PNNL-34847

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U.S. DEPARTMENT OF ENERGY

Prepared for the U.S. Department of Energy
under Contract DE-AC05-76RL01830

PACIFIC NORTHWEST NATIONAL LABORATORY
operated by
BATTELLE
for the
UNITED STATES DEPARTMENT OF ENERGY
under Contract DE-AC05-76RL01830

Printed in the United States of America

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Abstract

This work focuses on the problem of RF geolocation in complex multipath environments. Using 3D electromagnetic propagation modeling to characterize environments of interest will enable more accurate RF geolocation. Specifically, a path-loss radio map can be generated in simulation for use in received signal strength indicators (RSSI) fingerprinting, or pattern matching. RSSI fingerprinting is an example of data-based method that takes site specific information into account which should allow for better performance than other model-based methods that use a generalized model of electromagnetic propagation. This modeling capability will also be used to evaluate the relative performance of RSSI fingerprinting, pathloss model based RSSI methods such as differential received signal strength circles (DRSS), RSSI joint gaussian estimation, and time-difference of arrival (TDOA). New methods using this simulation derived electromagnetic characterization could improve the efficacy of currently deployed and future RF spectral monitoring solutions. Wireless InSite developed by Remcom is used as the simulation tool of choice in this work. An indoor location is simulated with a set of fixed receivers and a grid of transmit locations. Using the output of the Wireless InSite simulation the response from a given transmit location to a given receive location can be generated. During the first year of the project various geolocation methods have been evaluated on purely synthetic, but realistic, data. The second year focused on testing and validating the efficacy of simulation informed RF geolocation using two physical testbeds. This work has shown that data-based approaches are more accurate than model-based ones at the expensive of requiring measured or simulated site-specific training data.

Acknowledgments

This research was supported by the **National Security Mission Seed**, under the Laboratory Directed Research and Development (LDRD) Program at Pacific Northwest National Laboratory (PNNL). PNNL is a multi-program national laboratory operated for the U.S. Department of Energy (DOE) by Battelle Memorial Institute under Contract No. DE-AC05-76RL01830.

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1.0 Indoor Geolocation

For a variety of applications, it is important to be able to detect and locate RF transmitting sources. In place spectral monitoring system consisting of several wideband receiver nodes synchronized and positioned around the location of interest. This work is focused on the localization problem after a source has been detected. Signal detection itself is an ongoing area of research and is outside the scope of this work. To add to the challenge, RF sources may or may not be cooperative. An uncooperative RF source is one where nothing is known about the detected signal, the transmit power, transmit location, transmit time. Due to the nature of electromagnetic propagation in complex indoor multipath, environments localizing uncooperative sources is very challenging.

RF localization is extensively researched in the literature. There are many methods that attempt to locate an RF source based on an environmental model. For example, using the received power at each receiver node for a given detection, the detected signal's relative time shift between each receiver, or some other method of understanding the electromagnetic propagation. However, it is near impossible to create a model that will generalize to any possible location or even to everywhere within a single location. There are two practical methods to accurately characterize the site of interest. A physical site survey measuring the path loss between all locations of interest and each receiver node or using a 3D electromagnetic propagation simulation to generate a path-loss radio map. Using the path-loss radio map, from measurements or simulation, received signal strength indicators (RSSI) fingerprinting, or pattern matching, can be used to localize a detected signal. Three-dimiensional electromagnetic propagation modeling will facilitate high performance localization for current and future RF spectral monitoring solutions. Beyond RF geolocation, simulating site-specific electromagnetic propagation will enable many research topics such as signal detection, classification, localization, and others.

2.0 RF Geolocation Methods

Geolocation methods can be split into two categories, purely model-based methods, and data-based methods. Model-based methods make some assumption about the propagation characteristics of the environment, but do not in general take the site-specific characteristics into account. In other words, they try to use a model that is a reasonable approximation of how signals propagate in a representative indoor environment. The advantage of this approach is that it allows for geolocation in an environment without any site-specific information. The disadvantage is that inevitably the chosen model will have assumptions or generalizations that do not work in every scenario. On the other hand, data driven models are developed using either measured site survey data or electromagnetic propagation simulations. Data-based methods have the potential to be the highest performing. However, a model-based method would be the preferred solution, if the performance was adequate, since it would not require site-specific data. In the following sections the geolocation methods evaluated in this work will be detailed.

