Simulating and Modeling the Signal Attenuation of Wireless Local Area Network for Indoor Positioning

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ABSTRACT

Location is a key filter for mobile services, including navigation or advertising. However, positioning and localization inside buildings and in indoor spaces, where users spend most of their time and where the signals of the most widely-used positioning system, i.e. Global Navigation Satellite Systems such as GPS (Global Positioning System), are not available, can be challenging. In this regard, Wireless Local Area Networks (WLAN), e.g. Wi-Fi, can be used for positioning purposes by using a WLAN-enabled device, e.g. a smartphone, to measure and match the Received Signal Strength (RSS) of a signal broadcast by an access point. The challenges of this approach are that accurate maps of RSS are required, and that measuring RSS can be affected by many factors, including the dynamics of the environment and the orientation and type of a device. This paper provides a path-loss model to produce RSS maps automatically from floor plans and introduces an agent-based simulation approach to investigate different positioning methods. This provides a pathway to reduce the time and effort associated with WLAN positioning research.

CCS CONCEPTS

• Networks → Wireless local area networks • Computing methodologies → Modelling methodologies

KEYWORDS

WLAN signals, Indoor positioning, Signal fingerprinting, Agent-based modeling

1 INTRODUCTION

Many everyday services and applications, such as navigation, location-based advertising, and even emergency services, rely on location. While GPS, and generally Global Navigation Satellite Systems (GNSS), are the most widely used positioning technologies for outdoor use, the GNSS signals are not available or reliable for indoor use [14]. This is particularly important because we spend most of our time inside buildings. Studies in the US show that an average person spends over 80% of their time indoors [15]. Therefore, it is important to have a low-cost or ideally free, widely available and accessible technology that can provide an accurate and reliable Indoor Positioning System (IPS). Among many currently existing technologies, most of which use signals not initially designed for positioning, e.g. WLAN and Bluetooth Low Energy (BLE), Radio-Frequency Identification (RFID), Mobile Communication Networks, WLAN seems the best indoor positioning technology for a variety of applications and services such as indoor navigation, or emergency services [5].

WLAN antennas are cheap and already embedded in the smartphones, and broadcasting beacons can be found in many buildings. This provides high coverage and low cost, which have been identified as two important factors for an IPS to be used by a majority of indoor applications and services [5]. WLAN-based positioning mainly uses the Received Signal Strength Indicator (RSSI). The RSSI is a measure of signal strength between a WLAN beacon or Access Point (AP), which broadcast the signals and provides wireless connectivity to a wider network, and the antenna embedded in a WLAN-enabled device. However, WLAN signals can be easily affected by building features, e.g. walls and furniture, interference due to

other signals [6], and the dynamic nature of their environment, e.g. people moving around.

In order to convert the RSSI measurements to a location, it is normal to match the measured RSSI against a previously produced RSSI map. There are two main approaches to producing an RSSI map (A) modelling the signal propagation, and (B) fingerprinting [8]. Fingerprinting currently seems to be more accurate but requires measurement on-site, which can be time-consuming and costly. If signal propagation modelling can be improved to handle measurement noise and the effects of the environment, it could facilitate automatic RSSI map creation.

Understanding the effects of measurement noise and the environment on RSSI is highly empirical, requiring access to physical locations to undertake experiments. While some may share their fingerprinting data sets and position traces to help reproduce results and allow further research (e.g. Mendoza-Silva et al [19]), these do not directly help investigate fundamental variables of accuracy such as building layout, WLAN beacon locations, underlying environment dynamics, and measurement methodology.

In this regard, this paper introduces an agent-based simulation approach for an IPS based on signal propagation modelling.

Compared to other modelling approaches, Agent-Based Modelling (ABM) can have the potential to represent small-scale processes in a more detailed and specific manner, allowing researchers to gain precise information on how a system functions [18]. Another strength of ABM is its ability to represent space and the relative locations of individuals accurately and explicitly. This feature can be of particular importance in situations where the characteristics of a particular spatial behavior could have a significant influence on global outcomes [21]. In this investigation, local spatial structure is of fundamental importance to model outcomes, so this advantage of ABM is especially relevant.

