Improving the Accuracy of Wireless LAN based Location Determination Systems using Kalman Filter and Multiple Observers

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***Abstract*— Various RF based location determination systems have been proposed that use received signal strength fingerprints to identify locations. We implemented a Bayesian method [8] for location determination in a WLAN testbed and were able to get about 80% accuracy of estimation with a precision of 2.5 meters. We proposed two mechanisms to improve this accuracy: 1)Kalman filtering to remove noise in received signal strength readings and 2) a technique which uses estimates from multiple observers to determine the location. Results from an IEEE 802.11b based implementation of the first method shows that Kalman filtering during the training phase can increase this accuracy to 90%. The multiple observer technique that uses received signal strength readings *of* the mobile device *at* the access point, also shows a similar increase in accuracy. Since the multiple observer technique requires more time and resources, we conclude that Kalman filtering is a more efficient and simple way to increase the accuracy of location determination.**

I. Introduction

The mobile revolution has substantially changed the way people communicate. Consequently, the importance of value added services which can be provided through wireless interfaces has increased manifold. The knowledge of the position of the users can facilitate a wide variety of location specific services [11], [12], [14]. Location determination of a mobile user in outdoors is well studied and there exist many systems such as the *Global Positioning System* (GPS) [1] to determine the location with accuracies up to one meter. On the other hand, the problem of locating an indoor user is being studied only recently. The use of infrared, RF and ultrasonic technologies have been proposed for indoor location determination [2], [5], [8], [3], [6]. ActiveBadge [2] is such a system which is based on infrared technology while ActiveBat [3] and Cricket [6] are based on ultrasonic technology. Infrared technology is not being considered for use in large systems due to its short range visibility and requirement of line of sight. Ultrasonic based systems can locate a user with greater accuracy but are very costly. As a trade-off between the accuracy of location determination system and the cost, RF based methods are also being explored.

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Wireless LANs work on Radio Frequency (RF) technology which provide high data rates; up to 11 Mbps on IEEE 802.11b [4] based networks and 54 Mbps on IEEE 801.11a/g based networks. Traditionally, wireless LANs were only used to provide data services, while other methods were used to locate the user. However, with introduction of RADAR [5], wireless LANs have grown in popularity for providing cost effective location based services indoors. RADAR identifies locations by the value of the signal strength index of the transmission from access points that cover that location.

After the introduction of RADAR in the year 2000, many improved location determination algorithms have been suggested. [8] has suggested the use of probability distribution of the signal strength as the unique identifying "fingerprint" of a location. Other attempts to improve the accuracy of the system include applying user based profile information and using mobility models of users as in [16], [15], [17].

In this paper, we improve the accuracy of location determination by making use of two basic observations - one, that the received signal strength measurements have a noise component, which must be removed. We apply the well-known *Kalman filter* [9], to generate filtered samples for training our system, as well as for querying our system. Second, we use a technique of "multiple observers" in location estimation, applying which the accuracy of the system is improved. The basic idea in this method is that if estimates from more than one observers of the location of a user are available, the probability of correct estimation will be higher.

The rest of the paper is organized as follows. In Section II, we provide some the background related to RF based location determination systems. We introduce the RSS noise filtering mechanism and the multiple observers techniques in Section III. The details of the algorithms are given in Section IV. The experimental setup along with results are presented in Section V. We conclude the paper in Section VI.

II. Background

In this section, we briefly discuss the organization of IEEE 802.11b infrastructure networks, their RF channel characteristics, existing RF based location determination methods and in particular, scene analysis based methods.

A. IEEE 802.11

An IEEE 802.11b infrastructure wireless LAN is based on cellular architecture where the system is divided into cells. Each cell, known as a *Basic Service Set* **(BSS)** is controlled by an *Access Point* **(AP)**. The AP connects to the wired backbone.

Direct communication between an access point and the IEEE 802.11b based radio card on a mobile station (MS) occurs over a common channel frequency. The channel is set by the access point, and the MS's radio card tunes its transceiver to the frequency of the access point having the strongest signal, by listening to *beacons* sent out regularly by the APs. Once one channel is chosen, the mobile station associates itself to the AP and is ready to communicate with it. The IEEE 802.11b standard defines a total of 14 frequency channels while the FCC allows only channels 1 through 11 out of which the only channels that do not overlap with each other are 1, 6 and 11 which can be used without causing interference between access points.