2.1 Highest Power Received Signal Strength Indicator

The simplest geolocation method using an in-place monitoring system is to use the location of the receiver node with the highest received power for a given observation as the location estimate. The localization accuracy of this method is proportional to the number of receivers in the system, with more receivers yielding higher accuracy. This method should always be employed as it requires almost no additional data or computation and serves as an important baseline to compare other methods against. However, due to multipath effects the receiver node with the highest received power is not necessarily the closest.

2.2 Weighted K-Nearest Neighbor RSSI Fingerprinting

There are many examples of using K-Nearest Neighbor (KNN) based approaches for RF source localization in the literature, (Poulose and Han 2020; Honkavirta et al. 2009), including some that have used ray-tracing models to develop the radio map, or reference data, (Renaudin, Zemen, and Burgess 2018; Laaraiedh, Amiot, and Uguen 2013). For a given observation the received power at each receiver is taken as a feature vector, or fingerprint. Each feature vector is then normalized by the maximum in the set to scale all elements between 0 and 1. Training data must be generated by taking measurements at a grid of locations in the space of interest and or using electromagnetic propagation modeling. The training set makes up the radio map that is used to do position estimation. During the inference phase, the closest N (N = 4-8) fingerprints are weighted by the inverse of their Euclidean distance to the observed signal fingerprint to calculate the location estimate. Weighted K-Nearest Neighbor (WKNN) has shown to be one of the most effective methods but, requires a large amount of site-specific training data.

2.3 Time Difference of Arrival

For uncooperative sources, absolute time of transmission from a source is unknown. However, the time difference between time-synchronized receivers can be calculated by evaluating the cross correlation of the time series IQ data of the signals. The time differences are proportional to distance differences between a pair of receivers which form a hyperbolic path. To get a unique position estimate at least three receivers are required. The correlation functions for each pair represent time or distance differences and can be readily mapped to a 2D search space in the area of interest (Qi et al. 2019). There were two variations of TDOA evaluated. The first is estimating the time difference based on the peak of the cross correlation and then assigning a gaussian width to the hyperbolic path. This type is labeled TDOA Gauss in the results. The second variation is using the cross correlation itself as the width for the hyperbolic path, labeled XCorr TDOA in the results. All the cross-correlation functions or hyperbolic paths can be summed over the 2D/3D search space, or heatmap, and the location of highest amplitude becomes the location estimate. An example TDOA heatmap is shown in Figure 1.

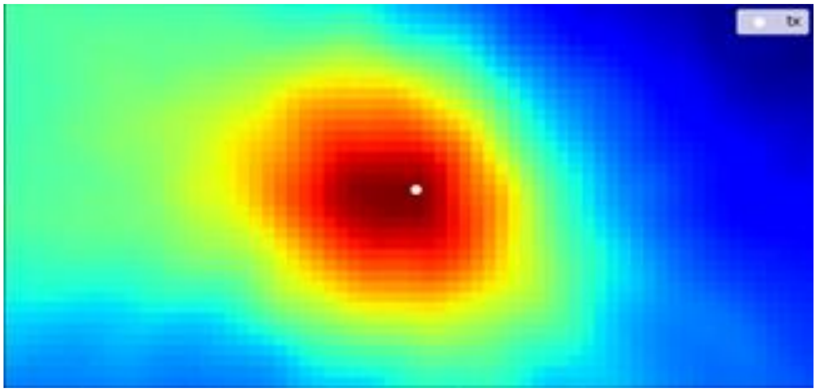

Figure 1. TDOA heatmap. The white dot represents the true transmitter location.

Some of the disadvantages of TDOA are that very precise time synchronization of receivers is required, the full IQ capture from each receiver must be transferred to a central location to perform the cross-correlations, and the accuracy of TDOA is highly dependent on the transmit signal bandwidth, accuracy = speed of light / (4x Bandwidth) ("How Accurate Is TDOA Geolocation?" 2017). TDOA works best in open environments and can have severe performance degradation in indoor multipath environments. The main advantages are that there is no training data required, for spaces with little multipath distortion TDOA can provide very accurate localization, and using the cross-correlation function directly in the generation of the heatmap can localize multiple concurrent sources (Boora and Dhull 2020).

2.4 DRSS Circles

Differential received signal strength circles (DRSS) is a method that uses a log-distance path loss model and the power differences between two receivers to create a circle of constant power ratio in the search space with some gaussian width. The combination of all receivers is used to overlay many circles over the search space. The location with the most circle intersections becomes the location estimate (Lee and Buehrer 2009). An example heatmap from the DRSS Circles method is shown in Figure 2.