One issue that has often been highlighted with respect to ABM research is the difficulty of verification and validation of a model and its results. ABMs typically require different approaches from other computational models [27] and while various authors have presented their own schemes for "verification" and "validation", there is not universal agreement on what the terms mean in the context of ABM. For model verification, for example, some focus on good programming practice [10], others on whether a model replicates large scale patterns observed in the real world [21], while others have proposed narrower mathematical procedures, involving the representation of models in alternative forms (e.g. [11]. Since this paper serves to introduce a model as a foundation for future work, verification and validation are considered only in the sense of how well certain model behaviors match the findings of empirical research. Further work could include a deeper approach to these questions, along with considerations of sensitivity [10], and robustness [9].

The IPS produces maps of signal strength automatically from floor plans. Several experiments evaluate the effect on accuracy of the positioning solution of both map error and noise during signal strength measurement. A better understanding of error correction methods allows for faster, more robust data collection, including by crowdsourcing, which can further improve signal propagation models in a virtuous circle.

The paper is structured as follows: section 2 explains the WLAN-based positioning techniques, map creation and the sources and the impacts of noises on RSSI. Then the simulation methodology is discussed in section 3. Finally, section 4 discusses the experiments and the results, followed by a conclusion.

2   WLAN-BASED POSITIONING

There are several methods to convert RSSI measurements to a location [23]. The most straight-forward are geometric techniques, such as trilateration, however these are not generally used as they are based upon signal propagation in free space and are poorly suited to non-Line of Sight (LoS) readings typical of an indoor environment [23]. Instead, the main approaches match signal data to an RSSI map through deterministic and probabilistic methods. Deterministic methods associate each map location with a single set of RSSI values and find the best fit to the measured RSSI through minimizing a cost function such as a Euclidean distance [23]. A typical deterministic algorithm is k-nearest neighbor [4]. On the other hand, probabilistic methods consider each location to have a range of RSS values due to noise in RSS measurement. These may be described as histograms based on the results of fingerprinting [29] but are more compactly described as parametric distributions, e.g. Gaussian [12]. Probabilistic methods naturally lead to extended Bayesian approaches which maximize the probability over a set of measurements over time, such as conditional random fields [28], Kalman filters [1] and particle filters [20], or Hidden Markov Models [24].

Fingerprinting is the most accurate and widely used approach for RSSI map creation[4]. Fingerprinting is based on measuring RSSI at known locations through site survey, with considerable time and effort [4]. This initial effort must be repeated to update the fingerprint as it will otherwise decrease in accuracy as the underlying environment changes. Approaches to lessen or eliminate the survey effort include improved mapping and localization algorithms which require less fingerprinting data [2], proposals to crowdsource the fingerprinting data [26], and improvements to signal propagation modelling [16]. Signal propagation models use simplified knowledge of how signal strength reduces with distance and presence of obstacles to estimate RSSI from some inputs, e.g. an internal plan of the building.

RSSI measurements are highly dependent on the measurement methodology. An RSSI value may be attenuated by several sources of systematic noise in the measurement: fading due to multiple signal paths [29]; device-based e.g. the choice of device used and device orientation [25]; user-based e.g. user orientation and the way a device is held [22]; and dynamic changes to the environment such as the presence of other people [22]. In a research setting, collection of testing data can be controlled to ensure the methodology is similar to the underlying fingerprint, however, any widely used IPS must allow for user heterogeneity. This requires methods to correct for this noise in measured RSSI data before comparison to an RSSI map. Additionally, the map itself needs to be as independent of measurement noise as possible. For fingerprinting, this is often obtained through additional effort e.g. multiple measurements are taken in different orientations at each location to account for this source of noise.

3   METHODOLOGY

Agent-Based Modelling typically involves the creation of a computer simulation in which entities in a real-world environment and their behaviors and interactions are represented explicitly, in order to study key features of a system [10]. The utility of this technique for the representation of human systems is well-established [3,7].

The Netlogo package was used to build a model of a user being located by an IPS. This is not a traditional agent-based-model – it has only a single agent, whose only action is to move randomly to create RSSI readings for an IPS – however Netlogo can readily implement this and has the ability to systematically test changes to inputs.

