Optimization of Wi-Fi Access Point Placement for Indoor Localization

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Abstract—**The popularity of location based applications is undiminished today. They require accurate location information which is a challenging issue in indoor environments. Wireless technologies can help derive indoor positioning data. Especially, the Wi-Fi technology is a promising candidate due to the existing and almost ubiquitous Wi-Fi infrastructure. The already deployed Wi-Fi devices can also serve as reference points for localization eliminating the cost of setting up a dedicated system. However, the primary purpose of these Wi-Fi systems is data communication and not providing location services. Thus their positioning accuracy might be insufficient. This accuracy can be increased by carefully placing the Wi-Fi access points to cover the given territory properly. In this paper, our contribution is a method based on simulated annealing, what we propose to find the optimal number and placement of Wi-Fi access points with regard to indoor positioning. We investigate its performance in a real environment scenario via simulations.**

Keywords-Indoor positioning; Wi-Fi; Simulated annealing; MATLAB

I. INTRODUCTION

Location-aware services and applications become widespread today due to the rapid development of pervasive communication and the proliferation of mobile devices. In these services, collecting or computing position information is a key issue. Gathering this information in an open-air environment is a routine task for quite a while thanks to the Global Positioning System (GPS). However, indoor positioning has been a challenging issue and an intensively researched domain. The number of systems and technologies developed for indoor location sensing is almost endless [1]. The most popular technology is Wi-Fi (IEEE 802.11 standard family) because the low cost Wi-Fi equipments of existing local network setups can be easily reused for deriving location information.

However, Wi-Fi systems used today were not originally designed for positioning services. Therefore, the localization accuracy they can provide might be insufficiently low. The most common way to compute the position of a mobile device is the use of some triangulation technique [1]. For such techniques, the basic condition is the reception of a strong enough signal from at least three reference APs (Access Point) everywhere in the given territory. Unfortunately, a typical Wi-Fi system does not satisfy this condition. Furthermore, the number and position of the reference points can influence substantially the accuracy of position computation, too [2]. Hence, the design principles of legacy Wi-Fi systems have to be reconsidered when providing location sensing is also required.

In this paper, extending our former work [3] we investigate how to place Wi-Fi access points to perceive strong enough signal from at least three reference APs everywhere in the given indoor territory, but keep the number of necessary APs as low as possible. Hence, the overall cost of the indoor positioning system and its operation expenses can be minimized. Our contribution is a simulated annealing based algorithm that we propose to find the optimal number and placement of the APs in a given area. Our method has *O(n)* complexity and finds a solution, a good approximation of the global optimum, showing linear runtime behavior. Furthermore, we have developed a simulation tool in MATLAB [4] environment for the given problem. We used this tool to implement our algorithm together with the ITU indoor wireless signal propagation model [5] and to investigate the algorithm's behavior.

The rest of the paper is structured as follows. In Section II, we overview related work. Our simulated annealing based algorithm is proposed and described in Section III, and we present its evaluation via simulations in Section IV. Finally, we give a short summary in Section V.

II. RELATED WORK

Several indoor positioning systems have been developed based on the Wi-Fi technology, such as the Microsoft's RADAR system [6], the COMPASS system [7] or the Horus system [8]. They use different methods for deriving the location information. For instance, location fingerprinting [1] is also a widely applied technique besides triangulation. In this case, signal fingerprints are collected in advance at every position in the given area and later compared to the actual measurements. The location belonging to the best fit is selected as the position estimate.

The optimal AP placement for the fingerprint based scheme is a similar issue to our problem which has been investigated in recent works. It was shown via measurements in [9] that the number and placement of the APs can have substantial impact on the position accuracy. But in this work, a systematic way was not proposed for finding an optimal AP deployment, rather the results are based on experiments.

An AP location optimization method was proposed in [10] based on the Differential Evolution algorithm. In this method, the Euclidean distance of the RSS (Received Signal Strength) array between all the sampling points is maximized, by which the positioning accuracy can be improved. The experimental results seem promising, but the model does not take into account the effect of walls, doors and other obstacles.

A rapid and optimal AP deployment scheme was introduced in [11] based on genetic algorithm, which maximizes the signal space Euclidean distance between the APs. The simulation results pointed out that “the more the better” rule does not necessarily hold, though the number of APs usually increases with the size of the target area. Similarly to the previous work, the authors used a simple signal propagation approach and did not consider the attenuation effects of the indoor environment.