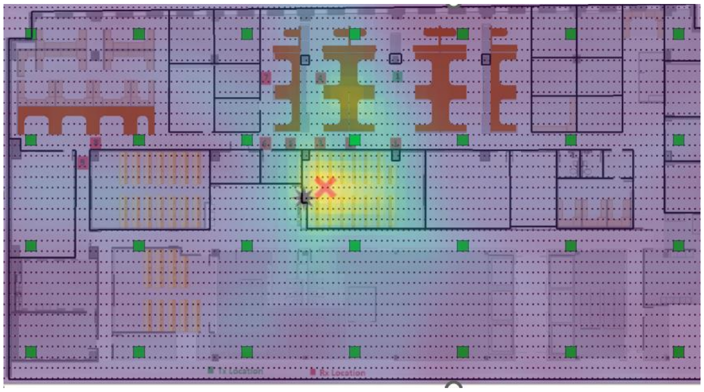

Figure 2. DRSS circles heatmap

2.5 Received Signal Strength Indicator Gaussian Joint Estimation

A method to estimate a posterior distribution of transmitter likelihood at a given test point to enable building a probability map over an area of interest was evaluated. This method is based on a log-distance path loss model. The joint gaussian probability density function based on the power differences between each combinatorial pair is estimated over the search space. Because the method is relying on power differences between each receiver node the absolute transmitter power is eliminated from the model. Figure 3 shows an example heatmap from this method.

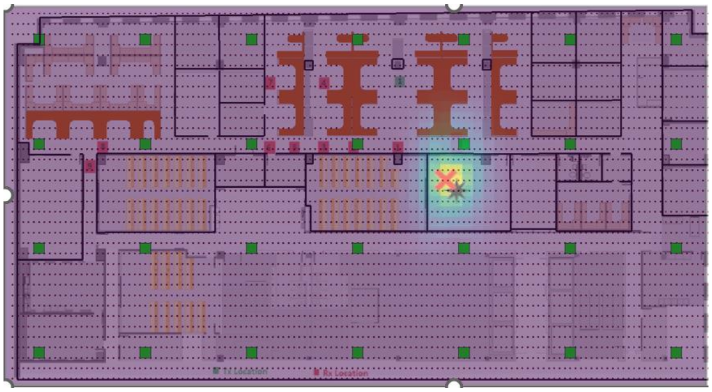

Figure 3. RSSI gaussian joint estimation heatmap.

This joint gaussian estimation method was one of the top performing methods evaluated. However, like TDOA, if the location of interest doesn't match the assumptions, the path loss model, then the performance can be unpredictable.

2.6 Neural Network based RSSI Fingerprinting

A convolutional neural network (CNN) or artificial neural network (ANN) perform very similar to WKNN. Neural network-based approached are advantageous when the number of observations in the training set or radio map becomes very large. WKNN computes the Euclidean norm between the observation and each sample in the training data and as the number of points grows a neural network-based approached can be more computationally efficient. In addition, it was found that neural network-based methods had fewer catastrophic outliers, or in other words there were fewer observations that had wildly inaccurate position estimates. The following is a summary of the specific network architectures that were evaluated in this work.

The specific artificial neural network is a convolutional neural network with three convolutional layers leading to a fully connected regression head. The activations were changed to leaky ReLU. The input space was a 4x7 grid of observations representing each RX in the space, therefore we decided to use non-symmetric kernels to reduce the feature space throughout the layers. Our choice of kernels was ((3,3), (2,3), (1,3)), with strides 1, which reduces the image to a single value in each filter by the end of the feature extraction layers. The number of filters was chosen as (64, 128 ,256).

3.0 Electromagnetic Propagation Modeling

Using 3D electromagnetic propagation simulation to characterize environments of interest will enable more accurate RF geolocation. For this work Remcom's Wireless InSite was used as the tool of choice. Wireless InSite is able to provide fast estimates of electromagnetic propagation in complex environments. Figure 4 shows an example simulation with different beam patters in an indoor environment.

