

# Enhancements to RSS Based Indoor Tracking Systems Using Kalman Filters

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## ABSTRACT

This paper describes the site survey issues when deploying a wireless local area network (WLAN), the implementation of a location system over the deployed network, and the application of a Kalman filtering algorithm to enhance the tracking performance. We have made a site survey in the Electrical and Computer Engineering (EECE) department of University of New Mexico (UNM) to optimally position the access points. Ekahau Positioning Engine [1] was used to find the coverage areas of all available access points throughout the building. After having the network up and running, the signal strength values at certain locations are recorded and an indoor propagation analysis is made. A nearest neighbors algorithm and its variants are used to construct a location system and possible ways of improvements are discussed. Improvements in the estimation error using a Kalman filter algorithm are then presented.

## General Terms

Algorithms, Measurement, Experimentation.

## Keywords

Wireless LANs, Indoor Location Determination, Indoor Tracking, Kalman Filters, Signal Attenuation, IEEE 802.11, Ekahau, Site Survey.

## 1. INTRODUCTION

Locating objects and people outdoors is becoming trivial by using technologies like Global Positioning System (GPS), but due to indoor channel characteristics, accurately estimating location indoors remains a difficult problem. There are actually various ways for determining and tracking position indoors, but to do so accurately remains very costly. Deployment of sensors all around a building or the usage of expensive hardware might be required. Available wireless LANs structures make it possible to implement indoor positioning inexpensively. In this research, our goal was to decrease location and tracking errors in an office environment using the existing structure of a wireless LAN. The research required studying different domains, from wireless LAN

deployment to indoor propagation analysis, from implementation of pattern matching algorithms to applying Kalman filtering techniques to enhance tracking performance.

Our basic motivation behind this research was the current trend in deploying wireless LANs and their many applications. Wireless LAN sales are expected to grow, and the number of mobile PCs equipped with wireless capability in 2003 is expected to total 50 percent of all mobile personal computers (PCs), compared to only 9 percent in 2000. Wireless networks are appearing everywhere from universities to airports, and from restaurants to shopping malls. Considering the growth trend of wireless LANs, it is easy to see that they will be everywhere soon, and so will be the various applications of wireless LANs, with location determination being one of the most important. We have also noticed that although there are many published applications of Kalman Filters, they have not yet been widely applied to indoor tracking systems, rather than [8,14,15]. Kalman filters benefit from the information about the motion of the mobile for enhancing the accuracy of the estimation.

In order for mobile computing devices to fully benefit from the large number of resources and services available, it is important to locate the device and any resources in its vicinity. There are various applications of indoor geolocation systems in commercial, military and public safety, with some of them listed as [1, 3, 16]:

- Finding in-demand personnel (doctors in a hospital), or in-demand equipment (the closest available printer),
- Positioning and guiding soldiers or fire-fighters in a building,
- Locating the nearest restaurant/bookstore or a friend on campus,
- Location sensitive billing,
- Location specific advertisement (sending information to shoppers based on their location),
- Guided tours with a wireless PDA in museums, university campuses or exhibitions,
- Distractive free pervasive computing, as described in Project Aura [ref].

The granularity of location information changes from application to application. In order to print to the closest printer, our system does not need to be very accurate, but for a fire fighter trying to find his/her way out of a building, accuracy is very essential.

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The organization of the paper is as follows. Section 2 describes the site survey of the EECE department. Section 3 presents the application of the Nearest Neighbors algorithm to locate the mobile, and Section 4 gives the improvement in indoor location after the application of Kalman filters.

## 2. RF Site Survey

The EECE department/UNM has recently deployed a wireless LAN for use by students and faculty. We have conducted a radio frequency (RF) site survey prior to the placement of access points.