A framework was presented in [12] for linking the placement of APs and the positioning performance. The algorithm aims at choosing a proper set of APs’ locations so that the signal is maximized and the noise is minimized simultaneously. The location system is developed in a real-world environment collecting realistic measurements. However, collecting and comparing the measurement results of the different AP setups can be a cumbersome work especially in a large area to be covered.

Our simulation based method can complement the measurement based approaches by considerably reducing the number of valid AP setups.

III. ACCESS POINT PLACEMENT

The triangulation method is commonly used technique for positioning purposes in wireless environment. However, it demands the fulfillment of some basic requirements. Thus, the common indispensable condition for triangulation is to receive the signal of at least three reference APs, otherwise triangulation based positioning cannot be accomplished. In this work, we investigate how to place the APs to provide perception with strong enough signal strength of at least three reference points everywhere in the given indoor area, but keep the number of required APs as low as possible. By reducing the number of deployed APs, the overall cost of the indoor positioning system and its operation expenses can be decreased.

A. Problem of Optimal Wi-Fi Access Point Placement

Finding the optimal positions for the APs in real environment is a challenging task for analytical methods, because the propagation characteristics of wireless signals are too complex to be realistically modeled. Nevertheless, in order to find a deployment with minimum number of reference APs an obvious approach is to analyze and compare all the possible AP setups. Unfortunately, in real word this process is almost impossible to be accomplished, therefore simulations are to be used.

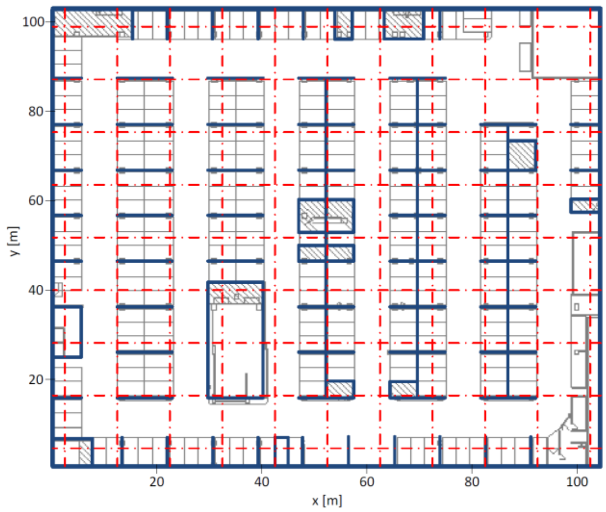

Figure 1. Territory map with a grid representing the possible AP locations

Actually, the number of AP position combinations is infinite because the territory, where the APs can be deployed, is continuous and contains infinite number of points available for AP deployment. To handle this problem, we assume that the APs can be located only in discrete points of the territory map. If the density of these points is high enough the original situation can be approximated well. For example, if we consider a 106m×102m indoor territory where the APs can be placed into the junctions of a grid with 10cm grid distance, than the number of possible AP locations is 1081200. Fig. 1 illustrates this scenario but showing a grid with around 10m grid distance for better visibility.

Unfortunately, analyzing all the possible AP location setups with a brute force algorithm cannot be accomplished due to the huge number of location setup combinations. In the previous example, 21081200 different AP position setups exist that cannot be processed in acceptable time. To solve this problem, alternative solutions must be found.

B. Method for Optimal Wi-Fi Access Point Placement

We propose the following top-down AP placement algorithm to find the optimal AP location setup(s).

The first step is to place an AP in every discrete grid junction point of the territory map. In the next step, the coverage area of each AP must be estimated using wireless signal propagation models in order to determine the number of perceived APs in each point of the territory where a mobile terminal can be located. In real environment, this can be almost any point of the continuous space, but we consider only discrete points with high density, equals to the map resolution in our simulations, in order to make the calculations possible. If there is no point on the map where the number of perceived APs is less than three, than one AP can be removed. If the number of perceived APs still fulfills this criterion another AP can be removed and so on, otherwise the algorithm stops.

This method can be modeled with a tree graph, where the states are the AP combinations represented by binary numbers.

