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A ROBUST INDOOR LOCALIZATION APPROACH EXPLOITING MULTIPATH

RAHUL MUNDLAMURI, DEVASENA INUPAKUTIKA, KRISHNA SANDEEP AYYAGARI, GANESH REDDY GUNNAM, DAVID AKOPIAN ;The University of Texas at San Antonio; San Antonio, Texas

Abstract

In recent years, localization systems have gained significance in the indoor environment due to an increase in demand in various applications. WLAN fingerprinting-based indoor localization has gained popularity due to its stable performance and widely available infrastructure. The traditional fingerprinting approaches utilize received signal strength (RSS) and recently, the Channel state information (CSI) as location signatures. CSI is considered to lump all the multipath components. This paper presents the performance study of CSI- and RSS- fingerprinting in two different multipath landscapes: static and dynamic. We utilized artificial neural network (ANN) and compare the localization error of each scenario with RSS- based fingerprinting.

Introduction

With the rising requirement and use of location-based services, precise positioning in indoor and outdoor environments has become critical need. The global positioning system (GPS) continues to feature prominently in the outside environment, with high localization accuracy in most cases. However, its performance would suffer significantly in certain circumstances, such as metropolitan locations with tall buildings, steep terrain, and inside settings [1]. Due to this, indoor positioning services (IPS) have gained popularity. Most of the IPS systems use trilateration, triangulation, and fingerprinting-based methods [2].

Time of arrival (TOA) is a popular trilateration technique. Using TOA receiver's location can be estimated by calculating the packet travel time between the access point (AP) and the receiver, then the packet travel time is multiplied by the speed of light, which yields receiver location. However, calculating the travel time usually requires synchronization between AP and receivers [3]. Moreover, the method requires at least three APs for exact localization [4]. Triangulation technique like the angle of arrival(AOA) is a widely accepted technique in IPS. In AOA, the principle of measuring angular directions from an AP is placed at a known location to the angle at which the signal meets the receiver. The angle is measured by computing the phase of the receiving radio signals. However, directional antennas are required to measure precise angles [5], and the need for computationally expensive processing algorithms is more [6]. AOA estimation is highly constrained by the number of receiving antennas, their sizes, and line-of-sight propagation effects. Overall, original AOA techniques are not common for indoor positioning, but there were reports on hybrid AOA and fingerprinting techniques [6]. The accuracy of TOA and AOA methods gets affected significantly due to the multipath components since these methods require a direct line of sight between AP, and the receiver [7]. Unlike fingerprinting methods, TOA and AOA methods require knowledge of the AP's location [8].

Compared to the earlier methods, fingerprinting method has become a suitable candidate for indoor localization because of its high accuracy. In fingerprinting, we primarily collect and preprocess data in the selected area. Then the fingerprinting approach needs to establish a a database of location-dependent radio frequency (RF) measurements called fingerprints as they are quite unique for each location. fingerprint database by training the preprocessed data with a suitable neural network in the training stage (also known as the offline stage). Finally, in the online positioning stage, the testing data is compared with the training data stored in the database. The target positions are estimated by some localization algorithms covered in [9]. Most of the present and previous works have applied the fingerprinting approach for indoor localization based on either the RSS or CSI [10] [11]. However, the performance of RSS-based techniques is not robust due to low number of access points, fading and shadowing in indoor cluttered environments despite of a potential attaining meter-level accuracy in basic contexts [12]. On the contrary, CSI channel estimate data provide more robust multipath measurement components, which help to achieve 1 meter accuracy even with one access point [9] [13] in complicated environments such as narrow hallways.

So far as the online stage of location estimation is concerned, the aforementioned fingerprinting-based IPS have been utilizing different fingerprint matching methods, including deterministic methods such as k-nearest neighbors, probabilistic methods, and machine learning advanced neural networks such as convolutional neural networks (CNN) [14]. Therefore, the predicted location is as accurate as the data utilized for training the networks. Hence, the accuracy and reliability of CSI-based IPS also depend on the choice of CSI characteristics that include either amplitude [9], phase [15], or a combination of amplitude, phase, and derived features [16] based on statistics such as kurtosis [17]. Of all the research efforts towards the realization of a robust WLAN fingerprinting-based IPS, most of them have conducted database creation in controlled environments such as a dedicated although cluttered indoor laboratory area without any human movement or human movement activity during the collection process. Such experimental environments actively shield noise and hence do not reflect the real-world setting. Since CSI measurements have high sensitivity, in order to meet with the demands that arise from the varying location signatures between the offline and online stages of the fingerprinting process, the influence of multipath components and noise, we present a detailed study towards the realization of a robust WLAN IPS in a natural indoor environment. The main contribution of this paper is as follows:

