Small-Scale Compensation for WLAN Location Determination Systems

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***Abstract*— To limit the radio map size and the time required to build the radio map, current WLAN location determination systems do not handle small-scale variations. This contributes to most of the estimation errors in the current systems. We propose a general technique, the perturbation technique, to handle the small-scale variations problem. The system uses user history to detect small-scale variations and then perturbs the signal strength vector entries to overcome it. The results obtained show that the accuracy can be increased by more than 8%. Moreover, the worst-case error is enhanced by more than 60%. We also show that the perturbation technique can help in enhancing the accuracy due to temporal variations in case of change in the environment conditions, thus increasing the accuracy of the current WLAN location determination systems beyond their limits.**

I. Introduction

With the current increase in mobile devices and wireless LANs, detecting the position of a mobile user has become a pertinent issue. There have been many applications that provide context-aware services to the users based on their location [1] including automatic call forwarding to the user based on his current location, helping shoppers through the stores based on their location, providing information to the tourist about his current location and office assistant that interacts with visitors and manages the office owner's schedules.

Many systems over the years have tackled the problem of determining and tracking the user position. Examples include GPS [2], wide-area cellular-based systems [3], infrared-based systems [4], [5], various computer vision systems [6], physical contact systems [7], and radio frequency (RF) based systems [8]-[16]. Of these, the class of RF-based systems that use an underlying wireless data network [8]-[14], such as 802.11, to estimate user location has gained attention recently, especially for indoor application. Unlike infrared-based systems, which are limited in range, RF-based techniques provide more ubiquitous coverage and do not require additional hardware for user location determination, thereby enhancing the value of the wireless data network.

RF-based systems usually work in 2 phases: offline phase and location determination phase. During the offline phase, the signal strength received from the access points, at selected locations in the area of interest, is tabulated, in some form, in what has been called in literature the radio-map. During the location determination phase, the vector of samples received from each access point (each entry is a sample from one access point) is compared to the radio-map and the"nearest" match is returned as the estimated user location.

RF-based systems need to deal with the noisy characteristics of the wireless channel. Those characteristics lead to the deviation of the environment from the stored radio map and thus limits the accuracy of such systems. Our research focuses on identifying the noisy characteristics of the wireless channel and developing techniques to overcome them. More specifically, we identify three main causes for signal strength variations: temporal variations, large-scale variations, and small-scale variations. We show that most of the estimation errors can be attributed to small-scale variations, though none of the current WLAN location determination systems address these variations. In order to enhance the accuracy of these systems beyond their current limits, researchers need to develop techniques to handle small-scale variations. This paper presents a technique to address small-scale variations. The technique is general and can be implemented within any of the current WLAN location determination techniques. The rest of this paper is organized as follows. In Section II, we explain the different causes of variation in the signal strength and their effect on the accuracy of WLAN location determination systems. Section III describes our technique to handle small-scale variations. We show the results of an experimental evaluation of the proposed technique in Section IV. Finally, Section V concludes the paper and gives directions for future research.

II. Noisy Characteristics of the Wireless Channel

We can identify three main causes for the variation of the signal strength in an environment:

1) *Temporal variations:* When the user is standing at a fixed position, the signal strength measured varies over time. The histogram range can be as large as 10 dBm or more (Figure 1). This time variation of the channel can be due to changes in the physical environment such as people movement.
2) *Large-scale variations:* The signal strength varies over a long distance due to attenuation of the RF signal

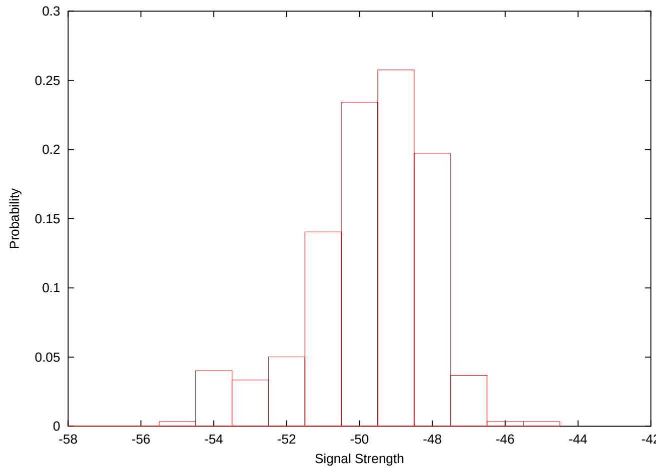


Fig. 1. Temporal variations: An example of a histogram of the signal strength of an access point.

