A Toolkit-Based Approach to Indoor Localization

Yu Wang and Adam Harder
Dept. of Computer Science and Software Engineering
Auburn University
Auburn, Alabama 36849
Email: wangyu1@auburn.edu, hardead@auburn.edu

Abstract

Location is one of the most important contexts used in the applications in the pervasive computing environments . It helps the application do the right thing at the right place. On the other hand, location is the most difficult context to acquire and process. Location information cannot be obtained using a single sensing system. It has to be abstracted to application-specific meanings before an application can understand it and utilize it. Since 802.11 networks are used widely, we use its RF signal strength to derive a client's location. To facilitate the indoor location determination system development, we build a location toolkit, which includes several utility programs. The toolkit not only performs some common functionalities used in various location determination approaches, but also provides a straightforward visual interface to researchers and users. This paper presents our approach to developing an indoor location determination system based on the toolkit, and some research results we have obtained.

1 Introduction

As the computing devices become more light-weighted, mobile, and human-centered, distributed computing is evolving towards its extreme form: pervasive computing [1]. Devices that operate in these environments include not only heavy-weighted servers and PCs, but also embedded and mobile systems, such as PDA, Pocket PC, Tablet PC and other handhold devices. These devices usually use wireless communication means, form numerous wireless networks to exchange information [2]. Pervasive computing represents the concept of computing everywhere at anytime. In such environments, computing technology tends to be transparent to users who can use the technology conveniently even without knowing it [3].

Situation-awareness is a promising mechanism to fulfill the "transparency" goal of the Pervasive computing vision [4]. Situation consists of contexts variation that is interesting to the application in the system and therefore meaningful to the application's future actions and behavior. Context is any instantaneous, detectable, and relevant condition of the environment or the application's residing device, such as locations, time, temperatures, and resources availability. These contexts are collected through the residing device and/or surrounding sensor networks. Certain variation of contexts that follow a specific pattern forms a situation, which is interesting to an application. Being situation-aware, applications can autonomously recognize a situation, make decisions and automatically trigger further actions (e.g. computation and communication) without user intervention [5].

Location is one of the most important contexts used in the applications in the pervasive computing environments [6]. It helps the applications do the "right thing at the right place" [7]. With location aware capability, incoming calls can be forwarded to the current room of the recipient. A conference attender can download the corresponding material based on the meeting room he or she is located. In-door surveillance can be easily implemented. Location-aware security policy can be enforced as well.

On the other hand, location is the most difficult context to acquire and process. Global Position System (GPS) [8] has been widely used to detect out-door location, but it does not work well for indoor environments. Indoor location information is difficult to acquire because of its inherent characteristics. First, indoor location context information is not a signal source that can be detected by a sensor like most other contexts, such as noise and light. location information cannot be obtained using a single sensor. In order to "sense" location, artificial information "sources" must be placed in the building. The sources may include ultrasound, infrared, or RF signals. Then the "sensor" part is embedded in client's mobile devices or clothes. Complex and reliable algorithms are required to calculate location based on the sensed signals. Second, location information has to be abstracted to application-specific meanings before an application can understand it and utilize it. For instance, raw location information is a set of three-dimension coordinate values (length, width and height based on an origin point), which must be transformed to application-specific building name and room number so that an application can use it.

Researchers have strived to build various indoor location determination systems, using different signals, aiming to different application-requirements [9–18]. This paper proposes our approach - build a toolkit to bootstrap the development of increasing sophisticated indoor location determination systems. This toolkit includes several programs that provide the most frequently-used functionalities of location determination system and better user-interface to facilitate the development. The rest of the paper is organized as follows: Section 2 surveys the existing indoor location determination systems. Section 3 presents our approach, the design of the location toolkit. Then we discuss the implementation details in Section 4. Section 5 lists our research results using this toolkit. Section 6 concludes this paper and future work.

2 Existing Indoor Location Determination Approaches

The existing indoor location determination approaches can be roughly separated into four categories, although many implementations mix and match the various approaches as required by the application domain [19].

2.1 Scene Analysis Approach

This approach emerges from robotics field, and it operates much the same way humans localize themselves and provides symbolic localization. Using this approach, an robot must equipped with a digital camera. Using image processing techniques, the location and orientation of the camera is determined from the image by identifying and comparing image elements with a database of landmarks of known size, shape, and location. The database can be generated by a separate robot performing an "exploratory" tour through the environment [20, 21].

