WLAN-based Real-time Asset Tracking System in Healthcare Environments

Jong-Hoon Youn[a], Hesham Ali[a], Hamid Sharif[b], Jitender Deogun[c], Jason Uher[b], Steven H. Hinrichs[d]

[a]Dept. of Computer Science., Univ. of Nebraska-Omaha, Omaha, NE 68182
[b]Dept. of Computer Electronics & Engineering, Univ. of Nebraska-Lincoln, Lincoln, Nebraska 68588
[c]Dept. of Computer Science & Engineering, Univ. of Nebraska-Lincoln, Lincoln, Nebraska 68588
[d]Dept. of Pathology and Microbiology, Univ. of Nebraska-Medical Center, Omaha, Nebraska 68198

Abstract: *In the busy and crowded environment of health care, accurate location information of mobile medical devices and personnel (e.g. patients or physicians) is often a major challenge. In this paper, we present a real-time asset tracking system deployed within a hospital clinic setting, which tracked a set of mobile assets using small Wi-Fi tags. The deployed system utilized radio signals received from wireless access points to estimate location of tagged assets. The system performed with resolution of within 1.5 meters, which is an acceptable range in such an environment. We developed a web-based graphical interface and a data management system which was capable of tracking and reporting status of an asset and providing an alert signal when it moved out of a designated area. Additionally, detailed logs of asset tracking information were available for archival purposes.*
This deployment demonstrates the feasibility of a Wi-Fi based positioning system in dynamic medical environments.

Keywords-Wireless Local Area Networks, Asset Tracking, Wi-Fi positioning

I. INTRODUCTION

One of the defining trends of the 1990's was the explosive growth of mobile devices and wireless technologies. However, the penetration of these technologies into a number of domains has been limited. One of the domains in which the integration has been particularly slow is the medical domain. This can be attributed to perceived lack of high levels of reliability, security, and performance. This in turn, has prevented high performance wireless networks from replacing traditional networks in critical medical applications.

In hospitals and health care facilities, there are a number of problems which can be solved effectively and efficiently by wireless networking technology. A related study estimated that as many as 98,000 people die in the U.S. hospitals each year due to medical errors [1]. The number of casualties caused by medical errors can be substantially reduced by a system that will provide medical personnel with accurate medical information. For example, a wireless network can be deployed for detecting conflicts while administering medication to patients. This can be achieved by having each patient wear a wireless tag that carries private medical information which helps avoid medication errors.

This paper presents a Wi-Fi based, real-time, asset tracking system based on measurement of the strength of radio signals from at least three Wi-Fi access points. The pilot system, deployed in a clinic environment, provided the location of assets as well as alerts when an asset moved out of a pre-defined area. The rest of this paper is structured as follows: Section II surveys related work; Section III discusses the development of Wi-Fi based tracking system deployed for real-time asset tracking in hospital environments; Section IV presents experimental results of the deployed tracking system; and concluding remarks are presented in Section V.

II. RELATED WORKS

There are a number of indoor positioning systems in the literature. Among these systems, common positioning techniques include *trilateration*, *multilateration*, and *location learning*.

- *Trilateration* uses range estimates of the distances between devices and calculates positions of target devices using geometric identities and known locations of other devices. Distances can be estimated with time of arrival (TOA), or loss in signal strength. With TOA, two devices must be synchronized, and messages between the devices are time stamped upon sending and receiving in order to calculate propagation delay. The known propagation delays of signals in a particular medium allows the devices to estimate distance.
- *Mutlilateration* uses time difference of arrival (TDOA) estimates in which several reference devices measure the difference in arrival times of signals. Round-trip time can be used when synchronization is not possible. For triangulation, the angle of arrival (AOA) of a signal is measured using several antennas, and then geometric identities are used for estimating position.
- *Location learning* makes no range or angle measurements, but merely correlates the properties of newly received

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signals with data available on previously observed signals at known locations.

The basic techniques listed above can be used with a variety of signal types in wireless systems. In the remainder of this section, we briefly review the research in application of these techniques to Wireless Local Area Network (WLAN), wireless sensor, ultra-wide band (UWB), and RFID systems.