B. Characteristics of RF channels

The power of the transmitted signal from the AP is different from that received at the mobile device, due to attenuation and other factors. The *received signal strength index* **(RSSI)** of an AP at a location is an indicator of how strong the signal from that access point is at that location. RSSI is measured in dBm as follows:

$$RSSI\ [dBm] = 10 \log\left(\frac{received\ power\ in\ watt}{0.001\ watt}\right) \quad (1)$$

This RSSI is used in location determination, by either establishing a physical relationship between the RSSI and the distance from the AP, or by using empirical methods as discussed later.

RF channels are prone to noise, and when used indoors the effect of the noise on RSSI values is much more than when used outdoors. Factors such as multipath fading, interference, presence of humans or water, change in temperature and moisture contribute to noise in IEEE 802.11b channels [7], [8].

With the presence of noise, it has been observed in [8] that, (1) at a fixed location, RSSI value of the access points measured at the MS is not stable; however, it is distributed within a small interval, and (2) the number of access points covering a location varies with time. However, even with the presence of these noise factors, since the signal-to-noise ratio is high, RSSI can be used as an identifying feature of a location.

C. Existing RF Methods

Proximity, triangulation and scene analysis are the three broad classes of RF-based location estimation methods. Triangulation requires an accurate and predictable relationship between distance and RSSI, which may not always work in an indoor environment due to the noise factors discussed above. The proximity method simply identifies the mobile device to be in the region of the AP to which it binds.

Empirical methods have been shown to work to a finer level of granularity [5] of location. In these methods, termed *scene analysis methods*, the received signal strength index from each AP that is "visible" at the MS is measured at the MS's WLAN adapter card. A statistic based on such RSSI tuples (RSSI received from each AP) is then used as a fingerprint of that location. All the scene analysis methods are two phase methods, with an offline training phase and an online estimation phase. In the offline phase, the location determination system creates a *radio map* [8], which is a database of various locations and their corresponding RSSI fingerprints. In the online phase, location is determined by querying this radio map with the fingerprint extracted at that particular location.

In the scene analysis method proposed in [5] a single RSSI fingerprint tuple, which is the mean of the measured RSSI tuples during the off-line training phase is saved in the radio-map as an identifier of location. In the online phase, the location which has closest RSSI finger print to the measured one, in terms of Euclidean distance is reported back as the identified location. This method is simple and efficient but but does not deal with the problems caused by access points whose beacons are missed in greater numbers. We also do not have the information of the variance of the distribution of RSSI of a particular access point at the location.

The use of probability distributions, instead of means, as fingerprints of various locations, was introduced in [8]. In this method, RSSI from each AP, are read and stored in the radio map in the form of a probability distribution for that location. In the online phase, the system reports the location which has the highest posterior probability of observing the measured RSSI tuple.

Specifically, let the sampled fingerprint tuple during the on-line phase be $< rss_1, rss_2, ..., rss_n >$, where n is the number of access points). Then, assuming that the RSSI values from the access points are independent, and that unconditional probability of being at a location L is uniform, the location selected will be [8]: $argmax_L[\Pi_{i=1}^{n} Prob(RSS_i = rss_i|L)]$.

III. Improving the Accuracy

The scene analysis mechanisms described above, specifically the probability distribution based method achieves fair accuracy in terms of the probability of identifying the location within a certain "error distance". In [8] the system is reported to have achieved 90% accuracy within about 2 meters error distance. We implemented this mechanism, but were able to achieve only about 70-80% accuracy within this distance (see Figures 3 and 4). This was possibly due to a more "noisy" experimental set-up. Some improvements were therefore needed to re-gain the accuracy of 90% within 2 meters. The rest of the section describes two mechanisms we proposed to improve the accuracy: one, filtering the measurements to remove noise, and a second "multiple observer" approach, which can be applied under certain conditions. The actual algorithms that implement these approaches along with some heuristics, are described in Section IV.