2.2 Sector Approach

This approach uses radio signals to determine location by allowing the coverage areas of various radio signal transmissions to overlap. Stationary units are placed in the location space, each with a unique identification tag. There units broadcast their tag continuously over 802.11b compliant wireless adapters. users with computers running 802.11b wireless adapters can receive and read their signals. The set of visible broadcast tags forms an identifying code, which determines the location from a table of vertex-code pairings [22].

2.3 Probabilistic Approach

This approach is well suited to indoor environments where multi-path fading and signal absorption are most problematic. Since line of sight between transmitter and receiver cannot be guaranteed, any geometric approach will lose accuracy. The approach [16] as presented here is discussed using the terminology of a wireless LAN. Radar is a location determination system using this approach [15].

The probabilistic approach is based on two observations. The first observation is that the strength of the radio signal changes (usually decreasing) as the distance between the client (the antenna of the client's wireless NIC) and the wireless access point increases. The second is that the strength of the radio signal observed at a position is stable if the access point is statically positioned and the environment is relatively calm.

2.4 Geometric Approach

This approach is based on the geometric properties of circles: given the distance between an unknown position and three known positions, the position can be determined. The distance between the unknown position and a known position requires that the unknown position lie somewhere on the circumference of a circle centered about the known point with a radius of the known distance. Three such circles will intersect at the unknown position. The position can be determined easily from a diagram, but calculating the position is more difficult. The position can be calculated via multi-lateration, the procedure is explained in detail in section The geometric approach is the most widespread and mature of the localization approaches. It is also the approach used in the GPS [8] and the Cricket location system [13].

3 Our Approach

Since 802.11b wireless networks are widely used in business, school, and home environments, we propose using the RF signal strength of this type of networks to facilitate indoor localization. Therefore, users of the location determination system will not need to install any special purpose hardware such as infrared and ultrasound devices. The wireless infrastructure used in our everyday life will also serve as the "location signal source" in our system. User only needs to install a software location system in the host machine to make it location-aware.

As discussed earlier, indoor location information has to be abstracted to be meaningful to an application in the host device. Similarly, a location determination system needs to be customized to fit in each environment (building, room, etc). This customization process is the first phase in our approach. It is called ”training” phase, meaning the process that trains the system to the new environment, including recording the location name and sensed location signal: RF signal strength. The precondition of training phase is given locations and sensed signal strength. The output and learning result of this phase is certain mapping relationship between the locations and signal strengths. Therefore this is a preparation of the location determination system before it really starts working.

Second phase is called the ”working” phase, where the system does its normal job: determine location. In this phase, the system sensed the RF signal strength, and used the mapping relationship acquired in the training phase to resolve the location it stays at.

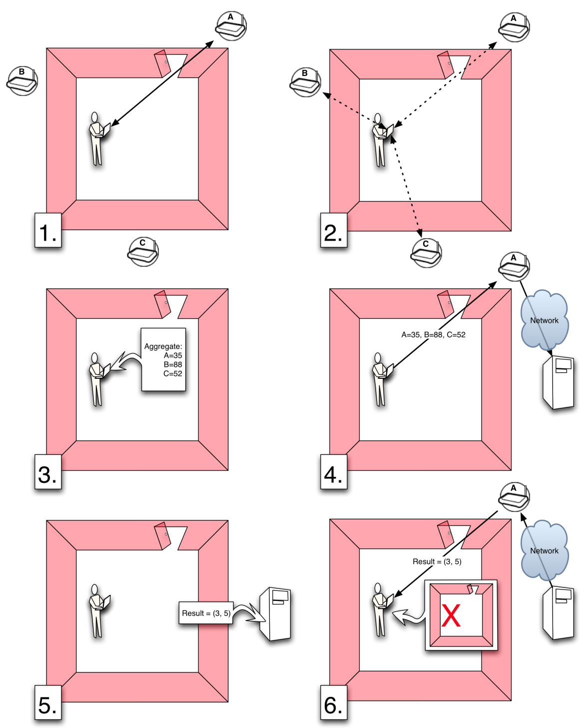

Figure 1. The process of location determination

Figure 1illustrate the process of location determination using our approach, where Steps 1 to 4 are of Phase 1 and Steps 5 and 6 are of Phase 2.