A. Wireless LAN Based Systems

Because the environments in which WLANs are deployed often contain obstacles such as walls and furniture, the use of RF properties for ranging becomes difficult. For this reason, localization in WLANs often relies on learning techniques.

One WLAN based tracking system is the RADAR indoor tracking system developed at Microsoft Research. RADAR is a learning-based approach which can use existing WLAN infrastructures. Localization and tracking with RADAR consists of two phases: *a reference signature collection phase* and *an online estimation phase*. During the signature collection phase, a user with a laptop clicks his or her perceived location on a map interface and records the signal strength of all access points within range. After collecting a sufficiently large database of reference signals, location can then be estimated in the online phase by taking the geographic centroid of the locations of the k nearest (in terms of signal-strength space) reference signatures [1]. The same process may be used with other traditional machine learning algorithms and has been studied on Artificial Neural Networks [2, 3], Bayesian techniques, and Markov models [7, 6]. Variants of the RADAR system are available from commercial vendors such as PanGo [11] and Ekahau [4].

B. Wireless Sensor Based Systems

MoteTrack [9] is a sensor based system which runs on 802.15.4 based motes but uses a process based on RADAR. With MoteTrack, the environment must be equipped with several fixed sensor motes as the existing LAN infrastructure cannot be used. Reference signature collection and the online estimation operate as in RADAR, but MoteTrack has been altered to run in a distributed manner. Moreover, MoteTrack is robust, and takes into consideration the possibility of beacon node failure. Finally, the learning algorithm has been improved to adaptively select the number of reference signatures used for localization based on the density of reference signatures available in a particular area.

MoteTrack has the advantage of being entirely based on RF signals and needs relatively fewer beacon nodes to cover a large area of a building even with many obstacles. However, it also has a disadvantage that it requires significantly more configuration prior to deployment.

C. Ultrawideband (UWB) Systems

Gezici et. al. discussed many of the positioning techniques described above in the context of UWB systems in which high bandwidths offer potentially high ranging accuracy. They note that the antenna arrays required for AOA make it unsuitable for UWB, but consider ranging with time-based measurements and signal strength measurements. They found that the best results can be obtained with hybrid schemes employing TDOA and TOA both with signal strength measurements [5].

Young et. al. noted that the high bandwidth of UWB systems allow for high time resolution leading to a natural advantage with TDOA localization. They present methods for overcoming the inherent distortion problems with UWB antenna responses, amplification, and filtering in an indoor multipath environment [14].

Zetik et. al. also approached UWB localization using TDOA. They conducted experiments in both the active and passive setting with custom designed SiGe circuit architecture. With their system, they were able to achieve a localization accuracy on the order of one centimeter [15].

D. RFID-Based Systems

Location determination using RFID tags is a difficult problem because tags have extremely limited computational ability to assist the application and a very short read range. Active tags contain a battery and generally have longer ranges than passive tags which do not. The simplest approach to localizing tags is to use the proximity with readers. The limited reading range can be used to estimate the location of a tag based on the location of a reader [12]. Some systems like the Ferret localization system use several readings over time to narrow down the actual position of tags [8]. Nara et. al. proposed a scheme for estimating the location of an RFID tag by building sensors which measure the spatial gradient of electronic fields created by the tags [10]. Experiments were conducted showing the feasibility of the approach, but it has not been implemented on a large scale.

III. Real-Time Asset Tracking System

In the dynamic environment of health care, mobile assets such as infusion pumps and wheelchairs are continuously relocated throughout a hospital, and hundreds or even thousands of patients and support staff are moving through a hospital at any time. In such a dynamic atmosphere, the accurate positioning of a particular mobile medical device or a patient is often a challenging problem. Therefore, in order to accommodate for lost or misplaced assets, hospitals usually acquire or lease more medical devices than they need, and often valuable time and resources are wasted for finding them.