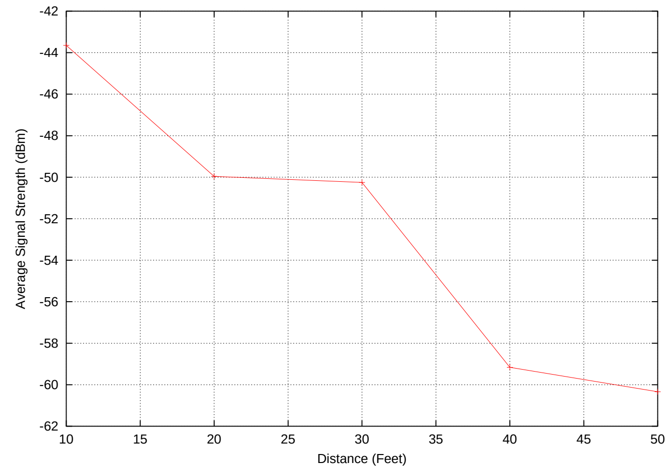


Fig. 2. Large-scale variations: Average signal strength over distance.

(Figure 2).

3) *Small-scale variations:* These variations happen when the user moves over a small distance (order of wavelength.) This leads to change in the average received signal strength. For the 802.11b networks working at the 2.4 GHz range, the wavelength is 12.5 cm and we measure a variation in the average signal strength up to 10 dBm in a distance as small as 3 inches (Figure 3).

Large-scale variations are desirable in RF-based systems as they lead to changing the signature stored in the radio map for different locations and, hence, better differentiation between these locations. Probabilistic techniques have been shown to give better accuracy when dealing with the temporal variations by storing the entire histogram of the received signal strength in the radio map, instead of storing only the average value. During the location determination phase, probabilistic techniques, including our original technique [9], [10], calculate the probability of each location given the received signal strength vector and return the most probable location as the location estimate.

Dealing with small-scale variations is the most challenging part and none of the current systems handle it. Since the selected radio map locations are typically placed few feet apart, to limit the radio map size, the radio map does not capture small-scale variations. This contributes to most of the estimation errors in the current systems. In order to boost the accuracy of RF-based location determination systems, new techniques should be devised to handle small-scale variations. One obvious way is to increase the granularity of the resulting radio map, which is not practical in terms in the size of the radio map and the time required to build this radio map. In the next section, we present a new technique to handle small-scale variations.

III. A SOLUTION: THE PERTURBATION TECHNIQUE

We start by describing an experiment to show the effect of small-scale variations and then present our perturbation technique to identify and overcome these variations.

A. *Small-scale variations*

We performed an experiment to measure the signal strength from different access points in an area of 12×21 inches (approximately 1×2 feet). The measurements were taken on a 3 inches grid. The sampler program was running on a Compaq iPAQ Pocket PC's (model H3650) running the Familiar distribution (release version 0.5) of Linux for PDA's. The wireless card used was Lucent Orinoco Silver card supporting up to 11 Mbit/s data rate.

To collect the samples from the card, we used our mwavelan driver [17] that supports the collection of the signal strength values from all access points in range using the active scanning technique [18]. We used our MAPI API [17] to interface the sampler program with the device driver.

Figure 3 shows the signal strength contours for different access points. We can note two things from this figure.