A. Applying the Kalman filter to RSSI measurements

As mentioned earlier, received signal strength at a MS is different from transmitted signal strength, due to attenuation and several noise factors. The Kalman filter [13], [9] method can be used to estimate the "actual" RSSI, by estimating and removing the *measurement noise* component. We assume that the *process noise*, which is the noise in the transmission power itself is negligible when compared to the measurement noise. Also note that this is a system in which the state (the RSSI) is not modified with any control input. With these assumptions, the simplified Kalman filter equations are as follows:

- Time update equations :

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

- Measurement update equations :

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

where k is the time instant, $\hat{x}_k^-$, $\hat{x}_k$ are priori and posteriori state estimate respectively, P_k^-, P_k are priori and posteriori estimate of error variance respectively, and K_k is the Kalman gain. Q is the process noise covariance and R is measurement noise covariance. We assume that Q is $1e^{-4}$ and $R = 4$. The Kalman filter equations do not need this noise variance to be exact; the value of this variance converges when a large number of samples are taken. Therefore, our initial estimate only affects the number of samples required. (For further details, see [10]).

Note that Kalman filtering has been used earlier for indoor location tracking [18] for moving devices (i.e. applied to successive estimates of a changing location) - here we propose to apply it to the RSSI at a location assuming it is currently unchanging.

B. Multiple Observers

All the location determination methods discussed so far involve only one perspective, the perspective the mobile station gets by scanning the beacons arrived from the access points. The mobile station estimates its location based on this perspective it gets. We conjecture that it could be beneficial to get multiple perspectives to improve the accuracy of the location determination system. The additional perspective the system could get is the RSSI values of the mobile station's signal measured at all the access points. This perspective does come with the cost that the mobile device should bind itself to the access point to get the access point measurement of mobile station signal strength. This binding is costly in terms of time as the mobile station has to connect to all the access points which support the measurement of MS's RSSI. Furthermore, using the MS's RSSI at the AP to identify the location assumes that all MS'es will be transmitting at the same power as was used during the training phase. In other words, this method works if the mobile devices to be located can be assumed to be uniform. Nonetheless, it is worthwhile to explore the performance of this method, since one can imagine many situations where devices could be the same, and location accuracy requirement is high (e.g. guided tours in museums).

1) Building the multiple perspectives: The two perspectives are based on two radio maps, built as follows:

- *MS Perspective radio map*: In this perspective, the mobile station scans the channels and measures the RSSI values of all the visible access points. That is, the finger print of a particular location, in this perspective is the tuple of RSSI values of signals from different access points represented by $< rss^{MS}_{AP1}, rss^{MS}_{AP2}, ..., rss^{MS}_{APk} >$. Where rss^{MS}_{APi} represents the RSS value of access point i measured at the mobile station.
- *AP Perspective radio map*: In this perspective, the mobile station scans the channels to find all the visible access points. It then binds itself to each of the access point and queries about the RSSI measurement of the signal received from the Mobile station. That is, the finger print of a particular location in this perspective is the tuple of RSSI values of signals from mobile station received at different access points. The finger print is represented by $< rss^{AP1}_{MS}, rss^{AP2}_{MS}, ..., rss^{APk}_{MS} >$ where rss^{APi}_{MS} represents the signal strength of the mobile station measured at the access point i.

2) Merging the two estimates: Each of the perspectives independently estimate the location of the mobile user. The location is reported as 3-D coordinate. We treat these two estimates again, as two measured samples of the state - the state in this case being the location of the MS. Since these measurements are also essentially noisy, we again apply the Kalman filter to produce a single estimate of the location. We assume that the coordinates of the location are mutually independent. The Kalman filter is applied independently to each of the dimensions. The location determination system reports the filtered x-, y- and z-dimension as the location of the mobile station.

IV. ALGORITHM

As in the case with any scene analysis method, our algorithm is also divided into two phases, offline and online. In the offline phase, the radio-maps for both the perspectives are built. In the online phase, the built radio-maps are used to answer the location queries from the mobile station.

A. Offline - Training Phase

The offline phase consists of three tasks: building the MS-perspective radio map, the AP-perspective radio map, and building *proximity lists* which help in reducing the search complexity of the algorithm.