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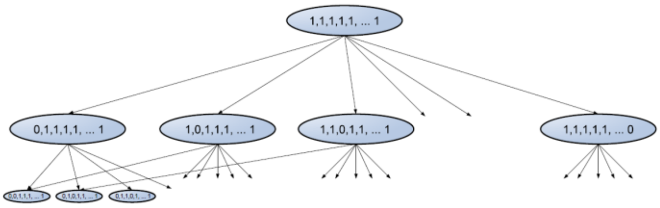

Figure 2. Graph representation of the proposed AP placement algorithm

After serializing the grid (creating from the 2D grid a 1D sequence by writing down the rows of the grid one after the other) the binary number determines which AP is part of the given setup. For instance, 010 means that the AP in the second position is installed, while the others are already removed. Fig. 2 illustrates the introduced algorithm. Note, that the Hamming distance of neighboring states is always one, because only one AP can be removed within one step.

The graph representation of the AP placement scheme can be used to originate our task in a graph theory problem. Thus, our goal is to find the state with the longest distance from the root, in which state the three perceivable AP criterion still holds. On each level of the tree the number of removed APs is the same, therefore the deeper we are in the tree the less APs are needed to cover the served territory. However, this "longest path" task is an NP-complete problem in graph theory [11].

Numerous heuristic optimization algorithms were developed to find the global optimum for NP-complete problems, like hill climbing, swarm intelligence, integer linear programming, simulated annealing, etc. For our case, we propose simulated annealing to approximate the optimal AP setup for Wi-Fi based indoor positioning. Simulated annealing is a generic probabilistic algorithm for the global optimization problem [13]. It tries to locate a good approximation of a given function's global optimum in a large search space even for NP-complete problems.

Our above-mentioned AP placement scheme can be extended with the simulated annealing algorithm. Hence, a previously removed AP can be added again with probability given in (1):

$$exp(-\Delta E/T), \qquad (1)$$

where ΔE stands for the cost function difference of the two neighboring AP setup states in question. The cost function is determined as the number of APs in the given state of the graph. Parameter T is called temperature and calculated as the sum of the number of perceived APs for each position on the territory map. This number is decreasing as more and more APs are removed (we are deeper in the graph), that can be interpreted as "cooling" in the context of simulated annealing. The possibility of putting a previously removed AP back prevents the method from being stuck in a local minimum that is worse than the global one.

Algorithm 1 shows the pseudocode of our extended Wi-Fi AP placement method.

Algorithm 1 Wi-Fi Access Point Placement Algorithm

initialization (add all APs)
While $counter > 0$
    Choose neighbor state randomly (add or remove AP)
        Case add
            If $random < exp(\frac{\Delta E}{T})$
                addAP()
        Case remove
            removeAP()
            If $perceivedAPs < 3$
                restoreAP()
    $counter = counter - 1$

The time required to get an appropriate AP topology for positioning purposes is an important issue that is affected by the complexity of the algorithms. To find the global optimum with the brute force method all the possible AP setups must be compared. Thus, it has an $O(2^n)$ complexity, where n is the number of possible AP locations. In case of our simulated annealing algorithm, a step limit, linearly dependent on *n*, is used to determine the total number of AP removals/restorations which limits also the runtime of the algorithm. Hence, our method, having $O(n)$ complexity, is able to find a good approximation of the global optimum in real time showing linear runtime behavior.

IV. EVALUATION

The proposed, simulated annealing based AP placement algorithm was evaluated via simulations. The simulation environment and the obtained results are introduced in the following.

A. Simulation Environment

We have used the MATLAB [4] environment to develop our simulation tool. In this tool, we implemented the ITU indoor wireless signal propagation model [5] what we applied in our simulations. The common parameters of this model are: frequency, transmitter antenna gain, receiver antenna gain and transmitted power. We set the default values of these parameters to 2.4GHz, 5dB, 2dB, and 100mW, respectively.

In wireless positioning systems, the RSS determines the range within the positioning service can be provided. If the signal is weak and the RSS is too low, the access point is not perceived by the mobile terminal and cannot be used for positioning purposes. Thus, in order to determine the AP coverage area we have introduced the sensitivity parameter of a terminal (-80dB). If the received signal strength is lower than the terminal sensitivity, the terminal is out of the AP's range.