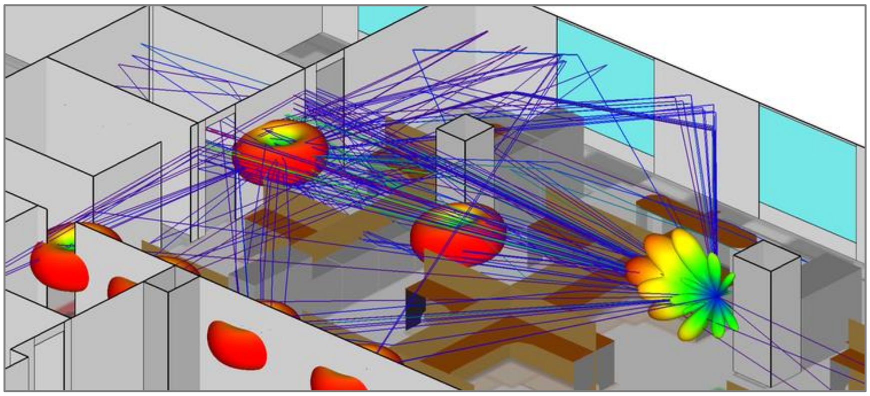

Figure 4. Example of Remcom's Wireless InSite ray tracing.

Wireless InSite generates the complex impulse response between each transmit and receive location. The complex impulse response consists of an attenuation, a phase shift, and a time shift term for each multipath component. By convolving the complex impulse response with an arbitrary time series signal realistic time series data in a multipath environment can be generated as shown in Figure 5. This is a powerful capability for further RF signals research.

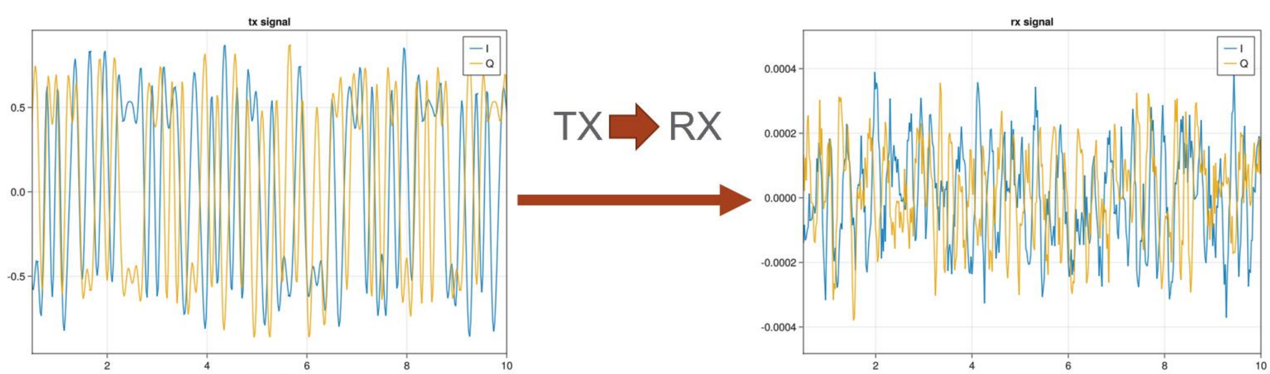

Figure 5. Transforming a transmit signal using the complex impulse response.

The downside to Wireless InSite is that it requires an expensive license for use, but it is a leading industry tool and well tested.

As an alternative Nvidia recently released a new open source solution called Sionna, (Hoydis et al. 2023). This tool is built on the AI/ML framework TensorFlow and is a differentiable ray tracer. This tool and will enable novel optimization and machine learning opportunities. There is ongoing work to evaluate the fitness of Sionna as an alternative to Wireless InSite. Doing away with the licensing cost would facilitate easier deployment of the simulation-based approaches presented in this work.

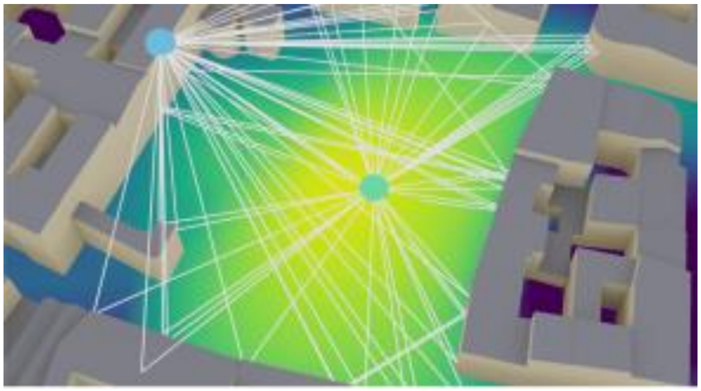

Figure 6. Nvidia Sionna ray tracing example (Hoydis et al. 2023).