1) Building the radio maps: At the mobile station, all the IEEE 802.11b channels 1 through 14 are scanned to get the list of the active access points. Beacons from these access points are used to measure the signal strength of that particular access point. The Kalman filter is applied to 20 raw samples of the RSSI tuples, to produce one "filtered sample". The RSSI probability distribution of an AP, for a location (MS-perspective radio-map) is created with 20 such filtered samples.

For the case of the AP perspective, access points are classified into 2 types; type 1 are those access points that can measure the strength of the MS's signal and type 2 being the rest of the access points. All the access points that are active at the MS's location and are of type 1 are queried to report the signal strength of the MS. The radio map is then again created with probability distribution of filtered samples.

2) Building the proximity lists: In the offline phase, we also build a list of locations for every access point, which are known to be near that particular access point. We define a location to be near a particular access point if that location receives a signal strength greater than a *proximity_threshold*. (set to -90dBm). This *proximity list* is used to narrow down the list of locations to be searched during the online phase of location estimation.

The algorithm of the offline phase is given in Figure 1. This algorithm is used separately for MS perspective and AP perspective independently to build respective radio-maps. It can be observed that the two perspectives differ only in the way the finger prints are collected at a location.

1: Collect RSSI finger prints in this perspective at a location
2: Filter them using Kalman Filter
3: Save the filtered RSSI tuple in Radio-Map
4: Repeat Steps 1-3, 20 times to generate the probability distribution
5: If the RSSI of an AP in the filtered tuple is greater than -90dBm, add the location to *proximity list* of the AP
6: Repeat the procedure for all the locations to be sampled

Fig. 1. Training the Perspective

Not that although symbolic locations were sufficient for earlier algorithms, we use physical locations represented by (x, y, z) co-ordinates, so that the Kalman filter can be applied to the two estimates obtained from the two perspectives. We can continue to use symbolic locations, if do not use multiple perspectives (only apply filtering).

B. Online - Estimation Phase

In the online phase, the mobile station collects multiple RSSI feature tuples and filters out the noise in the measurements. This filtered finger print of the location is used to query the radio-map of the MS-perspective for its location. Similarly, a filtered RSSI tuple is generated for the AP-perspective and is used to query the radio-map of AP-perspective.

Given the finger print whose corresponding location has to be estimated, we can find the approximate location of the mobile station by using the finger print tuple and the proximity lists created in the offline phase. We employ a heuristic similar to [8] that the location of the mobile station must be in the vicinity of the access point which provides the highest signal. That is this location must be in proximity list of the access point providing the highest signal. The search for the most probable location is then carried out only in the proximity list of that access point. If the highest signal strength is below the minimum threshold then we can not estimate the location.

Once the list of locations that are to be searched is narrowed down, the probabilities of the observed finger print belonging to various locations in this list are calculated using the Bayesian method discussed earlier. The location with the highest probability is the estimated location. The algorithm first returns this estimated location, with the probability of being at that location.

It is possible sometimes though, that the probability of the most probable location is itself very low. In this case, the confidence in the location determination system will be low. To address this problem, we employ a method of successive degradation of precision, until we are able to identify a location (of larger area) with a certain minimum probability.

We degrade the precision of the system by using the probability for an RSSI interval rather than that of a precise value in calculating the probability of observed RSSI feature belonging to a particular location. Let the RSSI reading in the online phase at an unknown location be given by tuple $< rss_1, rss_2, rss_3, ..., rss_n >$. The location that best represents the MS's location with *precision level* a is given by:

$$argmax_L(\prod_{i \in visible\ APs} P_{RSS_{Li}} \left(rss_i - a \leq x \leq rss_i + a \right)) \tag{2}$$

where $P_{RSS_{iL}}$ is the distribution at location L of Access point i. *Visible* access points are those access points, whose beacons can be identified by the mobile station at this particular location.

The degradation of the precision is done iteratively by increasing a, until the probability of the most probable location crosses *probability_threshold*. We have this threshold set at $(\frac{3}{4})^n$, where n is the number of visible access points at the location of the mobile user. Once such a location is found, it is reported as the estimate to the mobile station. The per-perspective location estimation algorithm is given in Figure 2.