The simulated area (map) has to be loaded at the beginning of the simulation process into our simulation tool. A .bmp image file can be used to determine the simulated environment by defining the rooms, walls, pillars, etc.

In the simulator, not only the simulated annealing based algorithm, but also a brute force method was implemented. In cases, when the number of possible AP positions is not too high the brute force method is a better choice providing always the global optimal solution. However, due to the NP-completeness of the problem finding the optimal AP topology with the brute force method in real scenarios is usually not possible.

Table I summarizes the parameter settings we used in our simulations.

TABLE I. SIMULATION PARAMETER SETTINGS

Wireless signal propagation model		
ITU indoor		
Frequency	**Tx antenna gain**	**Rx antenna gain**
2.4GHz	5dB	2dB
Tx power	**Terminal sensitivity**	
100mW	-80dB	
Step limit of our simulated annealing based algorithm		
10 × no. of the possible AP positions		

B. Simulation Results

In order to analyze the performance of our simulated annealing based AP placement algorithm we ran a number of simulations. In the first round, we have compared the brute force and our simulated annealing based method and investigated their limitations.

In Fig. 3, the average simulation runtimes are presented which were measured in function of the number of possible AP positions and iterated 10 times for each setup. We noticed some variance in the runtime, but the deviation of the values was always under 10%.

We repeated this investigation with increasing the number of possible reference point locations to see the scalability of our method. Fig. 4 shows the resulted values together with their 95% confidence intervals. In case of the brute force algorithm, we could not complete these simulations because they would have required too much time.

The obtained results show that our simulated annealing based algorithm is scalable and the simulation runtime remains almost constant even if the number of possible AP positions is increasing. On the contrary, the brute force algorithm does not scale well and the simulation runtime increases exponentially, as expected. In this experiment, the number of examined AP topologies was limited to 16, however, in a real environment this number can be tens or even hundreds of thousands, if the density of possible AP locations is higher.

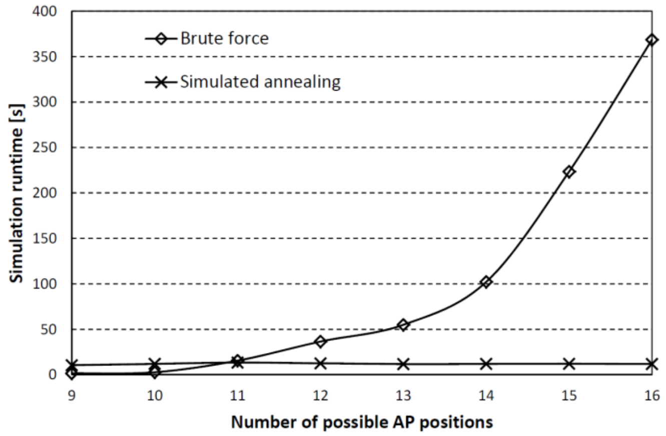

Figure 3. Simulation time vs. number of possible AP positions in case of the brute force and our simulated annealing algorithm

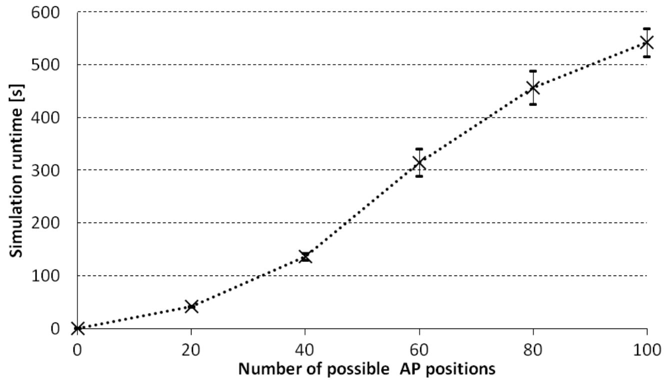

Figure 4. Simulation time increasing the number of possible AP positions

In the second round, we investigated further our simulated annealing based AP placement algorithm in a 106m×102m territory, where the grid distance was 5m. The used territory map (a parking garage) is illustrated in Fig. 1 but showing a grid with around 10m grid distance for better visibility. In this case, the number of possible AP locations is 440 meaning 2440 different AP topology setups. Of course, the grid density can be increased for the price of increased simulation runtime.