Using a simulation-based approach it is possible to generate a radio map or fingerprint map of the area of interest that can be using for localization of RF Sources. A purely simulation-based approach would eliminate or augment a physical site survey. A physical site-survey is costly, requires skilled technical staff, and specialized equipment. A simulation-based approach allows for more flexibility to change and adapt the mode if there are any changes to the site of interest.

4.0 Simulated Comparison of Geolocation Methods

A large part of the work was to evaluate the propagation modeling tool. Using the simulation, we were able to evaluate and compare relative performances of a variety of different geolocation methods. A model that was provide with the Wireless InSite software was used as the simulation test bed as shown in Figure 7. The model is based on a typical indoor office environment at New York University (Maccartney et al. 2015). The green squares are 28 receiver locations, and the small red dots are 2400 transmitter locations.

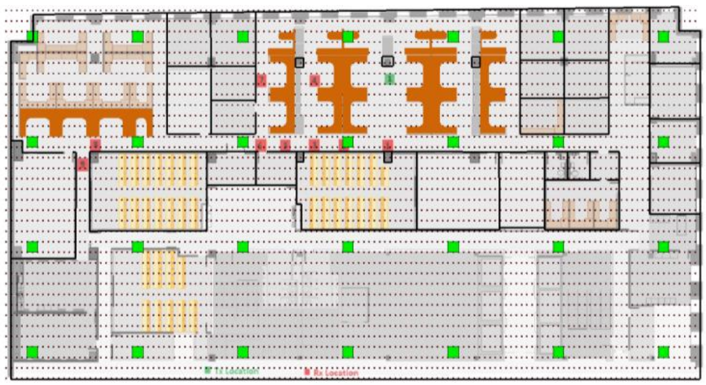

Figure 7. Simulation Test Bed, Green: RX, Red: TX

Using the data generated from this simulation the different geolocation methods were evaluated. The performance impact of the number of receiver nodes used in the localization was also tested.

When evaluating performance of different geolocation algorithms, it is important to look at the location of interest holistically. The electromagnetic propagation is complex and as a result there are locations where the location estimate error can be zero and others where the error can be very large (10's of meters). The root mean square (RMS) error and cumulative error curves are useful metrics to give a sense of the relative performance of each of the evaluated methods. The model was evaluated at a few different frequencies, but only the results for 2.4 GHz are presented here. All frequencies had similar trends in the localization results. The results are shown in Table 1 and graphically in Figure 8.

Table 1. RMS error in meters for all the evaluated localization methods for the simulated test case

Number of Receivers	HP RSSI	KNN RSSI	CNN RSSI	RSSI Gauss	RSSI Circles	Xcorr TDOA	Gauss TDOA
28	5.3	3.6	2.7	3.5	5.4	4.7	6.6
16	7.9	4.1	3.6	5.4	10.4	6.0	9.6
12	11.3	4.6	4.4	6.2	11.3	8.6	11.9
8	12.2	5.9	5.6	8.2	17.5	9.6	14.3
6	12.2	5.7	6.8	8.5	18.0	9.8	15.2
4	21.3	9.0	8.1	10.6	17.1	15.1	16.6

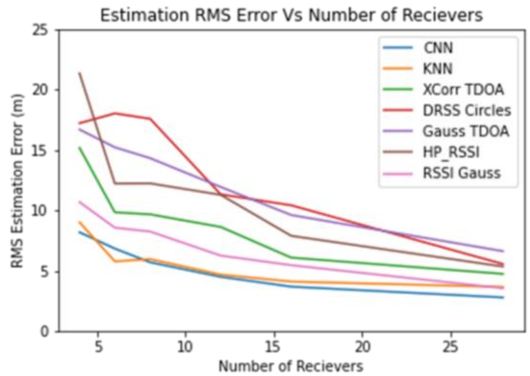

Figure 8. This is a graphical representation of the data in Table 1.

The results in Table 1 are an important outcome of this work. These results set expectations for what kind of performance can be expected in the in this kind of indoor environment. Figure 8 shows that the more receivers that are included in the localization process the lower the expected error will be. It is a cost vs performance trade off. The more receivers in a system (the higher the cost) the better the location estimation. To evaluate the absolute performance the RMS error is a helpful metric, but it must be realized that with RMS there are some locations where the error is much less than the RMS value and some locations where the error is much greater than the RMS value. Cumulative error plots are a helpful way to visualize the estimation error distributions. Figure 9 shows the cumulative error plots for the case of 28 receiver nodes (left) and 6 receiver nodes (right). Even in the case with the best performing algorithms (KNN and CNN) and 28 receivers there are a few locations with 10’s of meters of error.