To address the *lack of visibility* problem, we develop a reliable and cost-effective solution for tacking thousands of medical personnel, devices and equipment which are constantly moving across a hospital. After surveying various state-of-the-art wireless technologies for tracking, we conclude that WLAN-based tracking is the most cost-effective solution for asset visibility solutions in healthcare environments. This is because state-of-the-art wireless tracking technologies, such as wireless sensors, RFID, and proprietary WLAN based-sensors, typically require a costly dedicated network infrastructure. However, an 802.11 based tracking system can be deployed without significant additional costs since many hospitals are now rapidly deploying campus-wide 802.11 WLAN infrastructures. Therefore, a WLAN-based tracking approach would provide a tremendous opportunity for hospitals to take advantage of their wireless networks for asset tracking.

We deployed a real-time asset visibility system based on existing 802.11 infrastructure designed to track a large number of small WLAN tags. The deployed system uses empirical measurements of radio signals received to estimate location. Our experimental test-bed was deployed in a specialty care hospital clinic environment. The facility provides services for a wide range of patients including medical procedures and medication infusion. The location was selected because it is a state-of-the-art facility that allows the clinicians and researchers to develop and test innovative practice models and systems. The test area included more than 60 rooms in an area of 63 meters x 46 meters. There are four Cisco Aironet 1200 Series Access Points (APs), which are denoted by the black triangles in Figure 1. These four APs form the backbone of the tracking system; their job include transmitting signal to the Wi-Fi tags for location estimation and delivering data messages from the tags to the location server.

In order to determine the fine location using infrastructure wireless access points, we added six beacon APs. According to a recommendation from Cisco, a positioning system needs to receive a minimum of three strong and steady Received Signal Strength (RSS) measurements from APs to determine the fine location of Wi-Fi tags with room-level granularity. According to suggestion from Cisco's wireless location appliance guide [16], approximately one access point should be placed every 17-20 meters, and so roughly one access point is needed every 230-450 square meters. Therefore, after surveying the signal strength over the entire floor and counting the number of steady RSS measurements, we proceeded to add six more beacon APs to overcome the lack of strong signals. The positions of six beacon APs are indicated by black squares in Figure 1. The additional beacons ensure the Wi-Fi tags will receive at least three good signals from either the backbone APs or beacon APs at any location on the map. Since the beacon APs do not need to be connected to the network infrastructure, there is no additional cabling cost for the beacon APs. A beacon's primary function is to transmit its Service Set Identifier (SSID) to the Wi-Fi tags for location estimation.

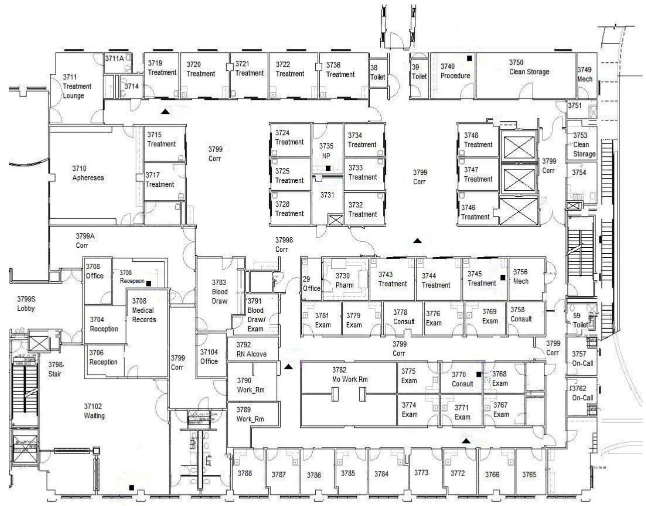

Figure 1: Map of the floor plan of the test site. The black triangles show the locations of the four infrastructure APs. The black rectangles denote locations of additional beacon APs.

The next step was the data collection phase. Once our APs were established, we began the data collection phase which records the RSS measurements from theses APs as a function of the mobile's location and orientation. For each data collection, the relative two-dimensional location of each surveying point should be given by the data collector. According to our measurements, the RSS value at a given location varies significantly depending on the mobile's orientation. Therefore, we collected RSS values in each of the four directions, north, south, east and west, at all physical locations on the floor.