1: Using the Proximity Lists, narrow down the search to the possible locations
2: Use Bayesian method to find the most probable location from above list
3: While probability of the *most probable location* at the present precision level is less than *minimum threshold probability*, degrade the precision and search again
4: Report location is reported by this perspective

Fig. 2. Online phase of the Perspective

To apply the multiple observer technique, the location estimates obtained in this manner from the MS-perspective and AP-perspective are then combined using the Kalman filter (applied to the x, y, z co-ordinates). The Kalman filter equations require an estimate of the variance of the measured samples. However, the degradation of precision of the RSSI values result in an increase in the variance of the location estimate. We empirically calculated that with one level of degradation in the precision, the variance of the location estimate increases by approximately 1 meter. We use this to generate an approximate value for the variance. The location estimated by applying the Kalman filter to the two estimates is then reported back to the mobile station as the location determined. Note that the multiple observer technique is a separate technique by itself, and can be used with our without Kalman filtering of the RSSI values.

V. Experimental Setup and Results

We studied the performance of our proposed mechanisms for improvement of accuracy by implementing them, and comparing each with the existing Bayesian method described in [8]. Specifically, two special cases of the algorithm described above were tested: one, where we test only the RSSI Kalman filtering approach (with only MS perspective) and one where we test only the multiple observer approach (with no Kalman filtering of RSSI values). This section describes the testbeds and results of these experiments.

A. *Wireless LAN Testbed*

We performed our experiments in two testbeds. Testbed A consisted of a circular hall of diameter 18 meters, with 4 IEEE 802.11b enabled access points providing coverage. We had 78 locations in the radio map covered by these access points.

Testbed B consisted of 31 access points covering a four-floor building. All of these access points were fixed, 28 of which were configured to operate in channel 6 and the rest three were configured to be in channels 1 and 11 of the IEEE 802.11b standard. The access points themselves interfered with each others' transmissions as most of them are configured to use the same channel.

For the experiments, the RSSI feature is measured at different locations using a DWL122 USB WLAN adapter which is interfaced with using *wlanctl-ng*. The network adapter is programmed to scan channels 1 through 11 to read the beacons transmitted by the access points. The network adapter scans the channel with a minimum channel duration of 200 milliseconds and a maximum channel duration of 250 milliseconds. These values were chosen, assuming that the access points are configured with a beacon interval of less than or equal to 200 milliseconds.

For the sampling purpose, we used a location granularity of 1 square meter. During the experiment, we collected the training set and the testing set with a time gap of 4-5 hours in order to estimate the accuracy correctly. We have used physical locations, measured with a reference three dimensional co-ordinate system within the building.