We repeated the simulation 10 times investigating the simulation runtime, consisting of the coverage map computation and the simulated annealing algorithm, and the resulted number of required APs. The results are collected in Table II.

TABLE II. COMPARISON OF 10 SIMULATION RUNS OF OUR METHOD USING THE SAME SCENARIO

Sim. #	Total sim. time [sec]	Coverage map calc. time [sec]	Sim. annealing alg. time [sec]	# of req. APs
#1	1202.13	1152.80	49.33	9
#2	1204.15	1140.72	63.43	9
#3	1211.89	1154.64	57.25	9

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#4	1212.33	1155.84	56.49	9
#5	1217.43	1153.31	64.12	9
#6	1205.20	1145.53	59.67	10
#7	1206.45	1141.17	65.28	9
#8	1214.78	1153.58	61.20	10
#9	1208.56	1147.89	60.67	9
#10	1209.12	1145.54	63.58	9
Avg.	**1209.2**	**1149,1**	**60.1**	**9.2**

The average simulation runtime was 1209.9 seconds, from which the time needed for the coverage map calculations was notable (1149.1 seconds), while only 60.1 seconds were required for the simulated annealing based algorithm. The reason behind it is, that in the analyzed indoor environment several walls, pillars and elevator shafts can be found making the signal propagation calculations more complex.

Note, that simulated annealing randomly chooses the neighbor states in the graph, therefore in case of several optimal solutions the resulted AP setup scheme can be different in consecutive simulation runs, even if the input parameters are the same. An output of the simulation is presented in Fig. 5 where the selected access point locations and received signal strength values are illustrated. The colors represent the highest RSS value in the given point of the territory which usually, but not necessarily, belongs to the closest access point in the vicinity of the measurement.

As we can see, 9 APs were enough to cover the territory by receiving the signal of at least three APs in each available position of the map. We have iterated the simulation process in order to examine whether the resulted number of APs is always the same (we reached a global optimum) or it is changing due to the randomness of the simulated annealing algorithm (we reached a local optimum). We found that in most of the cases the algorithm resulted in 9 APs, but rarely it gave 10 APs as a solution (Table II). We can conclude that in our scenario the global optimal solution contains 9 APs with high probability (we disregard the formal proof of this statement here) and the repeated simulation runs increase the probability to find a global optimum.

Analyzing several simulation runs we can notice that the algorithm locates the APs in the border areas in most of the cases and only few APs are placed in the center areas. The reason is that the perceivability criterion is censorious at the boundaries of the map; hence more APs must be deployed at the edges of the territory.

In the third round, we examined the AP coverage density achieved by our AP placement algorithm. As we discussed above, triangulation based positioning techniques require the reception of the signal of at least three APs to calculate the position of the terminal. The developed simulation tool makes it possible to analyze the number of perceived APs in the served territory. If the RSS is higher than the terminal sensitivity (-80dB), the AP is assumed to be available for positioning purposes. Fig. 6 illustrates the number of available APs, represented by different colors, in every point of the territory. This result corresponds to the AP position setup depicted previously in Fig. 5.

We can see, that the center of the territory is covered by 8-9 APs, while the terminals visiting the border areas can receive the signal of only few APs. Nevertheless, our perceivability criterion still holds everywhere in the territory.

In the fourth round, we investigated the impact of changing the perceivability criterion. The perceivability of at least three APs is a strict minimum requirement; however, by increasing the number of available APs in a given point of the map the position estimation accuracy can be improved. We have

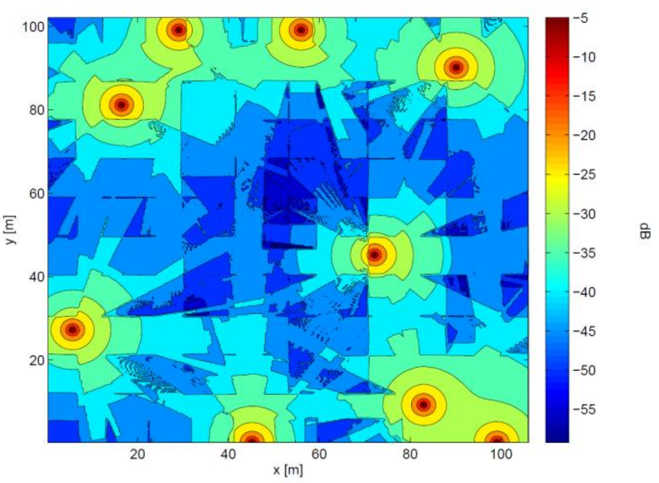

Figure 5. Selected AP locations and RSS values using our simulated annealing based AP placement algorithm.

