildings such as airports or offices (Kulyukin, Gharpure, Nicholson, & Osborne, 2006). Therefore, there is a need to improve upon the capabilities of using passive tags in industrial settings, which ultimately increase location accuracies and decrease the cost and time required to develop a robust location-system. This study presents research that utilizes the non-linear modeling characteristics of artificial neural networks (ANN) to estimate a tagged item's location given interference.

3. ARTIFICIAL NEURAL NETWORKS

RSSI values have been used in location systems to predict location (Seshadri, Zaruba, & Huber, 2005); however, most of them use prediction methods such as triangulation or trilateration, which are based on time difference of arrival or time of flight calculations (Hightower & Borriello, August 24, 2001) (Caron, et al., 2007). The premise of this research is to use the functionality of the Alien® RFID Developer's kit to derive a mathematical model that estimates a device's location given an RSSI value as an input. Thus, a machine learning method called artificial neural networks (ANN) will be used in this research to model the location of an RFID devise.

Machine learning is a form of artificial intelligence that is stochastic, which utilizes learning algorithms optimizes the parameters of a mathematical model through extensive training (Alpaydin, 2004). The mathematical model generated in this research provides an accurate estimation of the location of the tagged object using real-time RSSI information. In this experiment, a location system is created and tested in an empty space, where the tagged items are subjected to static interference from metal and human sources. This strategy was implemented in order to create a more realistic indoor environment to test the capability of an ANN's ability to predict the location of tagged object in the presence of noise (Mohammadi & Ailani, 2007). This procedure is significant because an ANN-RFID location system can ultimately improve the reliability in determining a tagged item's location as well as reducing the setup time required to implement a location system in a new facility. Predicting the location of an item location with an ANN is also significant because not all readings are needed from local antennas to make a prediction. In other words, other location methodologies require readings from all available antennas to determine a device's location as well as time elapsed information. ANNs are well known for their ability to generalize a system. Thus, they are capable of deriving a predicting with noisy or incomplete data. It is for this reason that ANNs are more suited for non-linear predictions with missing values than multiple linear regression models (Kumar, Rao, & Soni, 1995) (Brey, Jarre-Teichmann, & Borlich, 1996) (Young, Weckman, Thompson, & Brown, 2008). To support this claim, a comparison of multiple linear regression will be made to the predictability of an ANN for locating RFID tagged items with interference and a high likelihood of inconsistent antenna readings.

Despite many ANN methodologies, this research focuses primarily on the use of the multilayer perceptron (MLP) classifier networks. The multilayer perceptron is a feed-forward network that utilizes back-propagation to execute training across multiple layers (Principe, Euliano, & Lefebvre, 1999) (Vapnik, November 1999). These models can employ second order conjugate gradient learning rules, which are well suited to learn non-linear systems (Hestenes & Stiefel, 1952). Thus, it is proposed that this feature, paired with the ability of an ANN to model noisy data, has potential to create a robust, cost efficient RFID location tracking system.

4. LOCALIZATION ALGORITHMS

A localization algorithm is a mathematical model that estimates the position of an object given input data such as signal strength, distances, or angles. Location tracking systems use varying methods of prediction regardless of the technology used to collect information. 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 the power levels at which a tag can be read in order to estimate a perceived distance (Hodges, Thorne, Mallinson, & Floerkemeier, 2007). Alternative methods employ the use of mobile readers and passive reference tags that rely on random sampling to provide the algorithm with information for prediction (Xu & Gang, 17-19 Jan. 2006). Aside from the switch to passive tags, the system presented in this research 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 (Ding, Chen, Chen, & Yuan, 2008). Thus, the experiment preformed for this research application consists of estimating a tag's position given four RSSI values that are extracted from a fixed-position reader in a test space.

5. INDUSTRIAL APPLICATION

The system proposed in this research consisted of an Alien 9900 915 MHz RFID reader, four circular Alien antennas, and an Alien squiggle tag, which are considered Class 1, Generation 2 tag types. Ohio University's Automatic Identification and Data Capture Laboratory provided the RFID equipment used in the data collection for this research. The system proposed aims to predict the location of a tagged object in an indoor space with varying static sources of interference. The development of the system necessitates the completion of an initial site survey to collect data with a tagged object located in different coordinates. This data consisted of a relative signal strength value from each of four antennas and the corresponding 'x' and 'y' coordinates of the measured location of the tag. This data is subsequently partitioned into training, cross-validation, and testing data subsets for the creation of an ANN model. In addition, RF interference is introduced based on the absorption and reflection from human and metallic sources. This noise is introduced to the system, which is tested in four total arrangements. Ultimately, a localization algorithm that is extracted from the ANN provides an 'x-y' prediction of the location of the object for the various positions in order to assess the ability of the system to predict the location within the presence of noise.