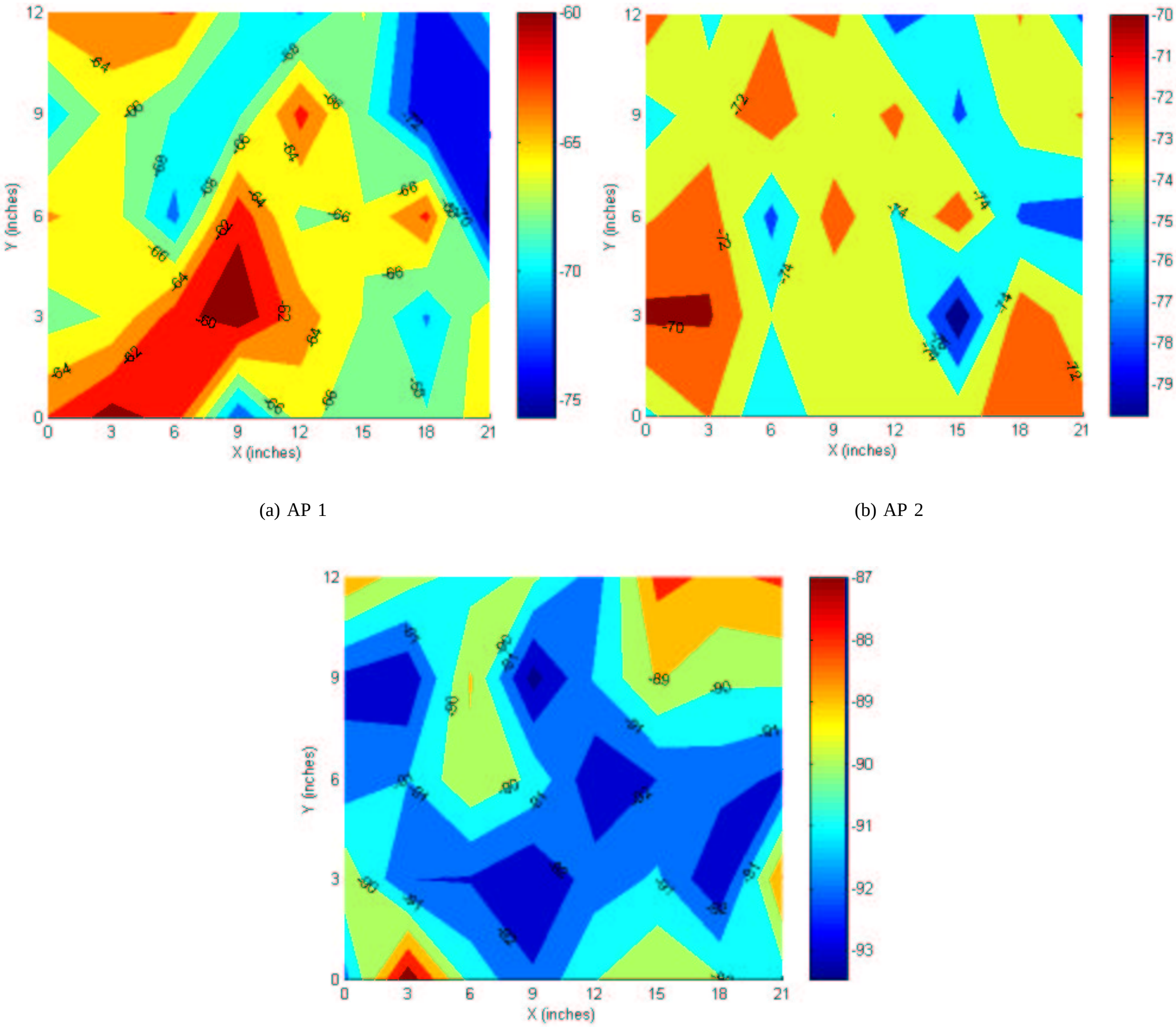
1) The signal strength can vary by as much as 10 dBm in a distance as small as 3 inches.
2) The degree of variation depends on the average signal strength: The higher the average signal strength, the higher the variations.

B. *The perturbation technique*

We propose a new technique, the Perturbation technique, to handle the small-scale variations. The technique is based on two sub-functions:

1) Detecting the effect of small-scale variations.
2) Compensating for small-scale variations.

In order to detect small-scale variations, the system calculates the estimated location using the standard radio map and the original inference algorithm [10]. The system then calculates the distance between the estimated location and the previous user location. If this distance is above a threshold, the system detects that there are small-scale variations affecting the signal strength.



(a) AP 1

(b) AP 2

(c) AP 3

Fig. 3. Small-scale variations: Signal strength contours

To compensate for these small-scale variations, the system perturbs the received vector entries, and re-estiamtes the location. The nearest location to the previous user location is chosen as the final location estimate. For example, if the received signal strength vector is $(s_1, s_2, ..., s_n)$, the system perturbs this vector to obtain the set of vectors: $(s_1(1 + x), s_2(1 + x), ..., s_n(1 + x))$, where $x \in \{-d, 0, d\}$ is the percentage by which to perturb the signal strength (0 for no perturbation).

Typically, three access points ($n = 3$) are sufficient to obtain good accuracy, so the number of perturbed vectors is limited. Moreover, the measurements show that the small-scale variations depend heavily on the strength of the signal strength received. This means that perturbing the component corresponding to the strongest access point can obtain sufficient results. The value of d is chosen to be relative to the received signal strength. The effect of the number of access points to perturb and the value of d on accuracy is described in the next section.