3.1   Environment and Entities

The environment of a building is represented by a two-dimensional (2-D) floorplan of walls. In this instance, the 70m by 100m floor of a stylized shopping center. Three types of entities exist within the environment, however only the user is referred as an agent in this paper, albeit the other two are modeled as "turtles" in Netlogo. Beacons are a static entity with nothing more than a location. The user is the entity being localized and moves around the environment. The third type of entity is people, moving around the environment and potentially affecting the RSSI measurement. While the user is affected by interactions with them, people themselves are not affected by interactions, hence they are not referred to in this paper as agents. In this simple instance, movements of the user and other people are assumed to be random and unconstrained by walls or other entities. A typical configuration is shown in Figure 1.
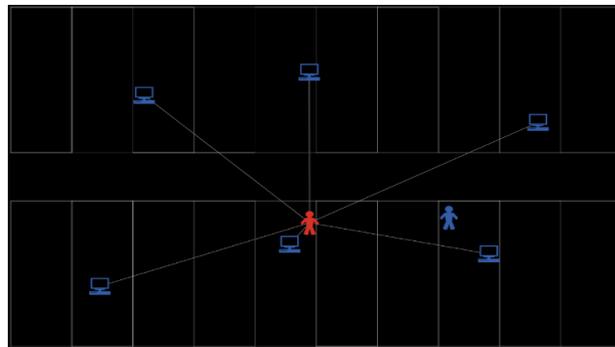
Figure 1: Simulation environment

3.2   Map creation

Creating synthetic RSSI values for the environment is achieved through signal propagation modelling. This will not be accurate to the real fingerprint for the reasons we are trying to improve signal propagation modelling. However, by producing a synthetic fingerprint with a detailed signal propagation model and then producing the map using a simplified signal propagation model with less floor plan information, it is believed that the spatially correlated errors are analogous to propagation modelling of real RSSI data, and that it is the relative error between RSSI value and the map which determines IPS accuracy.

Each 1m^2 cell has a synthetic fingerprint, generated by a standard signal propagation model known as the Wall Attenuation Factor (WAF) model [4] which takes the straight-line distance between the user and a beacon along with the attenuation effect specific to any intervening walls. The model formula is:

$$\text{RSSI} = PL(1) - 10n \log_{10} d - \sum WAF \qquad (1)$$

Where PL(1) is RSSI at a distance of 1 meter, d is distance in meters, n represents the decrease in intensity with distance (depending on reflection and attenuation effects); and *WAF* is the loss of signal due to attenuation through a wall.

Each cell also has a RSSI map approximation calculated with a simpler WAF model based on less information – not all walls are visible to the map model and the specific attenuation effect of each wall is unknown. 5 different map models were considered which provide a range of error against the fingerprint: the fingerprint itself can be used; two WAF models, one that has been fitted to the fingerprint data by linear regression and one with pre-determined parameters (based on the average wall attenuation); and two free space models which do not account for the presence of walls, again with one fitted to the data and one with pre-determined parameters. The simulation parameters controlling wall attenuation and visibility were modified so the fitted WAF had a typical Root Mean Square Error (RMSE) against the fingerprint of circa 3-5 dBm, reflecting empirical results [4].

3.3 Positioning

To estimate their position, the user generates an RSSI scan for their current position, generated by the fingerprint plus noise during measurement, and compares it against the map using an algorithm. The IPS accuracy is measured as the distance between the estimate and actual location.

There are 4 types of measurement noise considered in the model: fading, attenuation due to the movement of people across the signal paths, device heterogeneity and orientation. Parameters for each were chosen as follows: fading noise is represented as a Gaussian distribution with standard deviation 2.5dBm to give a typical range of 10dBm [29]; each person in the direct signal path attenuated the signal 5dBm, scaling down a 10dBm effect noted in LoS situations [22]; device heterogeneity was represented by a change in RSSI measurements between model runs, uniformly distributed between -10dBm and 10dBm [25]; and orientation was represented by a bell–shaped attenuation with peak of 15dBm and width of 1.2 radians.

Two well-known positioning algorithms were used: a k-nearest-neighbor (k-NN) algorithm with k=3; and a Bayesian algorithm based on each cell having a Gaussian distribution with mean equal to the fingerprint and identical standard deviation.