5.1 Test Space

The system proposed in this research was designed for a space with square sides that are approximately 20 ft. on each side. This distance was due to the constraining length of the coaxial cord and the read range for most passive tags. For a space 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. A square space with no obstacles initially supplied both a good benchmark for data collection and an opportunity to examine the arrangements of the antenna to determine the reading capability of available tags by evaluating the consistently of their read rates and over the location space.

For the experiment, tags were suspended above the ground on a PVC stand at the same height as the antennas to ensure that they were on the same plane. Before testing began, locations were generated randomly which covered the entire test space. From these generated locations, random locations were drawn without replacement in order to determine which locations would be used for testing the ANNs ability to model an RFID's location. Figure 1 depicts the randomly determined test space that has an origin of (0, 0), which refers to the lower left corner. Thus, the figure shows the randomly selected tag locations that will be used to collect the data for this investigation. It should be noted that this arrangement was not only used to model an RFID's location without the presence of interference, but it was also used in later in the experiment to determine the ANN's capability of determining a devices location with metallic and human interferences.

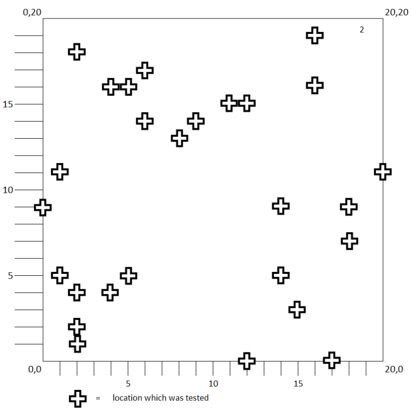

Figure 1. Orientation of Test Space

The data was collected using custom software that logs a 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' coordinates. Throughout the experiment, tags were manually moved to a new location and their position was recorded. After the tag was transferred to the new location, the software was then used to record the new readings. 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 since the data will be normalized, which 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. This encoding was simply used to represent the condition when no signal strength could be read.

5.2 Data Collection with Interference

The data was initially collected with a metal interference object in the 20' by 20' testing space.
Figure 2 shows the location of the tags as well as the location of the metallic object. The metallic interference consisted of a 12' high metallic ladder covering a 4' by 2' area and 12' tall. The human interference object was also positioned in the same location as the metal object for the sake of comparison as shown in **Figure 3**. The final scenario of data collection was when both human and metal interference objects were placed into the test space as shown in **Figure 4**. Since both objects where used, the human interference was randomly positioned on the grid at (16, 12).