IV. Experimental Evaluation

To test the performance of the perturbation technique, we implemented the original system [10] and the same system with the addition of the perturbation technique. We performed our experiment in the south wing of the fourth floor of the

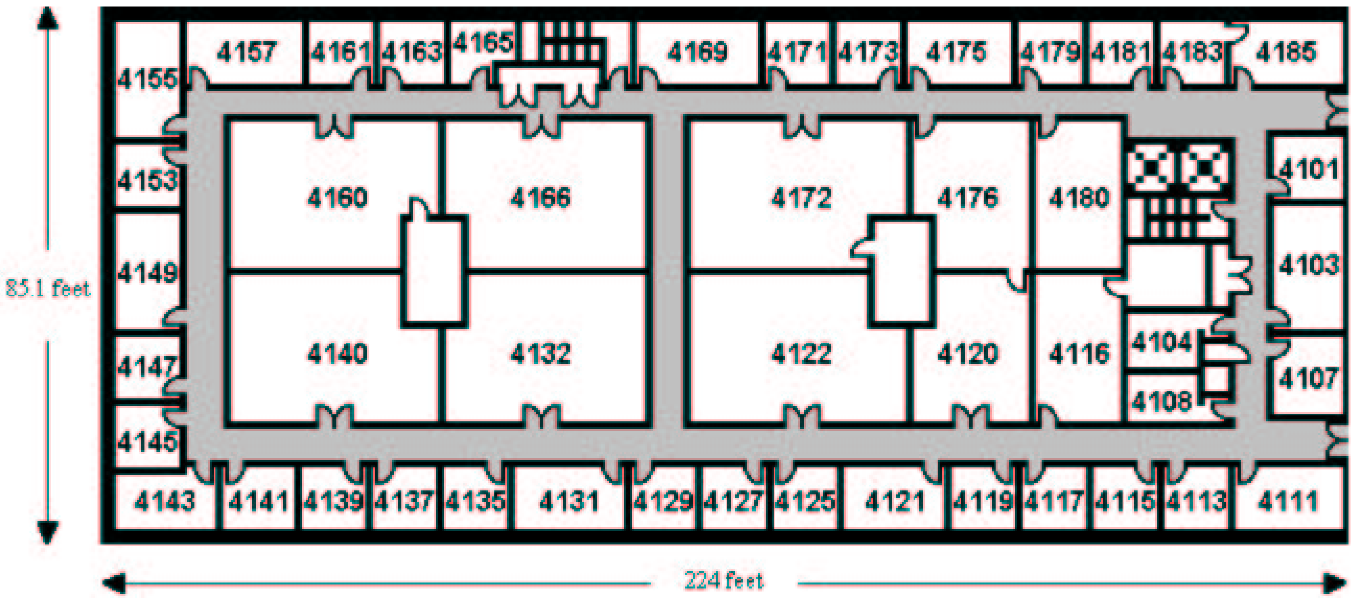


Fig. 4. Plan of the south wing of the 4th floor of the Computer Science Department building where the experiment was conducted. Readings were collected in the corridors (shown in gray).

A. V. William's building in the University of Maryland at College Park. The layout of the floor is shown in Figure 4. The wing has a dimension of 224 feet by 85.1 feet. The technique was tested in the Computer Science Department wireless network. The entire wing is covered by 12 access points installed in the third and fourth floors of the building.

For building the radio map, we took the radio map locations on the corridors on a grid with cells placed 5 feet apart (the corridor's width is 5 feet). We have a total of 110 locations along the corridors. On the average, each location is covered by 4 access points. The test set was collected by different persons on different days and time of days from the training set.

The *Threshold* parameter, used to detect small-scale variations, is dependent on both the user speed and location update rate. For the purpose of this paper, we set this threshold to 15 feet for a location update every 2 seconds (maximum user speed of 7.5 feet per second).

Figure 5 shows the effect of changing the perturbation percentage (amount by which to perturb each access point) on average error. We can see from this figure that the best value for the perturbation percentage is about 4%. We use this value for the rest of this ssection.