1. Testing the robustness of the RSS- and CSI- based indoor

localization in different multipath components testing environments and comparing CSI with RSS performance in terms of mean error.
2. Impact of hidden layers(HLs) sizes for the ANN model on CSI and RSS-based indoor localization.

The rest of this paper is organized as follows. The experiment setting section covers the experimental environment for multipath scenarios data collection. The preliminaries and methods section presents data preprocessing methodology, the neural network model trained on the fingerprinting data and its configuration details. The results section describes the performance and sensitivity analysis evaluating the impact of various parameters on localization performance. Finally, the conclusions section provides some concluding remarks and future directions.

Experimental Setup

In order to study the performance of CSI based indoor localization we explore two scenarios. The first scenario is a receiver localization in static multipath landscape as shown in Figure 1, while the second scenario assumes dynamic multipath landscape. CSI and RSS data are collected in both scenarios. Only the placement and orientation of the SDR-based CSI detector is moved to collect data at different locations where the AP is fixed. As a result, the surroundings stayed relatively unchanged throughout the trial, with the exception of the relative orientations between the AP and the CSI detecting equipment.

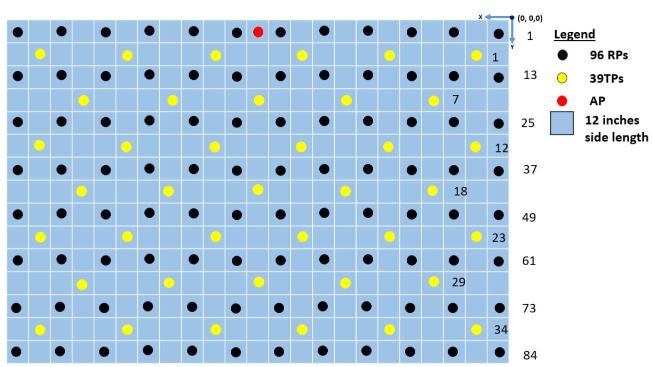

Figure 1: Hallway Layout for the Data Collection

The experiment is conducted at the hallway in the applied engineering and technology(AET) building at University of Texas at San Antonio. The total area of the experimental setup is 7×4.5 meters, with 96 reference points(RPs) for the training and 39 testing points(TPs) for the online testing. The beacon frame collected at the receiver is one sample, that consists of an RSS measurement, and complex-valued based CSI measurements corresponding to 52 subcarriers. For each RP and TP, we collect 1000 and 500 samples, respectively. We use a NI-USRP 2932 and collected a total of 96,000 samples for RPs, and 19,500 samples for TPs.