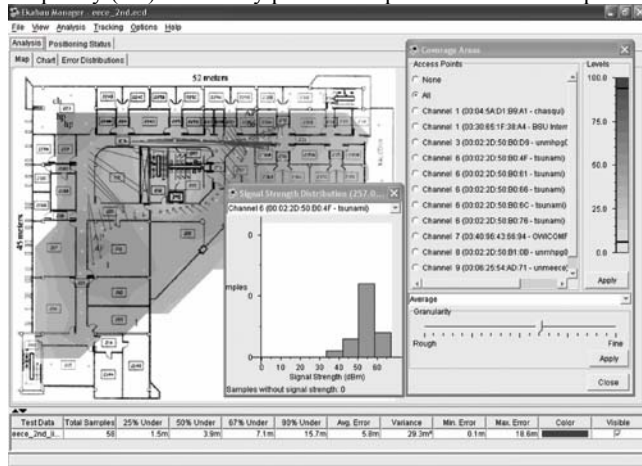


Figure 1: Ekahau Positioning Engine

### 2.1 Indoor Channel Characteristics

When deploying wireless LANs, indoor path loss is one of the primary design challenges for an effective solution. Wireless signals are attenuated with increasing distance and obstacles in their paths. Before deploying a WLAN, an RF site survey should be performed for determining optimal locations of access points to provide the best possible coverage. In free space, it is easier to predict the path loss behavior of the signal, where we mostly have a line of sight (LOS) path between the source and the mobile, and where diffraction, reflection, and scattering are less likely. But in indoor environments, we will have multipaths due to reflection, diffraction around sharp corners or scattering from walls, ceilings or floor surfaces. Even if we do not change our location, we have fluctuations in signal levels in the order of 2 to 3 dB. On top of that, changing indoor environment conditions such as the motion of people inside the building, and change of the positions of the doors also affect the signal levels. We also typically have *dead spots* where there is no received signal due to these effects. A detailed site survey is essential for good accuracy in location determination using pattern matching techniques.

### 2.2 RF Site Survey in EECE Department

We have used Ekahau Positioning Engine (Figure 1) to perform a site survey in the EECE department. At each floor of the EECE department, we have calibrated sixty to eighty locations. At each location, 20 RSS samples from all the available APs are recorded in a log file. In order to consider the effect of all the orientations, the mobile device is rotated slowly through all orientations. The resulting log file is then imported into MATLAB to perform signal attenuation and coverage area analysis, and to investigate

the location accuracy using different algorithms. Figure 2 shows the calibration locations on the second floor of the EECE department. The five APs used in the analysis are indicated on the map with the last two digits of their MAC addresses. The AP used for attenuation analysis in the next section is AP71, whose transmit power is 100mW (20dBm).

### 2.3 Indoor Attenuation Analysis

Path Loss in an indoor environment is given by;

$$PL = FSPL_{REF} + 10n \log_{10}(d),$$

Where PL is the signal attenuation between two locations separated by distance  $d$ ,  $n$  is the attenuation factor that varies with the indoor medium, and  $FSPL_{REF}$  is the path loss calculated at the far-field of the antenna.

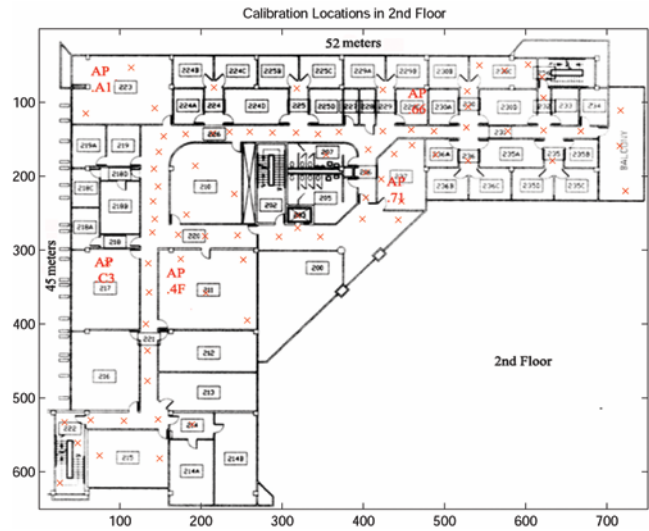


Figure 2: Calibration locations

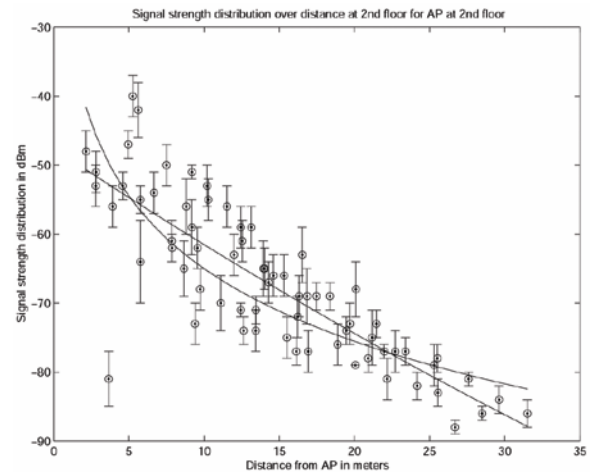


Figure 3: Signal strength distribution on second floor with respect to distance and function fits