Figure 6 shows the effect of changing the number of access points used in the perturbation technique on performance. The access points chosen at a location are the strongest access points in the set of access points that cover that location. The figure shows that accuracy can be increased by more than 8% (at 7 feet). Moreover, the worst-case error is enhanced by more than 60%. It is important to notice that the number of access points used in the perturbation technique has minor effect on accuracy. This means that perturbing the strongest access points only is enough to achieve better accuracy than

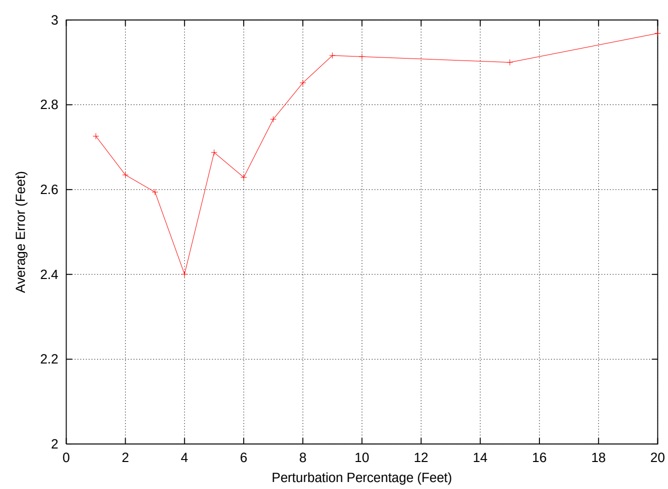


Fig. 5. Effect of changing the perturbation percentage on average error.

the original technique.

Figure 7 shows the effect of changing the number of access points used in the perturbation technique on the average number of operations per location estimates. Although the average number of operations per location estimates increases significantly for a large number of access points, *perturbing only one access point* leads to the desired accuracy with very low computational overhead.

V. Conclusions and Future Work

Current WLAN location determination systems do not handle small-scale variations. To limit both the radio map size and the time required to build the radio map, radio map locations are typically placed few feet apart. This means that the radio

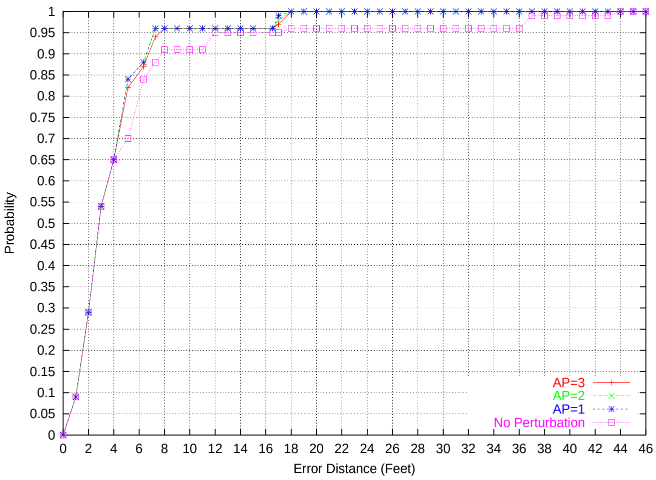


Fig. 6. Effect of changing the number of perturbed access points on accuracy.

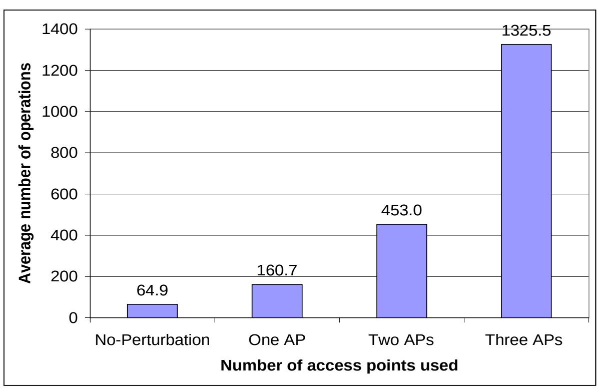


Fig. 7. Effect of changing the number of perturbed access points on computational requirements.

map does not capture small-scale variations, which happens in fractions of the feet for the 2.4 GHz signal. This contributes to most of the estimation errors in the current systems.

We propose the perturbation technique to handle the small-scale variations problem. The technique is general and can be incorporated into all the current WLAN location determination systems. The system uses user history to detect small-scale variations and then perturbs the signal strength vector entries to overcome it. The results obtained show that the accuracy can be increased by more than 8%(at 7 feet). Moreover, the worst-case error is enhanced by more than 60%. This increased accuracy *does not* come with increased computational requirements as perturbing the strongest access point only leads to the desired accuracy. The perturbation technique can also help in enhancing the accuracy due to temporal variations in case of change in the environment conditions.

Currently, we are working on developing models for small-scale variations in 802.11b WLANs. We believe that these models can help more in understanding the wireless channel characteristics and hence better accuracy.

Acknowledgment

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