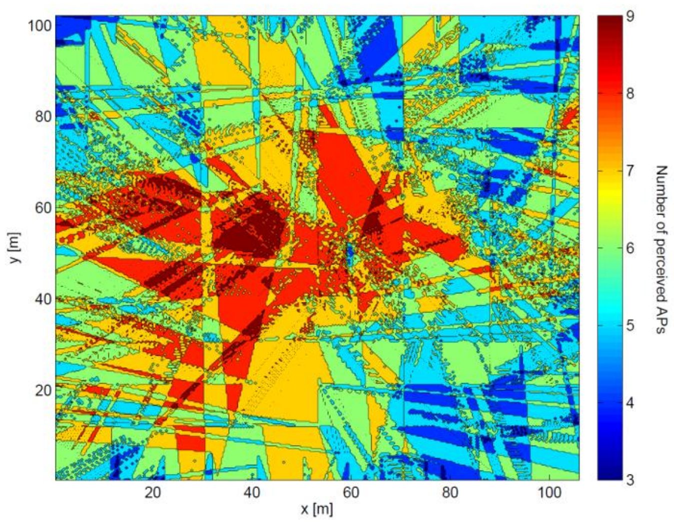

Figure 6. Number of APs available for positioning services in every point of the territory

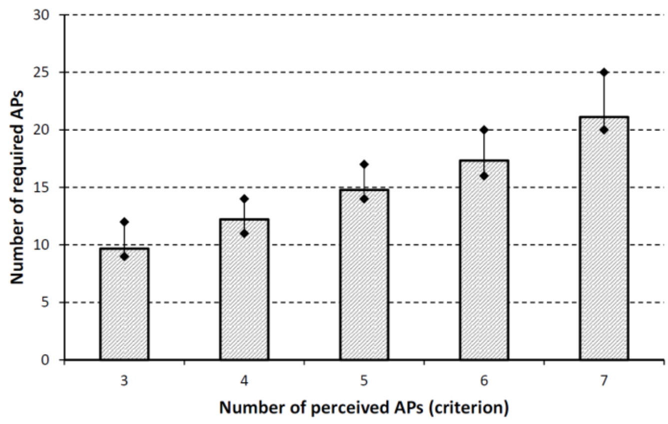

Figure 7. Number of APs required to fulfill the AP perceivability criterion

analyzed the total number of required APs if the minimum criterion of perceivable APs is increased. The simulations were iterated 20 times and the results are shown in Fig. 7 using the same territory map as in the previous experiments.

As it is expected, the number of required APs for the positioning system is increasing if more than three APs must be perceived in any point of the territory. As we noted before, the location and the number of APs returned by our method may vary due to the randomness of the simulated annealing algorithm. In Fig. 7 the average, the minimum and the maximum number of required APs are depicted using the same simulation setup. Although the differences are not significant, it is recommended to iterate the algorithm in order to find an AP topology close to the global optimum.

V. Summary

In this paper, we investigated the issue of optimal placement of Wi-Fi access points for indoor positioning. That means, how to place the access points to perceive the signal of at least three reference APs everywhere in the given indoor territory, but keep the number of deployed APs as low as possible. We proposed a simulated annealing based method, showing linear runtime behavior, to find a good approximation of the optimal solution. Furthermore, we have developed a simulation tool in MATLAB environment for the given problem. We used this tool to implement our algorithm together with the ITU indoor wireless signal propagation model and to investigate the algorithm's behavior.

Minimizing the amount of required access points the cost of deployment and the operation expenses can be reduced, but still an efficient positioning system can be operated. The developed simulation tool and our simulated annealing based algorithm are generic and they can be useful in planning radio-based positioning systems not just focusing on Wi-Fi technology. The simulator is adaptable to different wireless technologies by adjusting the signal propagation parameters or even replacing the propagation model.

As future work, we plan to further investigate the performance and limitations of our algorithm. We plan to collect real measurements and compare them with our simulation results.

Acknowledgments

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