As shown in Figure 2, we first identified around 430 data collection points over the floor, and then collected RSS measurements in each of the 4 directions at 430 distinct physical locations giving a total of over 1300 measurements. After the data collection phase, the signatures were imported into the tracking server and processed to enhance the accuracy of location estimation.

After constructing a database of RSS measurements, called *signatures*, along with their known 2-dimentional location and orientation, the system can estimate its position by comparing the difference between the measured RSS data and to the known signatures in the database. In other words, a mobile device takes a snapshot of RSS from visible APs, and compares it with signatures stored in the database.

To reduce the computation cost, the search is performed only on some portion of the RSS measurements in the database. If a mobile's previous location lies at a point P, then the search space is limited to its neighboring points within the distance d from P. These neighboring

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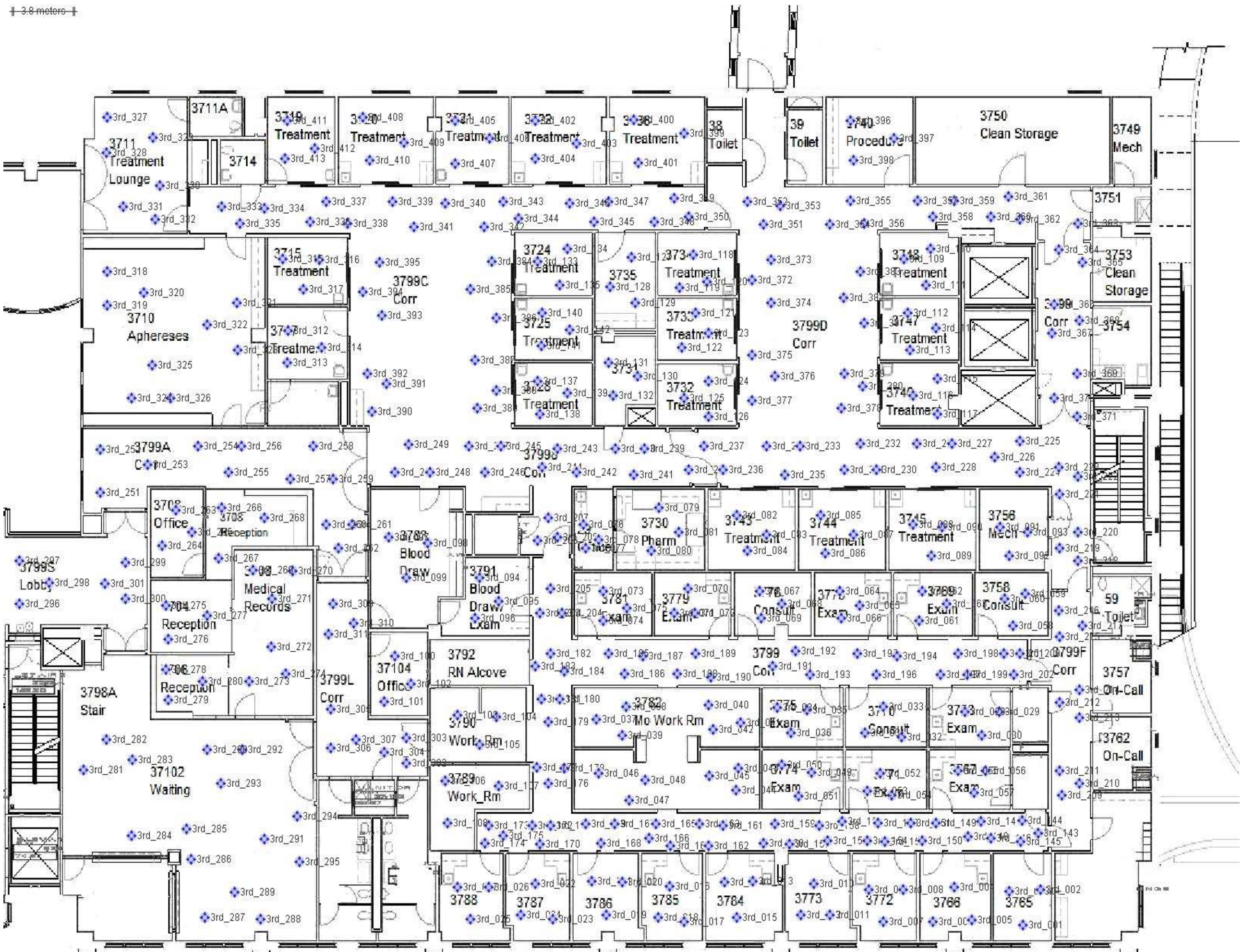