Figure 3 shows the distribution of signal strength in dBm with respect to distance. The error bars represent the variation of signal strength over 20 (or all available) samples. It is seen that at a

certain location, the variance is around 3 dB, while there are locations where the variance is as large as 10dB. In addition, note that for two locations that are equidistant from the AP, there might be large differences in the means of the RSS. It is possible to fit logarithmic functions by finding the best  $n$  for the described path loss equation, or a 2<sup>nd</sup> order polynomial to minimize the mean square error. Table 1 shows the logarithmic and polynomial functions for all floors of the EECE department and for EECE vicinity, which are also displayed on Figure 3 for the 2<sup>nd</sup> floor. Table 2 summarizes the attenuation caused by different building material.

**Table 1. Logarithmic and polynomial function fits to signal strength data**

Floor	n	Polynomial Function Fit
Second Floor	3.4	0.0054d <sup>2</sup> -1.44d-47.6
Third Floor	3.5	0.048d <sup>2</sup> -2.29d-51.8
First Floor	4.1	0.015d <sup>2</sup> -1.23d-62
Fourth Floor	5	0.113d <sup>2</sup> -4.37d-49.6
EECE Vicinity	3.2	0.0047d <sup>2</sup> -0.75d-60.1

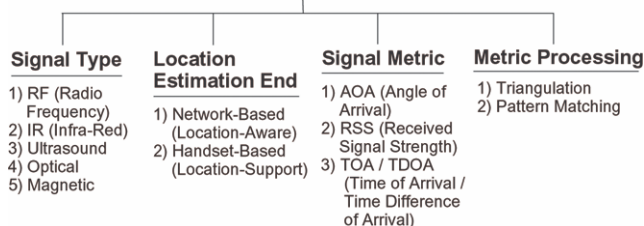
**Table 2. Attenuation caused by different building material**

	Attenuation
Elavator	23dB
Building wall	3dB
Wooden doors with windows	1dB
Seperating Floors	22dB

### 3. WIRELESS INDOOR GEOLCOATION

There are various approaches for estimating the location of a mobile indoors, as classified by the Figure 4. Using Time of Arrival (TOA) information, location accuracy in the order of 1 meter can be obtained, at the expense of high infrastructure cost and sensor deployment issues. The existing structure of wireless LANs offer an inexpensive alternative for performing indoor geolocation using the RSS metric. The triangulation method [16] is also possible, but is not very accurate due to large variations in RSS levels.

#### Classification of Location Methods

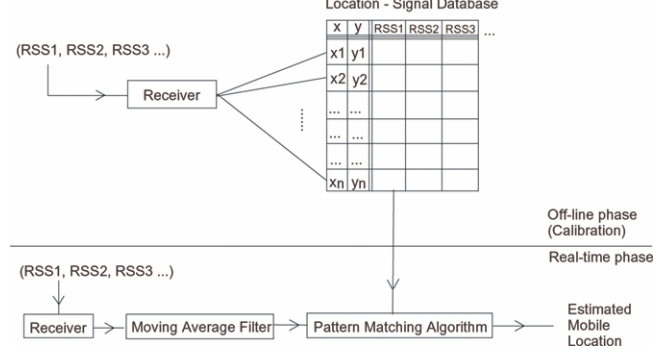


**Figure 4: Classifications of indoor geolocation methods according to different criteria**

#### 3.1 Pattern Matching Algorithms

Together with Microsoft's RADAR research [2,7], pattern matching algorithms gained importance and are the dominant

location determination approach today. Figure 5 summarizes the methodology of pattern matching algorithms. The off-line data collection phase corresponds to the