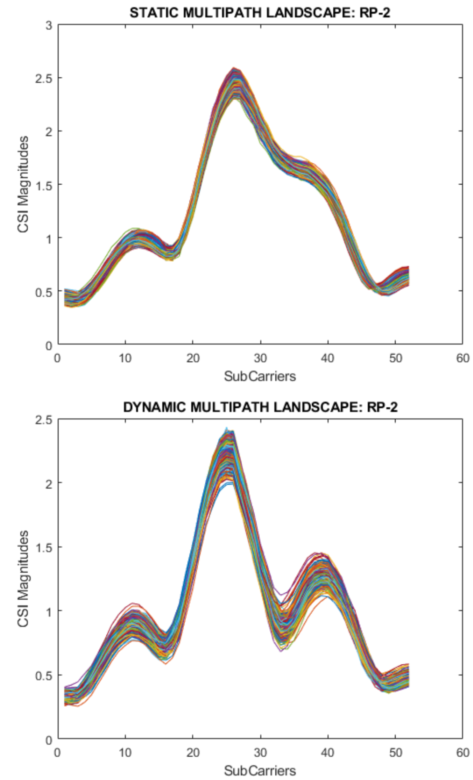

Figure 2: CSI plots of RP-2 at different multipath scenarios

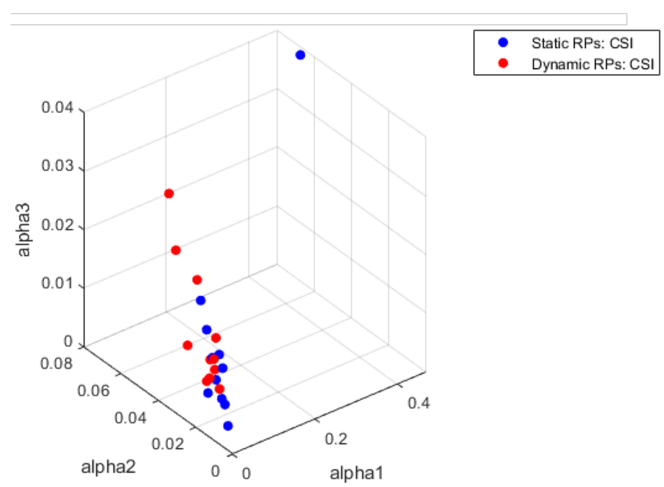

Figure 3: Feature distribution of CSI amplitudes

Preliminaries and Methods

Data preprocessing

This section presents a preprocessing methodology applied to the raw CSI data. Figure 2 represents the CSI amplitude measurements collected at RP-2 (see Figure 1) under static and dynamic landscape multipath scenarios. The difference in the location signatures is clearly observed in both the scenarios. To prove the effectiveness of CSI amplitudes as location signatures, and input features to the neural network model for location estimation in the online stage, we construct corresponding covariance matrix $\hat{H}$ from the CSI amplitudes. The covariance matrix is represented as follows:

$$\hat{H} = \begin{bmatrix} cov(\overline{H_1}, \overline{H_1}) & \dots & cov(\overline{H_1}, \overline{H_K}) \\ \vdots & \ddots & \\ cov(\overline{H_K}, \overline{H_1}) & \dots & cov(\overline{H_K}, \overline{H_K}) \end{bmatrix} \quad (1)$$

where cov(H_i,H_j) is the covariance between H_i and H_j, and $\overline{H}$ is the normalized version of the variable H. The peak normalization (dividing by the maximum subcarrier amplitude) is applied to each subcarrier amplitude.

We then calculate the maximum eigenvalues of the covariance matrix as the features from the CSI amplitude data. The results in three tuples corresponding to the three maximum eigen values α_1, α_2, and α_3 as below:

$$\alpha = max(eigen(\hat{H})) \tag{2}$$

For the α eigen values, the location signatures are more likely to be static, validating the case of fixed multipath scenario. On the contrary, the higher eigen values indicate that there is movement in the environment with either people intruding in the experimental environment or noise intrusion. To test the validity of the CSI amplitude features, Figure 3 shows the distribution of amplitude features α_i for the measurements at about 12 reference points (RPs) spread over the environment in both static and dynamic scenarios. Figure 3 shows the effect of movement and intrusion. The eigen values are more spread out in case of dynamic landscape as opposed to static case with some outlier values (Figure 3). It is observed from the distribution figures that the amplitude features are sensitive to the environment and therefore, the CSI amplitudes are the chosen features as input to the neural network.

Neural Network

In this paper, the neural network is trained to classify inputs, which are CSI measurements. The target classes are the radiomap locations. The size of the input layer depends on the dimensions of CSI data which is 52. The size of the output layer is based on the number of classes or locations i.e. 96. As shown in Figure. 4 the input dimensions correspond to the sub carriers(SCs) (per samples per location), i.e., 52×1. Initially, the inputs are computed and passed as weights and biases assigned to the neurons of the first hidden layer. A chosen entropy loss function is used to minimize the gradient. For all the hidden layers, we picked the hyperbolic tangent sigmoid *tansig* as the activation function. This function computes a layer's outputs from its net inputs and returns a value between -1 and 1 for each piece of net input. With *tansig*, having a stronger gradient and resultant positive and negative outputs make it easier to optimize. Scaled conjugate gradient (SCG) training algorithm is used to train the ANN.