Figure 2: Locations of the RSS measurements

points are grouped into clusters based on their physical closeness. For each cluster, the most probable location of the mobile node is calculated based on the Euclidean distance of RSS measurements. For example, the RSSI measurement (p_1, p_2, p_3, p_2, … , p_k) at a point P and (s_1, s_2, s_3, … , s_k) at point S are the closest if the $(p_1 - s_1)^2 + (p_2 - s_2)^2 + (p_3 - s_3)^2 + \ldots + (p_k - s_k)^2$ is minimum. After a number of computations, the system chooses the location with the highest likelihood as the current estimate of the user's location.

We have developed a Web-based Graphical User Interface (GUI) and added some useful functions to the GUI. The deployed GUI can provide the location of assets with sophisticated mapping, alerts when an asset moves out of a pre-described area, and has a multitude of reporting capabilities. The system consists of two key software components: a real-time positioning engine that calculates location of assets, and a Web-based GUI that manages system configuration, asset visibility, monitoring and reporting. The positioning engine is based on statistical modeling of received signal strengths and provides accuracy of up to 1 meter on average. The GUI provides a common-sense Web interface that makes it easy to find assets and improve everyday operations such as asset monitoring and notifications.

Since this tracking system is fully software-based, it requires no proprietary network infrastructure. The advantages of the 802.11-based real-time tracking solutions are summarized below:

- The system can efficiently locate an asset and reduce the likelihood of loss.
- Hospitals can evaluate and improve the facility's overall workflow and operational efficiency by monitoring the movement patterns of patients and staff through the facility.
- The system can be extended to address crucial problems caused by patient movement. For example, hospital staff can receive an immediate alert if a patient enters an unauthorized area.

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- Staff can be alerted when location-based events occur (e.g., wheelchairs exiting the floor or pumps remaining in a utility room for a week)

IV. Experimental Study

In this section, we present detailed experimental results of the Wi-Fi tracking system. Our goal of this study is to evaluate the accuracy of the system under a number of different Wi-Fi network configurations. We first assess the accuracy of the system as a function of the number of APs. Secondly, we study the relation between the AP layout and the location accuracy. The third experimental study is focused on the impact of noises on the accuracy.

A. Impact of the number of Access Points

First, we investigate how the accuracy of location estimation would be impacted as the number of APs. In this study, we pick 8 points in the floor and use these points to measure the Euclidean distance between the actual location and estimate point. Intuitively, the accuracy would be improved as the number of APs increases. The positions of ten APs and eight measurement points are shown in Fig. 3.

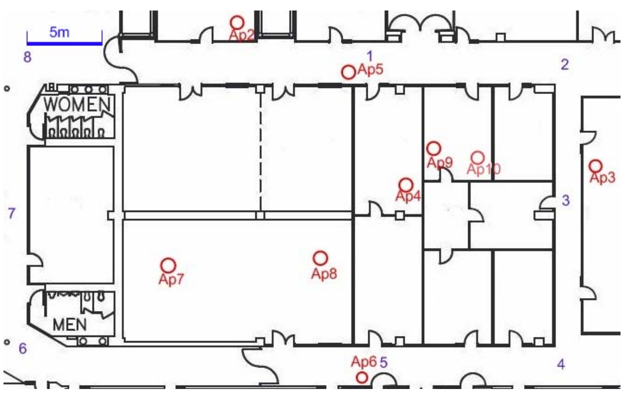

Figure 3: The layout of APs

We repeat every measure ten times for each point, and then calculate the mean value of the error distance. The averaged accuracy of the deployed system for each point is shown in Tables 1 and 2. As we predicted, the error distance gradually decreases as the number of APs increases. We also conduct the same set of experiments with more than 10 APs. Although the level of accuracy slightly improves for more than 10 APs, we do not find significant improvement in the accuracy of the position estimation. Figure 4 shows the average error distances as a function of the number of APs.