**Figure 5: RSS based pattern matching algorithm diagram**

calibration step mentioned in the previous section. The signal strength samples at corresponding locations are stored in a database. In real time, signals from the APs used in the calibration are sampled at each second. The obtained samples are smoothed using a moving average filter of size 3 centred at the current time step. The resulting signals are used to estimate the mobile's location using a *Nearest Neighbors* algorithm. The mobile's location is estimated to be at the corresponding database entry that minimizes the *Euclidian distance*  $D_k$  in signal space. Averages or weighted averages of multiple nearest neighbours can be used to decrease the variance of the errors as follows:

$$D_k = \sqrt{\sum_{i=1}^n (RSS_i - RSS'_{ik})^2}$$

$$\langle \hat{x}, \hat{y} \rangle = \frac{\sum_{i=1}^n (\frac{1}{D_i}) \langle x_i, y_i \rangle}{\sum_{i=1}^n (\frac{1}{D_i})}$$

#### 3.2 Location Estimation Results

We have used a nearest neighbors algorithm and investigated the effect of using multiple neighbors, a moving average filter, a number of access points, and various calibration frequencies for the path shown in Figure 6, where the indicated samples are taken at each second. Table 3 shows the results using a single neighbour, the average of multiple neighbours and weighted average of multiple neighbours. It is seen that using multiple neighbours decrease the standard deviation of the errors, but does not have a significant effect on the means. A path walked at a less frequently calibrated south part of the floor resulted in a median error of 3.7 meters. Improvements by using a moving-average filter and increasing the number of access points are shown in Tables 4 and 5. Figure 7 shows the RSS values from the five used APs.

Although the locations of the APs are not required to be known, as opposed to the classical triangulation approach, their actual locations have a direct influence on the location algorithms. As an example, the fifth AP used in the experiments was located at the far northeast corner of the building, and was more effective in improving the accuracy than the fourth AP. The more scattered

the APs are, the less likely is signal aliasing and the better is the accuracy.

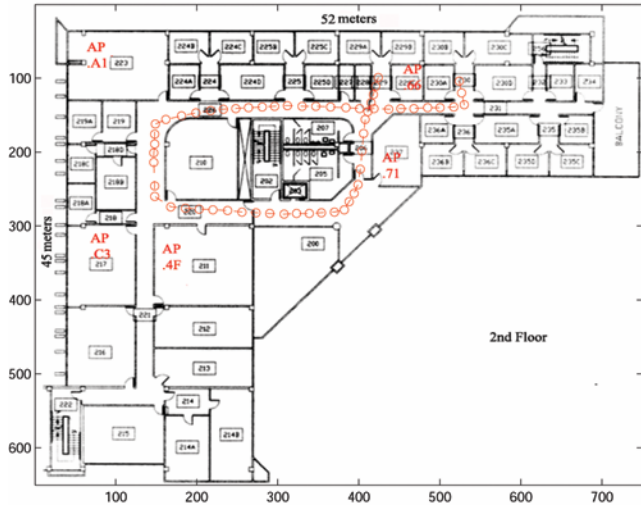


Figure 6: Investigated path with samples taken at each second

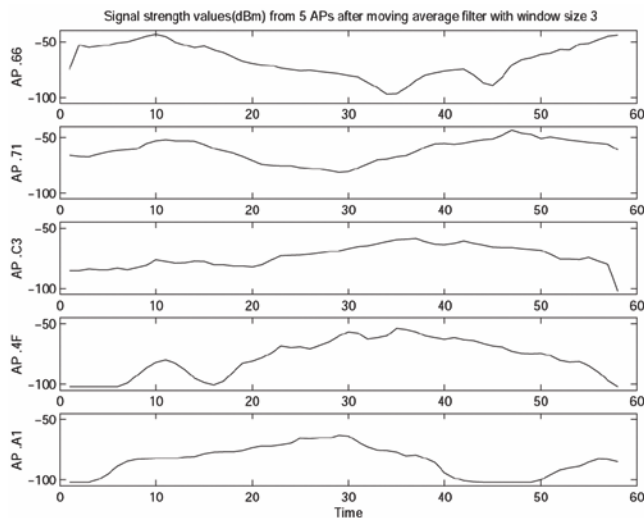


Figure 7: Signals received from the 5 APs after applying the moving average filter

The estimated path using nearest neighbors algorithm is shown in Figure 8. It is seen that many consecutive actual path locations are mapped to the same database locations due to signal aliasing. In order to avoid this and increase the accuracy of the system, we have used Kalman filters to model the 2-dimensional motion of the mobile, as will be described in the next section.