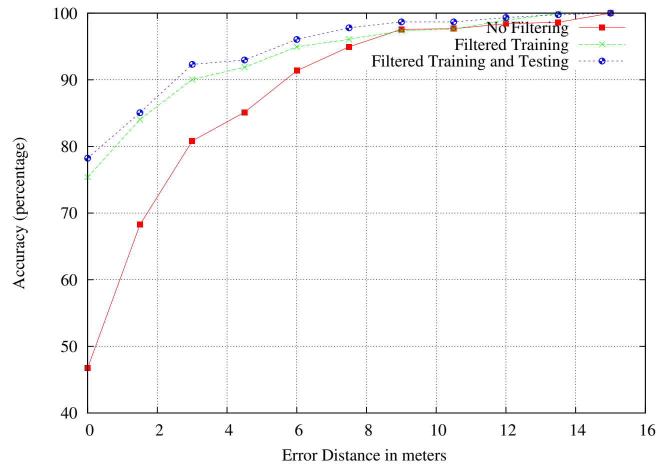

Fig. 3. Effect of noise filtering in RSS on Accuracy

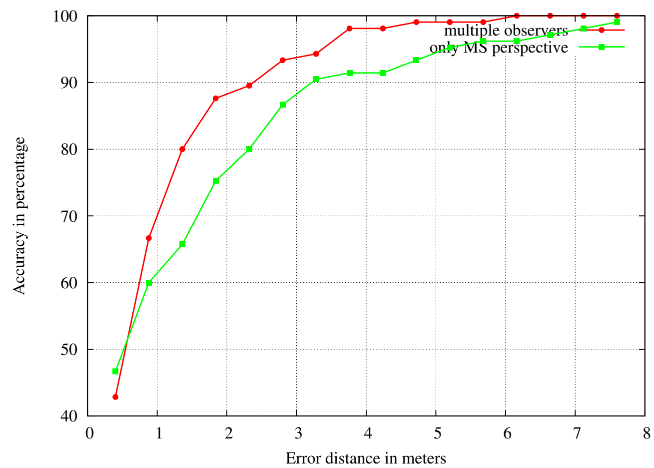

Fig. 4. Effect of multiple observers on Accuracy

B. *Results*

The two setups were used for two different sets of experiments. First, an experiment was carried out that studied just the effect of Kalman filtering on RSSI readings. This was carried out in Testbed A. Three cases were considered in this set: 1) basic Bayesian method with no filtering, 2) creating the radio map with filtered samples during the training but querying it with unfiltered sample and 3) radio map of filtered samples and query with filtered sample. Figure 3 shows these three cases, labeled as "No Filtering", "Filtered Training", and "Filtered Training and Testing" respectively. The distance between the actual MS's position and the location determined by the system is measured as error distance. The results show that Kalman filtering applied during training results in a big improvement in accuracy. E.g, accuracy with filtered training samples for a precision of 3 meters jumps from 80% to 90%. The additional gain by filtering the sample for querying during the on-line estimation phase is relatively negligible (from 90% to 92%). Thus, a major gain in accuracy can be achieved without incurring any additional computational cost during the on-line phase.

The second set of experiments were carried out to analyze the performance of the multiple observer approach. These experiments were carried out in Testbed B. This was compared, again, with the basic Bayesian method. During the training phase, we sampled in selected locations within the area covered by the system, and we tested our location determination system with more than 400 location identification requests from different locations within the area covered by the system. The test cases also include the locations which are not sampled during the training phase which should be reported as close to their sampled neighbors by the perspectives. Figure 4 shows the percentage of test cases that were reported with different error distances.

The results again show substantial gain in accuracy. The accuracy for a precision of 2.3 meters jumps from 80% with the existing method, to 90% with the multiple observers.

Although the experiments reported in Figure 3 and Figure 4 are on different set-ups, we can draw some interesting conclusions. For finer precision (e.g. 3 meters and less), the Kalman filtering seems to result in a higher gain in accuracy. For coarser precision, the multiple observer method seems to do better. E.g. in Figure 3, 99% accuracy is achieved by the filtering method only at about 13 meter precision, while this accuracy is achieved with multiple observers at about 5 meters.

C. *Complexity of the on-line phase*

The other performance metric of a location determination system is the computational cost or delay in location reporting. After the location determination system gets the RSSI feature measured at the MS's location, it has to search through all the sampled locations to find the most probable location. We reduced the search space by using the proximity method; using which we search only through the proximity of the most active AP (the AP whose RSSI is the strongest) as reported by the MS. Each access point typically covers 200 locations when the sampling granularity used is 1 square meter. Therefore, the time the location determination system takes to search the most probable location is independent of the total number of locations sampled. Hence, our location search algorithm is scalable and independent of the area covered by the location determination system.

VI. CONCLUSION

Among existing WLAN based location determination methods, empirical approaches, based on received signal strength fingerprints are known to work better. However, there is a significant noise component in these measurements. In our implementation of the existing method, we were able to get about 80% accuracy within 2.5 meter precision. We applied the Kalman filter for removing noise from the RSSI measurements, and showed that this results in increasing the accuracy of location determination to 90% within 2.5 meters. Another mechanism that was explored and tested was of using multiple estimates of location. We proposed using the access point's estimate of where the mobile device is, in addition to the device's estimate of its location. This also gave us an increase in accuracy to about 90% within 2.5 meters. This method, however, is costly and can be used only when all devices to be located are uniform. Among the mechanisms proposed, Kalman filtering is the more efficient one and results in significant gain in accuracy. Further work in this topic includes exploring computationally inexpensive techniques to improve the accuracy of location determination, quantifying the relationship between number of APs and accuracy, and determining location for moving devices.

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