Table 1: Error distances in meters (up to 6 APs)

Measured Position	Error distance (m)			
	3 APs	4 APs	5 APs	6 APs
#1	7.168	5.437	3.715	1.387
#2	3.027	2.773	0.836	1.192
#3	3.522	2.72	2.931	3.125
#4	2.08	2.092	1.69	1.477
#5	5.323	4.076	3.16	3.14
#6	3.971	2.611	2.351	2.294
#7	5.066	4.408	3.127	2.149
#8	0.614	0.53	0.472	0.306
Average	3.8464	3.0809	2.2853	1.8838

Table 2: Error distances in meters (up to 10 APs)

Measured Position	Error distance (m)			
	7 APs	8 APs	9 APs	10 APs
#1	1.693	1.16	0.813	0.781
#2	2.285	1	1	0.851
#3	1.048	2.047	1.972	1.174
#4	2.543	0.873	0.784	0.674
#5	2.253	1.9	1.876	1.78
#6	1.953	1.732	1.756	1.247
#7	0.245	2.5	1.396	0.807
#8	1.642	0.136	0.123	0.102
Average	1.693	1.4185	1.215	0.927

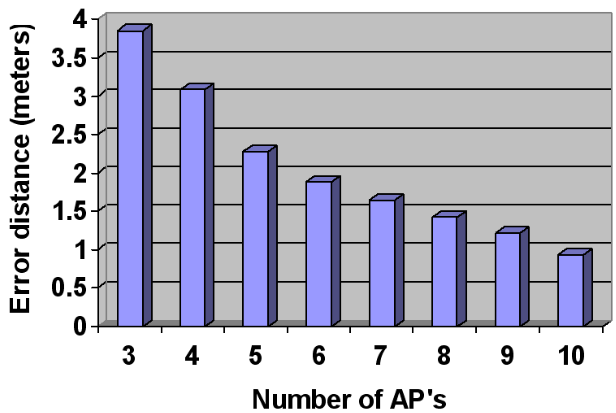

Figure 4: Impact of the number of APs on error distance

B. Impact of the AP layout

In this sub-section, we show the results of another experimental study to evaluate the relation between the position of APs and the error distance of the deployed system. In a Wi-Fi based tracking system, the density and position of APs are very important factor in the level of accuracy. Intuitively, APs staggered in a way that signals vary in each location, and preferably surround the deployment area, provide the greatest chance of achieving room-level positioning.

The following tables show the error distances for different layout of the APs. In this experiment, only RSS values from the selected 4 APs are used to estimate the position of Wi-Fi tags. As you can see from the table, the selection of APs has a significant impact on the system accuracy. For examples, the accuracy of the last scenario which selects AP#4, AP#5, AP$9, and AP#10, are quite poor compared with the results of other scenarios. This is

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because, with this AP layout, there are some spots where a tag cannot gather three or more consistent and strong RSS samples from the selected APs.