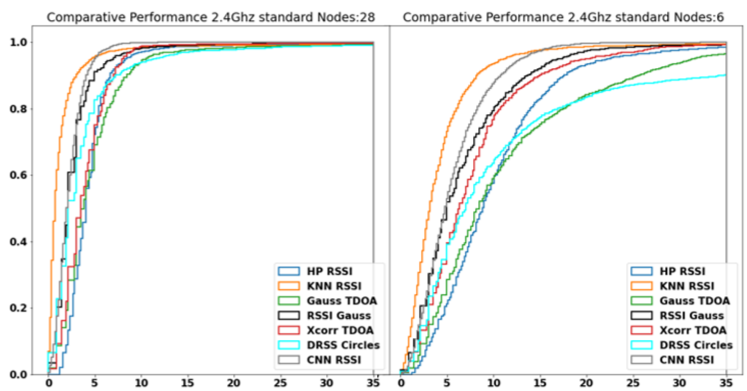

Figure 9. Cumulative error curve for each of the evaluated algorithms.

These results show the power of using an RF radio map or fingerprinting based method. The KNN and CNN methods consistently performed the best. The next best performer was RSSI Gauss and then XCorr TDOA. The power passed methods (KNN, CNN, DRSS, and RSSI Gauss) require less computation and data than TDOA, which requires the time series from each receiver. The results of this simulation show that for indoor environments power-based methods are preferable. In addition, methods that use site-specific information, KNN and CNN, will perform better than those that use a generic model such as RSIS Gauss or TDOA (Clark et al. 2023).

RSSI based fingerprinting for methods require some training data and as result require more up-front work for their use. Training data must either be collected with a physical site survey or through a simulation tool like Remcom’s Wireless InSite. A physical site survey is undesirable because it requires specialized equipment and skilled technical staff which makes it expensive and time consuming. A site-specific simulation would be an ideal answer to these concerns as it would allow the generation of large amounts and types of data for training. It would also be easy to modify the model and resimulate if anything about the location of interest were to change. This simulation based approach can readily be applied to existing in place monitoring systems because there are no required hardware modifications. In the next section the feasibility of using simulated data for RSSI fingerprint-based localization will be explored.

5.0 Physical Testbeds

The goal of this work was to test the feasibility of using electromagnetic propagation modeling to generate an RF radio map for RSSI fingerprinting-based geolocation of RF sources. Two separate physical testbed locations were evaluated, shown in Figure 10.

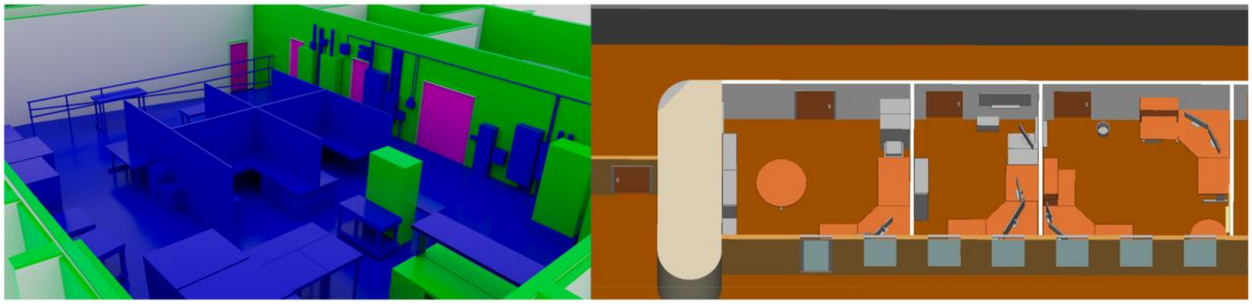

Figure 10. Testbed 1 (Left) and Testbed 2 (Right).

Testbed 1 had 6 receivers and Testbed 2 had 8 receivers. The CAD models are based on the floor plans supplemented with physical measurements. These models were then imported into Remcom's Wireless InSite and then the electromagnetic material properties were assigned to corresponding objects into the CAD model. To get a realistic simulation both the dimensions of the CAD model and the material properties must match reality as closely as possible. If the model is not true to reality the simulation results will not be of any use.