3.4 Experiments

Two experiments are undertaken to analyze the effect on location error:

- Investigating variance in the number of RSSI readings and algorithm, through changing the number of beacons and taking multiple scans for each position estimate (within a single second so with the user at the same location). The scenarios and observations are summarized in Table 1. For each of the 18 scenarios of interest, 80 permutations of path-loss and noise error were generated, with each permutation repeated five times, for a total of 7,200 different model runs. Each model was run for 300 steps, with average errors measured across all steps.
- Investigating the interaction of the errors in the path loss model and error due to noise effects. Beacon numbers and scans per estimate were held constant at moderate values. The k-NN algorithm was used as it had a shorter running time. The scenarios and observations are summarized in Table 2. There were 80 permutations of path-loss and noise error, as before, with each permutation repeated ten times for a total of 800 model runs. Each model was run for 300 steps, with average errors measured across all steps.

Table 1: Setup of experiment 1: variance in number of RSSI readings

Parameter	Variation
Number of beacons	3, 6, 12
Scans per estimate	1, 4, 8
Algorithms	k-NN, Bayesian
Path loss model	Fingerprint, WAF, unfitted WAF, free space, unfitted free-space
Noise effects	Device heterogeneity on / off Device directionality on / off Number of people 0 2 4 6
Observation	**Description**
Location error	Mean average location error (metres)
RSSI error	RMSE of error between expected RSSI at user's location and the actual RSSI caused by path loss errors and noise effects (dBm)

Table 2: Setup of experiment 2: interaction of location and noise error

Parameter	Variation
Number of beacons	6
Scans per estimate	4
Algorithms	k-NN
Path loss model	Fingerprint, WAF, unfitted WAF, free space, unfitted free-space
Noise effects	Device heterogeneity on / off Device directionality on / off Number of people 0 2 4 6
Observation	**Description**
Location error	Mean average location error (metres)
Path-loss error	RMSE of error between expected RSSI at user's location and the actual RSSI caused by path loss error (dBm)
Noise error	RMSE of error caused by noise effects (dBm)

4 RESULTS

For a constant number of beacons, increasing the number of scans decreased location error for a given level of RSSI error. The improvement is only material for low overall levels of RSSI error, in the order of 5dBm and below. This is as expected, as multiple scans at the same location generates multiple measurements of fading error but other errors are identical.

Hence, when fading error is a small contribution to overall error, additional scans do not improve accuracy.

Increasing the number of beacons decreased the location error at all values of RSSI error. It is believed that this effect is due to having beacons closer to the user. This improves positioning as closer beacons have greater signal change between adjacent cells.

The K-NN and Bayesian algorithms performed similarly. This is an artefact of the modelling process, as without knowledge of the RSSI variance at each location, maximizing the Gaussian probability is effectively identical to minimizing the Euclidean distance between signals, as per the k-NN algorithm.

At high levels of RSSI error, the location error appeared to have an upper bound of around 45m, based on the relative performance of estimating position randomly. This upper bound has no significance beyond the model environment size and modelling of user movement. For all categorizations of results there was a breakpoint around 5dBm RSSI where the gradient of location error against RSSI error decreased.

The combined effects of path-loss error and noise error (as calculated through an IDW interpolation) are shown in Figure 2. Location error increases most quickly as path loss and noise errors increase to 5dBm. The change in location error is less pronounced thereafter, which confirms the results shown in Figure 3. Both error types have a similar effect on location error, except that the worst-performing path-loss models (i.e. the unfitted free-space model) have an exceptionally high location error, which is likely due to its bias to over-estimating distances.
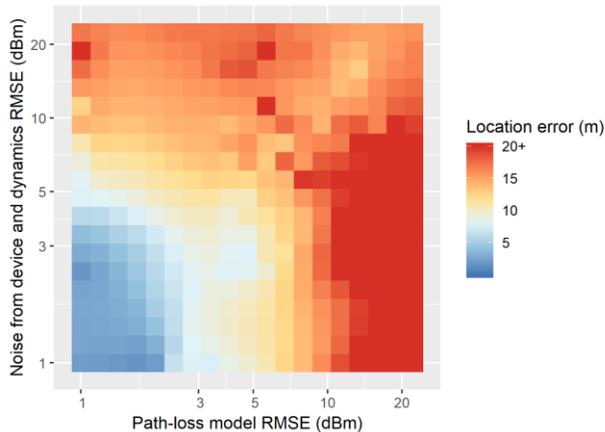
Figure 2: Effect of noise and path-loss errors on location error