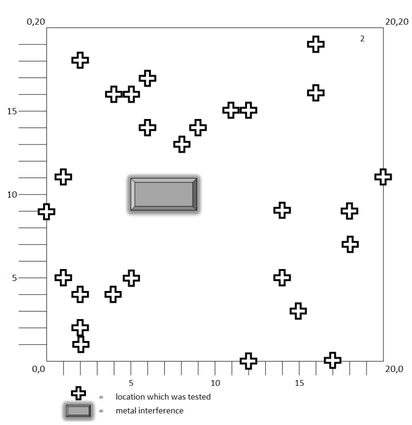

Figure 2. Tags with Metal Interference

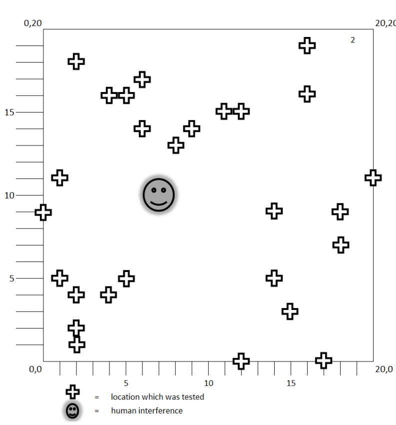

Figure 3. Tags with Human Interference

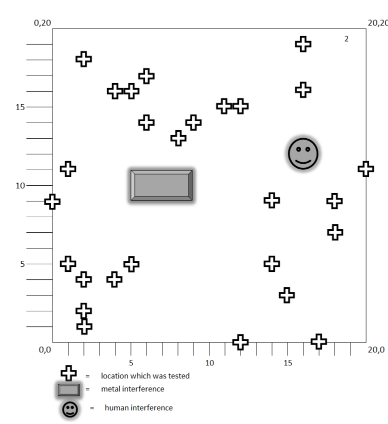

Figure 4. Tags with both Metal and Human Interference

5.3 Creation of ANN Model

An ANN is used to create a predictive model that generates a robust solution in the presence of noise. For this proof of concept, a traditional multilayer perceptron (MLP) architecture was used with hyperbolic transfer functions all if the network's layers. In addition, to determine the best performing ANN, the numbers of hidden layer nodes were varied from four to 24 during training. Data samples were also randomized and partitioned into three sub-sets of data, where 60% of the data was used for training, 15% was used for cross validation, and 25% was used for testing in each of the models. It should be noted that cross-validation was used in order to prevent the model from memorizing the system. The model was then trained over 30 iterations of 10,000 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 space and its contents. It should also be noted that linear regression models were constructed in order to test the ANNs ability.

5.4 Dataset Smoothing

Sample data can be collected very quickly from the RFID equipment. For example, in 22-24 seconds, over 100 instances can be recorded. Data preprocessing techniques can be used in order to reduce the effects of noisy or inconsistent data collection to improve the prediction accuracies of an ANN. Thus, the data that was collected for the experiment was aggregated using both moving averages and median values of the RSSI values. These moving values were calculated using a bin size of 5, 10, and 25 instances. For example, of the 100 sets of four RSSI values collected at each of the 28 locations used for the experiment, the sample data was aggregated to create a new instance. This process was repeated until the data set was reduced from 2800 lines of data at 28 locations to 560 lines of data representing 28 locations.

In addition to proving the concept that ANNs can be used as a localization algorithm, both the moving average and median data aggregation techniques will be compared. Thus, several models will be constructed to determine if one approach outperforms the other. In order to make this comparison, the coefficient of determination (R^2) will be presented that to show the amount of variation that is explained by the models as well as the actual predicted errors, which represents the distance the prediction was from the measured location in inches.

6. RESULTS

An experimental procedure was performed in order to determine which ANN architecture that produced the best results without the presence of interference from the metallic or human objects. Table 1 provides a summary of this procedure with the random arrangements of the RFID tags shown in **Figure 1**. Once the best network architecture was determined, it was used for all other remaining experiments. The best network that was found during this procedure was a 2-hidden layer MLP using the conjugate gradient learning rule. This network consisted of eight nodes in the first hidden layer and four nodes in the second hidden layer.

Table 1. Comparison of ANN Architectures

Learning Rule	# of layers / Processing Elements per layer	Avg. Error (in.)	Combined R^2
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

Using the network architecture found in the initial experimental procedure, an ANN was constructed for all four arrangements, which included Empty (or no interfering objects), Metal, Human and Metal & Human. Table 2 shows the results of the four arrangements when no data preprocessing techniques were used. In other words, the full dataset was used in order to determine if the data aggregation techniques improved the accuracy of the ANN-RFID location system.

Table 2. Full Dataset Performances for the Testing Arrangements

Coefficient of determination	R^2	Empty	Metal	Metal & Human	Human
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

6.1 Smoothing with Average Values

Once the baseline results were analyzed using all of the data that was collected for the RFID readings, the 'best' ANN model architecture was used to train with the aggregated data using the moving average data preprocessing technique. The results of this investigation are summarized in Table 3.

Table 3. Moving Average Dataset Performances for the Testing Arrangements

Error (inches)	Empty	Metal	Metal & Human	Human
Full Dataset	0.893	0.874	0.924	0.884
Average 5	0.942	0.952	0.973	0.926
Average 10	0.948	0.972	0.979	0.954
Average 25	0.973	0.940	0.966	0.961

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. Increasing the amount of data collected at each test location in the space; however, would greatly increase the setup time with only a slight upgrade in the accuracy

An average of between 10 – 20 values provided an accurate prediction for this system for all types of interference. 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. The usage of average instances enhanced the accuracy of the model without sacrificing a copious amount of time in the data collection or model creation process. This suggests that reducing the data down to 10 instances per location has approached a minimum error for most test cases.