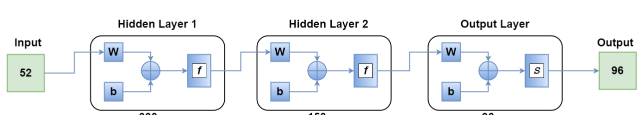

Figure 4: Two Layer Artificial Neural Network

This backpropagation approach searches in a direction that yields typically quicker convergence (conjugate direction) than the steepest descent path, while maintaining error reduction in all preceding phases. During each iteration, a single gradient descent step is taken that updates the weights and biases of each hidden and output block. The input (RSS or CSI) data is randomly divided into training, validation, and testing subsets by the model. To map the output weights to the estimated locations, the output layer uses a *softmax* function. As a result, each output neuron corresponds to an RP, and the final weights represent the anticipated probabilities and based on the probabilities each location will be classified, the proposed model of the neural network is shown in Figure. 5. In the proposed model the training and testing data is collected in different scenarios of the experimental environment i.e with static and dynamic multipath landscapes.

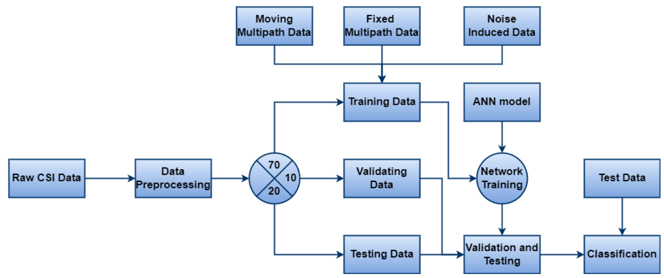

Figure 5: Block Diagram of ANN based CSI classification

Results

This section presents the performance analysis of fingerprinting-based CSI and RSS with static and dynamic multipath landscapes. To that end, we performed the comparative analysis in different multipath scenarios, and the impact of hidden layer sizes. The performance metrics were reported in meters for mean error and standard deviation.

Comparative performance in different multipath scenarios

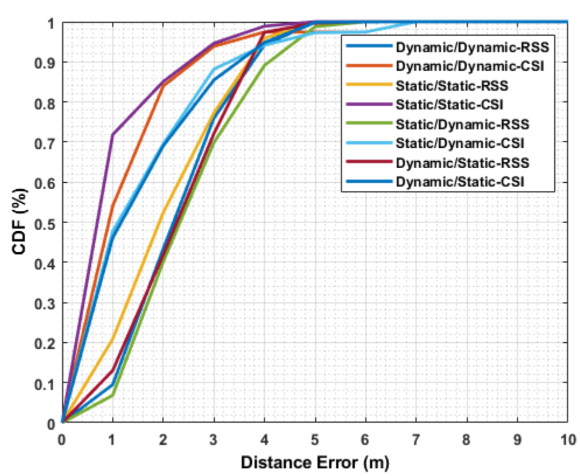

Figure 6: RSS vs CSI CDF plot of different multipath scenarios

Firstly, we conducted experiments in different multipath scenarios as mentioned above but in the same physical area with no movement representing static and a real-world setting without any movement constraints representing dynamic multipath landscape. The training and testing data are collected independently to examine the overall performance of RSS- and CSI-based indoor localization. We used ANN for training and testing with two, three, and four hidden layers initially. We observed that four hidden layer configuration with neuron sizes of $\{500, 450, 300, 50\}$, respectively, delivers optimal performance. We have trained and tested the ANN with four possible combinations of datasets collected in different multipath scenarios, as shown in Table 1. The CDF plots of RSS and CSI in different multipath scenarios are shown in Figure. 6.

Table 1: Multipath scenarios comparison

Train/Test Dataset	RSS Mean	RSS Std. dev	CSI Mean	CSI Std. dev
Dynamic/Dynamic	2.28	0.97	1.29	1.16
Static/Static	2.02	1.11	0.93	0.98
Static/Dynamic	2.43	1.09	1.55	1.31
Dynamic/Static	2.26	0.99	1.53	1.17

CSI clearly performs better than RSS as hypothesized. Moreover, as shown in Table 1, in each scenario, CSI performed well compared to RSS by 1 meter mean error. Whereas, in the second scenario, the training and testing dataset collected in a static multipath landscape, CSI not only performed well with a mean error of 0.93 meters, but it also outperformed RSS by 1.07 meters.