An interesting effect of the interaction between the two error types can be seen: location errors form two peaks with high path-loss error and low noise error, and vice versa. If error levels are already high, an increase in the other error type has little effect.
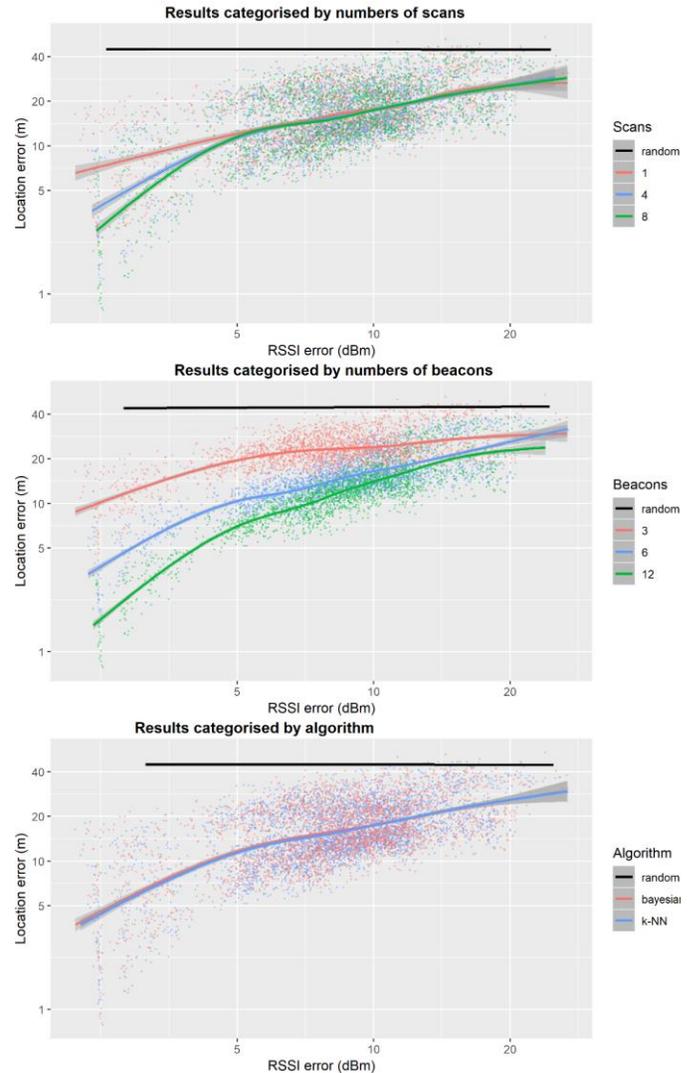
Figure 3: Results for varying measurements and algorithm

5 CONCLUSION AND FUTURE WORK

This paper demonstrates the capability of a simulation to evaluate different aspects of indoor positioning services performance. Specifically, it reproduces expected phenomena of greater accuracy with increased numbers of scans and beacons and it explores the relationship of IPS accuracy against two underlying types of error, RSSI map quality and measurement noise. It identifies a rapid decrease in accuracy within the first 5dBm of error, highlighting the difficulty of creating a system that works robustly in real-world conditions. The proposed system can work with a wide range of sources of error: the ability to consider different RSSI map quality, the inclusion of noise from other people, the possibility of heterogeneous devices and a sophisticated model of device attenuation.

Using this framework to replicate existing empirical research fulfils a dual purpose of validating the model and generalizing empirical results from their specific environments and methodologies.

Future work will hopefully include investigating the robustness and convergence conditions for recently proposed error correction methods based on crowdsourcing and unsupervised machine learning. This would require multiple agents with more sophisticated agent behavior e.g. movement. Also, comparing the results of models with real-world RSS data can give a better understanding of the replicability of the model. This will also help to recognize other potential sources of errors to be incorporated in an ultimately universal model. Such model needs a robust measure that can quantify the effects of the incorporated parameters. For this a variance-based global sensitivity analysis [13,17] can be carried out.

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