A physical site survey was conducted in each of the test beds. Signals from a transmitter were recorded at each receiver at regular spatial intervals. Half the data was designated as a training dataset and the other half as a validation dataset. TDOA will be excluded from the evaluation because time synchronized IQ data for TDOA measurements is logistically difficult to collect. There were relatively few data points collected in each testbed and as a result there was no advantage to using a neural network-based localization approach over using WKNN. The testbeds will be evaluated using KNN and RSSI Gauss. Both methods are high performing and will highlight the benefits of using a data-based approach vs a model-based approach. WKNN will be used to localize the measured validation dataset using measured training data and then using the simulated training data.

5.1 Testbed 1

In Testbed 1 the signal for each of the 6 receivers at 100 locations was collected. For each sample location the power of the simulated data was estimated and turned into a feature vector normalized by the highest power to a value between 0 and 1. Half the data was designated as the training dataset and the other half of the data was used as a validation dataset. The validation dataset location was estimated using KNN with measured training data, KNN with simulated training data, and using the RSSI Gauss estimation. The cumulative error plot is shown in Figure 11.

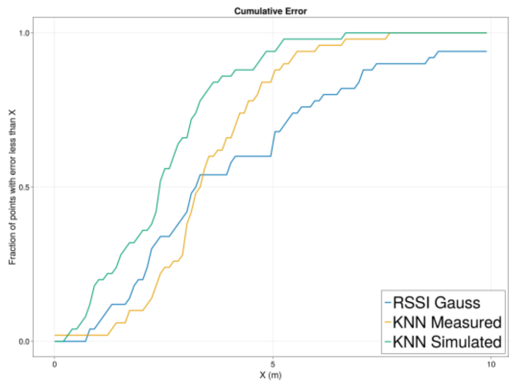

Figure 11. Testbed 1 geolocation results.

The simulated training data with KNN performed significantly better than KNN with measured training data. As predicted from the simulation test case, KNN methods take site specific data into account and as a result outperform the next best model-based algorithm, RSSI Gauss. This is an important result showing that RF geolocation informed by electromagnetic propagation can enable comparable or better performance as alternatives.

5.2 Testbed 2

500 data points were collected in Testbed 2 and again half were used as a training set and half as a validation set. In Figure 12, the RMS error of the three methods are compared for different subsets of the 8 receivers on the left and on the right is a cumulative average for the estimation error of receiver node set (2,5,7).

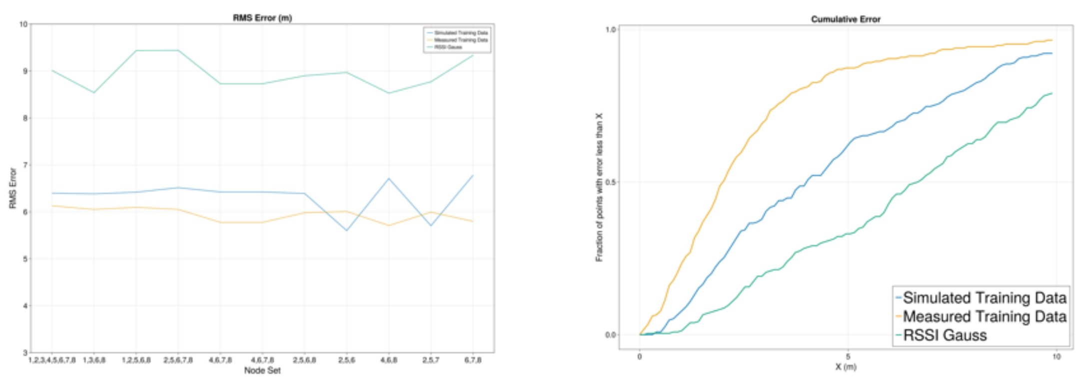

Figure 12. Estimation error for testbed 2.

The cumulative error plot in Figure 12 show that in contrast to Testbed 1, the KNN with measured training data performed much better than the simulated training data based KNN. Though KNN methods outperformed the RSSI Gauss estimation method. The simulation model in Wireless InSite must have some differences from reality. The errors in the simulation are most likely due to some errors in the spatial layout of the model and or material property differences. There is ongoing work to evaluate and understand this difference. While in this test case the simulated training data did not perform as well as the measured training data it still outperformed the next best model-based method, RSSI gauss. The simulation-based approach, even though it did not perfectly match reality, is still the best performing method that doesn’t require a physical site survey.