Table 3: Error distance vs. AP layout (with 4 APs)
(The position of APs are shown in Figure 3)

Measured Position	Selected APs			
	1,2,3,4	2,3,6,7	1,2,6,10	4,5,9,10
#1	5.437	0.967	1.923	2.58
#2	2.773	1.992	7.302	7.323
#3	2.72	2.418	1.674	16.375
#4	2.092	1.858	2.456	2.35
#5	4.076	1.525	3.282	27.817
#6	2.611	5.325	1.228	1.339
#7	4.408	2.658	2.845	4.254
#8	0.53	14.965	2.565	30.369
Average	3.0809	3.9635	2.909	11.551

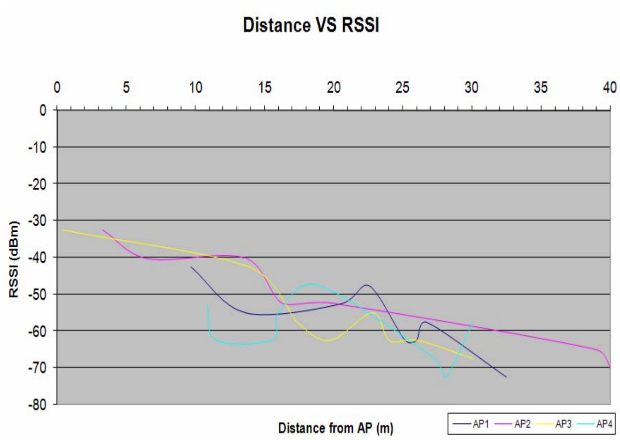

Figure 5: Distance vs. RSSI

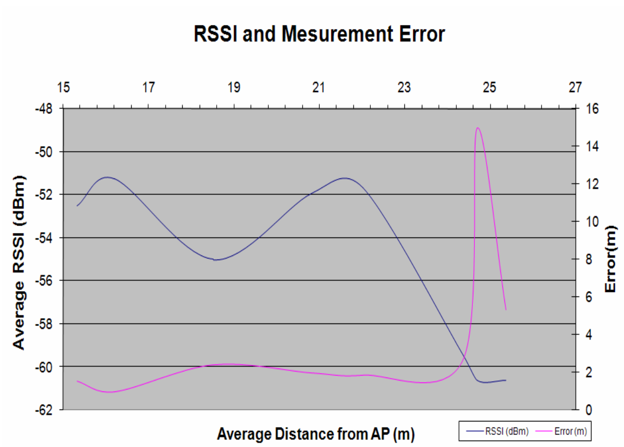

Figure 6: Error vs. RSSI

C. Impact of the level of noises

The first graph Figure 5 shows the RSSI from the 4 test APs at different distances. This chart shows the values taken from just one day of measurement. Our studies have shown that this data can vary greatly depending on a numerous factors including the building population, the internal and external temperatures of the building, and the presence of mobile objects like desks and tables. The data below clearly shows the non-uniform nature of the RSSI value with respect to distance.

Because of the unreliable nature of the RSSI shown by the graph, location based positioning can not rely on RSSI alone. A significant amount of work must be put into tuning an RSSI based locating system, both in terms of site surveys and statistical modeling. After the system has been calibrated, the RSSI based systems can be very accurate. Figure 6 shows that position can be determined with an error of less than 1-2m even when the RSSI is extremely low, which usually only happens when the subject is extremely far from the AP. For this data set, the accuracy begins to fall off at around 25m, which is at or beyond the usable range for typical WIFI systems indoors. Even though the error stays fairly low, it is clearly inversely proportional to the RSSI from the AP, signifying that that in order to achieve the best accuracy, APs should be distributed fairly heavily if a high accuracy is required.

V. Conclusions and Future Work

This project represents a significant contribution to an emerging research area--*application of wireless communications in a healthcare environment*. We have deployed a real-time mobile asset tracking system in a local hospital and evaluated the accuracy of the system under a number of different Wi-Fi network configurations. The positioning scheme is based on statistical modeling of strength of signals received and provides accuracy of up to 1 meter on average. We also have developed a Web-based GUI that enables us to find assets and improves everyday operations such as asset monitoring and notification. The system, investigated in this paper, demonstrates the feasibility of deploying a Wi-Fi based positioning scheme in dynamic medical environments.