6.2 Smoothing with Median Values

The median of a varied number of instances provides another method to smooth the inputs of the model. A median of 10 values has the unique ability to eliminate an outlier from skewing the average. As with the smoothing by way of average instances, the median of instances increasingly improves the accuracy of the model. Table 4 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 actual error and as shown by the average of instances.

Table 4. Median Dataset Performances for the Testing Arrangements

Error (inches)	Empty	Metal	Metal & Human	Human
Full Dataset	0.989	0.874	0.924	0.884
Median 5	0.902	0.933	0.949	0.943
Median 10	0.928	0.964	0.971	0.955
Median 25	0.951	0.937	0.960	0.971

The predicted error is slightly better on average for the median of 10 instances compared to a bin size of 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 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. The results also show that both predicted error and coefficient of determination are improved with a model constructed from an increasing number of average or median instances. These results show that reducing the dataset into averages of 10 instances has improved the accuracy of the model most efficiently. 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, but the model has to be more accurate than a multiple linear regression or the time needed to construct this model would be unnecessary.

6.3 Artificial Neural Networks vs. Multiple Linear Regression

To determine if the time necessary to drive an ANN is advantageous for a practitioner, a comparison of the ANN models will be made to a benchmark method of multiple linear regression. Table 5 shows the comparison of the regression models for the four types of RFID arrangements, where the error is provided in the average distance away an object is predicted from its true location.

Table 5. Comparison of regression models and ANN models

Error (inches)	Empty		Metal		Metal & Human		Human	
	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 (Kumar, Rao, & Soni, 1995) (Young, Holland, & Weckman, 2008), ANNs generally perform at least as well as linear regression when using linear or non-linear data, if the model is trained sufficiently. 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.

7. CONCLUSION

This research demonstrates a methodology to construct an accurate location system using RFID technology in conjunction with ANN models. 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 reasonably short, the cost of the equipment was competitive, and the ease of setup and maintenance is one of the best features of the system. The accuracy of the system is good (i.e. 12-18 inches), but not exceptional (i.e. <6 inches) for a 20’ X 20’ space. However, the benefit of tracking objects in a space with a good prediction of location would still provide more information than merely absence or presence. Additionally, a model was created for a 20’X 20’ space in 20-30 minutes after a site survey and data collection that takes approximately one hour. Thus, this portable system could be operational rather quickly and inexpensively to provide highly accurate asset tracking indoors.

The mathematical models, created in this research, 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 obtaining a significant amount of extra data. This is not a significant limitation due to the reader’s ability to acquire an abundant about of samples in a short period of time. The best result involved attaining the average of 10 samples to create a new reduced dataset. The best models created from the average of 10 instances were accurate within 12-18 inches for each of the arrangements of interference. 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 major limitation of this system is its inflexibility to an ever-changing environment. 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. Ultimately, the ability of the system to adapt to a changing environment will be the indicator of its success.

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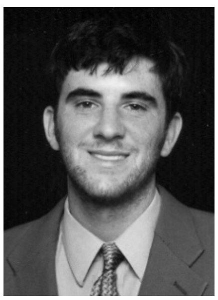
BIOGRAPHICAL SKETCH



William S. Holland is currently an Operations Research Analyst in Alexandria. VA. While attending Ohio University, Holland received a master's degree in Industrial and Systems Engineering in 2009 as well as a bachelor's in Applied Mathematics in 2005. In pursuit of his academic degrees, William studied RFID location systems, machine learning methods, sports modeling, green facility renovation and artificial neural networks. From these endeavors, he presented his research at annual conferences and research consortiums, which included the Alien RFID Solutions Center Expo, 2008 AIDCTI Conference at Ohio University, and the 2009 Industrial Engineering Research Conference in Miami, FL.

Dr. William A. Young II earned a doctoral degree in Mechanical and Systems Engineering at Ohio University in 2010 where he was the recipient of the 2009-2010 Outstanding Graduate Doctorial Student Leader Award. For his dissertation, Young developed a team-compatibility decision support system, which focused on providing supplemental information to hiring managers in the National Football League to improve a team's performance and spending efficiency. Young has worked on projects that were funded by the General Electric Aviation, National Science Foundation, and Ohio's Department of Labor. Young's research is focused on utilizing statistical and machine learning methodologies to develop decision support systems and has published research related to cost analysis, educational technology, team-compatibility, sports prediction, and environmental systems.

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