Impact of hidden layer size

In this section, we evaluate the impact of hidden layers (HLs) sizes for the ANN model. As observed in Table 1, the best performing scenario is of the static training and static testing dataset combination. Thus, we test with 2, 3, and 4 HLs by changing the neuron sizes as shown in Table 3. It is difficult to determine a suitable network topology from several inputs and outputs. The fact is that a fair number of hidden layers can reduce training time with high accuracy. Many approaches are defined to standardize the number of hidden layers required for a neural network, but the approximation depends on the type of database each time [18].For the proposed dataset we can clearly observe an improvement in performance in Table 3 with an increase in HLs.

Table 2: Impact of various Hidden layers

Hidden Layer Size	RSS Mean	RSS Std. dev	CSI Mean	CSI Std. dev
300-150	2.42	1.11	1.33	0.90
300-150-100	2.22	1.11	1.17	1.16
300-150-100-50	2.03	1.11	1.07	0.99
500-450-300	2.02	1.11	1.00	1.00
500-450-300-50	2.01	1.11	0.93	0.98

Conclusion

In this paper, we presented the performance study of CSI based and RSS based fingerprinting in static, and dynamic multipath landscapes. We observed in both the scenarios that CSI outperformed the RSS based indoor localization. An impact of HLs performed by varying HLs size to the ANN model for the CSI and RSS based fingerprinting further indicated the robustness of a deep learning model trained with CSI location signatures. Furthermore, it is observed that with increase in the number of HLs, the mean error and the standard deviation increase linearly with both CSI and RSS. Overall, CSI performed better over RSS. For future work, we may consider utilizing CSI phase alongside amplitude data characteristics from fingerprinting as opposed to only a single CSI signal characteristic. Additionally, we intend to extend the current work by adapting advanced neural network models for further fine-grained indoor localization under different multipath landscapes.

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Author Biography

Rahul Mundlamuri received a bachelor's degree in electronics and communications engineering from JNT University, India, in 2014, and a master's degree from the University of Houston, Houston, TX, USA, in 2016. He is currently pursuing the Ph.D. degree in electrical engineering with The University of Texas at San Antonio, TX. From 2017 to 2018, he was a Data Engineer with VRN Technologies, Austin, TX. His current research interest includes neural network-based localization services and data processing. For correspondence. Email: Rahul.mundlamuri473@gmail.com.

Devasena Inupakutika is working with Samsung Semiconductor Inc. She received Ph.D. in the Department of Electrical Engineering at the University of Texas at San Antonio (UTSA). Her research is in the development and performance analysis of systems and methods for enhancing mobility. Her research interests include web and mobile application development, cloud-IoT integration and deep learning based wireless LAN indoor positioning systems. For correspondence. Email: Devasena.inupakutika@my.utsa.edu.

Krishna Sandeep Ayyagari received his bachelor's degree from Jawaharlal Nehru Technological University, India, in August 2010 with distinction. For the next six years, he pursued his career as Sr. Electrical Engineer at Musimmas Oil Refinery, India. After gaining the industrial experience, he moved to the United States of America for higher education. In August 2018, he received his Master's degree in Electrical Engineering from the University of Texas at San Antonio, where he is currently pursuing his Ph.D. His research interests include smart grids, controls, optimization, and machine learning. For correspondence. Email: krishna sandeep.ayyagari@utsa.edu.

Ganesh Reddy Gunnam is a Ph. D. candidate in the Department of Electrical Engineering at the University of Texas at San Antonio (UTSA). He received his MS degree in electrical engineering from the University of Texas Rio Grande Valley (UTRGV) in 2017. He is pursuing his studies in the Smart Deep-logic Chatbot Design, Development and Performance Assessment Methodology. His research interests include Chatbot cloud deployment, virtualization and cloud computing. For correspondence. Email: Ganeshreddy.Gunnam@utsa.edu.

David Akopian is a Professor and Associate Dean of Research at the University of Texas at San Antonio (UTSA). Prior to joining UTSA, he was a specialist with Nokia from 1999 to 2003. From 1993 to 1999, he was a staff member at the Tampere University of Technology, Finland, where he received his Ph.D. degree in 1997. His current research interests include signal processing algorithms for communication and navigation receiver