Table 3. Pattern matching error levels for the path in Figure 5

	1 NN	2 NN	3 NN	Avg.3 NN
Mean Error	3.24m	3.25m	3.18m	3.02m
Median Error	2.6m	2.75m	2.9m	2.75m
STD	2.2m	1.98m	1.6m	1.56m

Table 4. Effect of moving average filter

	Before Filter	After Filter
Mean Error	3.53m	3.2m
Median Error	2.78m	2.56m
STD	2.44m	2.24m



Figure 8: Estimated path using nearest neighbors

Table 5. Effect of number of used access points

	3 APs	4 APs	5 APs
Mean Error	4.79m	4.12m	3.2m
Median Error	3.43m	3.42m	2.56m
STD	5.47m	3.31m	2.24m

## 4. KALMAN FILTERS

### 4.1 General Bayesian Tracking Model

A mobile's motion can be modeled using a general Bayesian tracking model as follows:

$$x_k = f_k(x_{k-1}, u_{k-1}, w_k),$$

$$z_k = h_k(x_k, u_k, v_k)$$

Table 6. Comparison of error levels with Ekahau Positioning Engine constrained to use 5 APs

	Ekahau	NNSS	Kalman Filter	Kalman Smoother
Mean Error	2.6m	3.2m	2.7m	2.48m
Median Error	2.7m	2.6m	2.4m	2.5m

The current location of the mobile depends on the previous location, which is modeled by the non-linear function  $f_k$ . The observations depend on the locations through the non-linear function  $h_k$ . The current location of the mobile can be estimated recursively at each time step with prediction and update stages as follows:

### 1. Prediction Stage:

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|z_{1:k-1})dx_{k-1}$$

### 2. Update Stage:

$$p(x_k|z_{1:k}) = \frac{p(z_k|x_k)p(x_k|z_{1:k-1})}{p(z_k|z_{1:k-1})}$$

$$p(z_k|z_{1:k-1}) = \int p(z_k|x_k)p(x_k|z_{1:k-1})dx_k,$$

If the process and observation noise are assumed to be Gaussian and if the dynamics are linear, the general filtering reduces to a Kalman filter.

## 4.2 Kalman Filter

The process and measurement equations for the Kalman filter are given as follows [12];

$$x_k = F_k x_{k-1} + w_k, \quad w_k \sim N(0, Q), \quad x(0) \sim N(X(0), V(0))$$

$$z_k = H_k x_k + v_k, \quad v_k \sim N(0, R).$$

The process and measurement noise are assumed to be independent, and are defined by the covariance matrices  $Q$  and  $R$ . They are initially estimated by measuring the covariances of different paths, and then are used for all the experiments.

The predict and update stages for the Kalman filter are as follows;

### 1. Predict Stage for the Kalman Filter

$$\begin{aligned} \hat{x}_k^- &= F \hat{x}_{k-1}, \\ P_k^- &= F P_{k-1} F^T + Q \end{aligned}$$

### 2. Update Stage for the Kalman Filter

$$\begin{aligned} K_k &= P_k^- H^T (H P_k^- H^T + R)^{-1}, \\ \hat{x}_k &= \hat{x}_k^- + K_k (z_k - H \hat{x}_k^-), \\ P_k &= (I - K_k H) P_k^-. \end{aligned}$$

Initially, a prediction of the current location is made using the previous location. This estimate is updated using the observations weighted by the Kalman gain  $K_k$ . If the variance of observations is high, the process noise covariance matrix  $R$  will be large, which will decrease the Kalman gain and the effect of the observations. If  $R$  is small, observations will be more trustworthy and weighted more heavily by the Kalman gain. If a posteriori error covariance  $P_k^-$  is low, it will make the Kalman gain smaller, which will give more importance to the predictions.

The two dimensional model describing the motion of the mobile is taken as follows;

$$\begin{bmatrix} x_k \\ y_k \\ V_k^x \\ V_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ V_{k-1}^x \\ V_{k-1}^y \end{bmatrix} + \begin{bmatrix} w_k^x \\ w_k^y \\ w_k^{V^x} \\ w_k^{V^y} \end{bmatrix}$$

$$\begin{bmatrix} z_k^x \\ z_k^y \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_k \\ y_k \\ V_k^x \\ V_k^y \end{bmatrix} + \begin{bmatrix} v_k^x \\ v_k^y \end{bmatrix}$$

The current location of the mobile is assumed to be the previous location plus the velocity, while the samples are taken at each second, and is subject to Gaussian noise whose covariance is constant and pre-estimated based on off-line trials. The current observation is the current location corrupted with Gaussian noise.