Although the positioning system developed was validated for tracking only wheelchairs, the system is capable of tracking any equipment and personnel such as IV pumps, vital signs monitors, patients and medical staff that have 802.11- based tags,. During the normal use of the system, we have identified a few key issues that we plan to address our future research. First, once a wheelchair moves out of the site, the system cannot monitor it any more until it comes back to the site. Although we can retrieve the time and date at which the wheelchair exited, there is no information regarding who took the wheelchair out of the facility. Second, the current system lacks availability information. For example, we cannot tell whether a wheelchair is in use or not. In future, we plan to integrate a

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pressure-sensitive or infrared sensor into Wi-Fi tags to provide the availability along with location of mobile assets.

REFERENCES

[1] Kohn L, Corrigan J, Donaldson M, To Err Is Human: Building a Safer Health System, Committee on Quality of Health Care in America, Institute of Medicine, 2000.

[2] P. Bahl and V. N. Padmanabhan. RADAR: An in-building RF-based user location and tracking system. In INFOCOM (2), pages 775–784, 2000.

[3] R. Battiti, T. Le Nhat, and A. Villani. Location aware computing: a neural network model for determining location in wireless lans. Technical Report DIT-02-0083, University of Trento, February 2002.

[3] P. Castro, P. Chiu, and and R. R. Muntz T. Kremenek. A probabilistic room location service for wireless networked environments. In Proceedings of the Third International Conference on Ubiquitous Computing (Ubicomp), September 2001.

[4] Ekahau. http://www.ekahau.com.

[5] S. Gezici, Zhi Tian, G.B. Giannakis, H. Kobayashi, A.F. Molisch, H.V. Poor, and Z. Sahinoglu. Localization via ultra-wideband radios: a look at positioning aspects for future sensor networks. IEEE Signal Processing Magazine, 22(4):70– 84, July 2005.

[6] A. Haeberlen, E. Flannery, A. M. Ladd, A. Rudys, D. S. Wallach, and L. E. Kavraki. Practical robust localization over large-scale 802.11 wireless networks. Proceedings of the 10th annual international conference on Mobile computing and networking, pages 70–84, New York, NY, USA, 2004. ACM Press.

[7] A. M. Ladd, K. E. Bekris, A. Rudys, L. E. Kavraki G. Marceau, and D. S. Wallach. Robotics-based location sensing using wireless Ethernet. In Proceedings of the 8th Annual International Conference on Mobile Computing and Networking (MOBICOM), September 2002.

[8] X. Liu, M. Corner, and P. Shenoy. Ferret: RFID localization for pervasive multimedia. In Proceedings of the 8th Ubicomp Conference, September 2006.

[9] K. Lorincz and M. Welsh. Motetrack: A robust, decentralized approach to RF-based location tracking. In Proceedings of the International Workshop on Location and Context-Awareness (LoCA 2005), May 2005.

[10] T. Nara, H. Onoda, J. Yamane, and S. Ando. Dipole estimation from the magnetic field gradient for rfid tag localization. Transactions of the Society of Instrument and Control Engineers, ES- 1(1):16–20, 2005.

[11] Pango networks. http://www.pangonetworks.com.

[12] M. Philipose, K. Fishkin, D. Fox, D. Hahnel, and W. Burgard. Mapping and localization with rfid technology. Technical Report IRS-TR-03-014, Intel Corporation, December 2003.

[13] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan. The cricket location-support system. In MobiCom ’00: Proceedings of the 6th annual international conference on Mobile computing and networking, pages 32–43, New York, NY, USA, 2000. ACM Press.

[14] D.P. Young, C.M. Keller, D.W. Bliss, and K.W. Forsythe. Ultra-wideband (uwb) transmitter location using time difference of arrival (TDOA) techniques. In Conference Record of the Thirty-Seventh Asilomar Conference on Signals, Systems and Computers, 2003, volume 2, pages 1225–1229, November 2003.

[15] R. Zetik, J. Sachs, and R. Thoma. Uwb localization-active and passive approach. In Proceedings of the 21st IEEE Instrumentation and Measurement Technology Conference, 2004. IMTC 04., volume 2, pages 1005–1009, May 2004.

[16] Cisco 2700 Series Wireless Location Appliance Deployment Guide. http://www.cisco.com/univercd/cc/td/doc/product/wireless/loc2700/l2700/depgd.pdf

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