6.0 RF Geolocation Study Conclusions

Using a simulated testbed, the relative performances of a wide range of geolocation methods were compared. The results showed that geolocation informed by electromagnetic propagation modeling, the KNN and CNN, methods had the highest performance followed by RSSI Gauss and TDOA respectively. Then the KNN and RSSI Gauss methods were compared in a physical testbed with KNN using a measured training set and a simulated training set. It was shown that if the simulation model is good enough that simulated training data is just as effective as measured training data. Even in Testbed 2 where the simulated data was not as good as the measured data it still outperformed the next highest performing algorithm, RSSI Gauss. A simulation-based approach to generate a radio map, or training data, has been shown to provide very high-performance geolocation and could be easily applied to current and future in place spectral monitoring systems.

A key outcome of this work is to understand that models are sometimes wrong. RSSI Gauss, TDOA, etc. will always have difficulties because they don't take site-specific information into account. KNN and CNN data-based methods take site-specific information into account but will also sometimes fail if the training data is wrong or insufficient. Going forward propagation modeling should be a key part of RF geolocation, but an ensemble approach is likely the most robust strategy. Deploying KNN or CNN and RSSI Gauss for instance would be useful to give multiple position estimates. The methods studied in this work can readily be applied to current and future in place spectral monitoring systems.

7.0 Xilinx RFSoC – Future Capability

A new hardware solution from Xilinx called the RF system on a chip (RFSoC) was evaluated for in place spectral monitoring. The RFSoC can have 8 – 5 Gsps analog to digital converters (ADCs) or 16 – 2.5 Gsps ADCs with 8 or 16 - 10 Gsps digital to analog converters (DACs) depending on the model. In a small package, a single chip, there are multiple synchronized transceivers capable of digitizing or generating RF signals at speed. The RFSoC is capable of capturing signals multiple times the Nyquist limit, 2.5 GHz for the case of 5 Gsps sampling, by digitally down converting and filtering the aliased signal (“Beyond the First Nyquist Zone - Analog - Technical Articles - TI E2E Support Forums” 2015).

The RF ADCs and DACs are coupled to a high-performance FPGA for onboard processing at the edge. This small platform can be the foundation for a new high performance spectral monitoring node. As a proof of concept for spectral imaging we setup a simple test case as shown in Figure 13. An analog signal was generated on an external function generator as the input to a channel of the RFSoC. In the FPGA Fabric we implemented a Fast Fourier Transform (FFT) processing step and compared that with computing the FFT from the time series capture on a computer using Python. A very crude signal detection algorithm was implemented (threshold detection) for spectral monitoring.

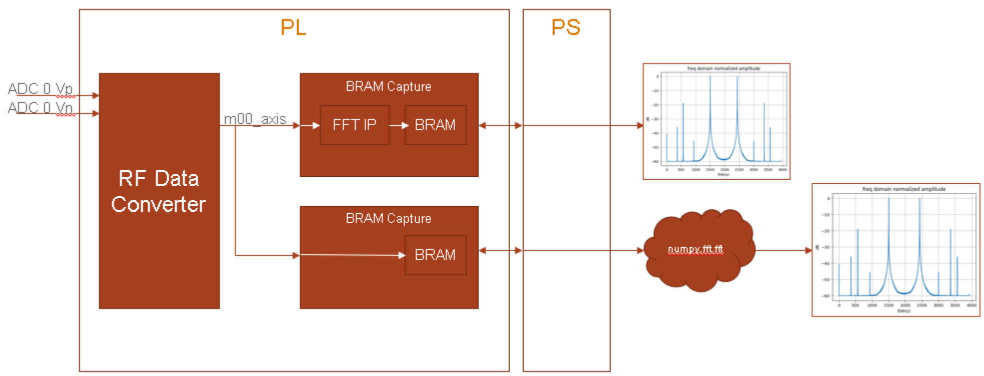

Figure 13. RFSoC test setup.

In addition to being able to monitor and detect signals at the edge the RFSoC intrinsically has 8 or 16 parallel fully synchronous RF transceivers. This capability opens the door for more advanced receiver nodes in an in-place monitoring system capable at “looking” at different parts of the spectrum simultaneously. This type of platform can use an array of receiver antennas to use angle of arrival (AoA) for geolocation. The RFSoC is a future hardware capability for more advanced sensor nodes and, due to the small form factor, a mobile standalone monitoring and localization solution.

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