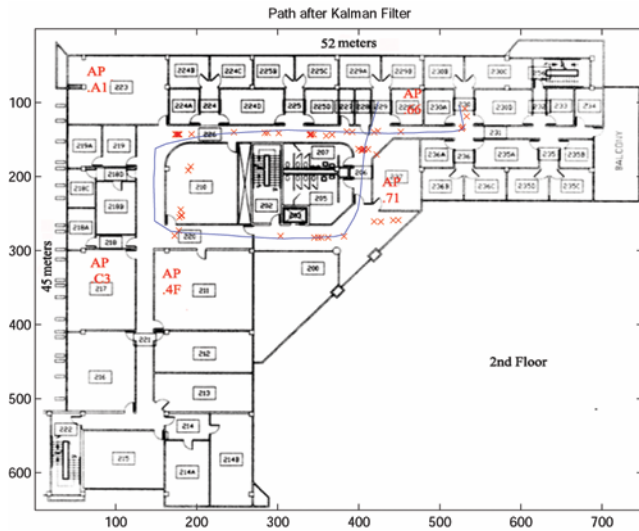
The error levels using the described model are given in Table 6. It is seen that the Kalman filter produces comparable accuracy to Ekahau. Although Ekahau claimed accuracies up to 1 meter, our experiments resulted in lower accuracy. This is partly because we have constrained Ekahau to use only the five APs that we used in our experiments, and can also be enhanced using more frequent calibration locations. A Kalman smoother is an off-line filter, and requires the availability of all the data. One possible application of Kalman smoothing is finding the most accurate path for a mobile that traveled inside a building in the past. Figure 9 shows the estimated locations using the Kalman filter. It is seen that nearest neighbor estimates are shifted closer to the actual path.

## 5. CONCLUSION AND DISCUSSION

In this paper, we have investigated the site survey issues when deploying a wireless LAN, analyzed many pattern matching algorithms, and offered a way of improving the location accuracy using Kalman filters. There has already been various research papers about the location estimation issues, but it can be said the tracking performance using Bayesian inference methods still needs further research.

Our future work will consist of applying other filtering techniques to improve accuracy. Although the noise statistics of the NNSS estimates were not Gaussian, Kalman filters decreased the location error, so more sophisticated filters (which do not assume Gaussian noise) are expected to perform even better. We have also assumed that the mobile's motion followed a linear model, which is not actually true. We believe that better tracking may be achieved using Extended Kalman filters [15], Unscented Kalman filters [4,13] or particle filters [13].

Adaptive Kalman filters which use time dependent state ( $Q$ ) and measurement ( $R$ ) covariance matrices may also be considered to improve the results [10]. The EM algorithm is another possible approach for finding the parameters of the mixture model that might have produced the measurements. There are also other navigational algorithms that make use of force fields [4], which are more effective than Kalman filters if the target is maneuvering frequently.



**Figure 9: Kalman Filter Estimates**

In our calibration phase, we have taken twenty samples at a certain location, while rotating throughout all orientations. In real time, the mobile is usually oriented to particular directions, and including only these directions during calibration might improve accuracy.

We have applied Kalman filters only on the single nearest neighbor estimate. It can be applied on multiple nearest neighbors, or it can be directly applied to signal strength values instead of the nearest neighbor estimates, which will make the algorithm, run faster.

The time complexity of the Kalman filter algorithm was not considered. This might require further research if the run-time performance introduces large delays in estimating the location. However, while the Kalman filter used a simplistic model, it will run faster than more accurate but complex filters, meaning less delay in the estimation.

Information about the building layout may be used for defining probable locations and thus avoiding improbable estimations. Image processing techniques may also be used to extract information from the floor maps. Although we have not applied the algorithm to multiple floors, it is straightforward to do so by including a floor coordinate for each entry in the database. The number of APs then can be kept the same, or new APs may be included to improve the results.

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