4 A Toolkit for Location Determination

Almost all the location determination approaches consists of a training phase and a working phase. The variation exists in the types of media used as location signal and the techniques in setting up the relationship between the location and the signal. Moreover, each location determination system goes through the training phase to a distinct working environments. Thus there are many ”common” tasks in location determination systems. Based on this observation, we develop a toolkit including a set of utility programs performing these common tasks. The toolkit consists of three components presented in rest of this section. Each component program is Windows-based, and is invoked in a single-line Dos command window.

4.1 Floor Plan Processor

The Floor Plan Processor is a GUI-based Python program for constructing position maps and visualizing oneself in the physical space. A floor plan is a GIF image representation of the physical space that the location determination system has been deployed and trained on. The floor plan can be scanned from the architectural blueprints of the room or building of interest. The main functions are as follows:

1. To load the floor plan GIF image. User can open a GIF format image file out of a window and work on it. Currently only GIF format is accepted.

2. To add access points. User can use mouse to click on the floor plan image to specify a set of points that represent the locations of access points used in the area.

3. To set the scale of the floor plan. User can use mouse to click two points in the floor plan image and then specify the real distance between these locations represented by these two points. Therefore, the scale of the floor plan image is set up.

4. To set the point of origin. The location determination system uses a two-dimension coordinate value to identify a location at first (and resolve to a location name later), so the point of origin needs to be specified as well. User uses mouse to click the origin point in the floor plan image.

5. To add location names. To abstract the coordinate value represented location as application-specific location names that make more sense to an application, use can use this feature to click at some point in the floor plan, and specify a name, such as ”room D22” or ”Center of Hallway”.

6. To save the floor plan. This feature is used so that the floor plan with all the above setups can be saved.

Figure 2depicts the Floor Plan Processer’s user menu.

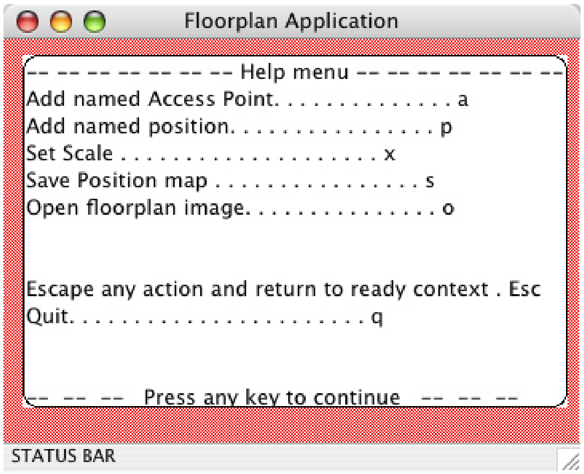

Figure 2. The Floor Plan Processor User Interface

4.2 Floor Plan Compositor

The Floor Plan Compositor creates images from a floor plan and marks the image with locations out of user-given coordinate values. The coordinate values are given in the Dos command that invokes the Floor Plan Compositor.

This component is a good tool in testing a location determination algorithm. We can take a set of testing locations in a room, run the system, and use the Floor Plan Compositor to display all the testing locations and their corresponding estimated locations derived by the location determination algorithm. The Floor Plan Compositor is a directly perceiving tool for the developer to test a location determination system, and a nice visual interface for a user of the system as well.

Figure 3shows a floor plan displayed by the Floor Plan Compositor.

4.3 Training Database Generator

The Training Database Generator requires two pieces of information: a collection of wi-scan files and a location map (a text file of location names and coordinates). Training databases are really collections of observation records, and are easier to work with than wi-scan file collections and location maps because they are compressed, which makes them easier to move and transmit over a network, and they can be loaded into memory more quickly than reading multiple wi-scan files line by line.

Each wi-scan file in the collection represents the data collected at a named location in what will become the training database. This collection is passed to the Training Database Generator as a string representing either the name of a directory containing the wi-scan files or a zip file containing the wi-scan files. There are two things the Training Database Generator must correctly deal with when handling wi-scan file collections: directory structure and file format.

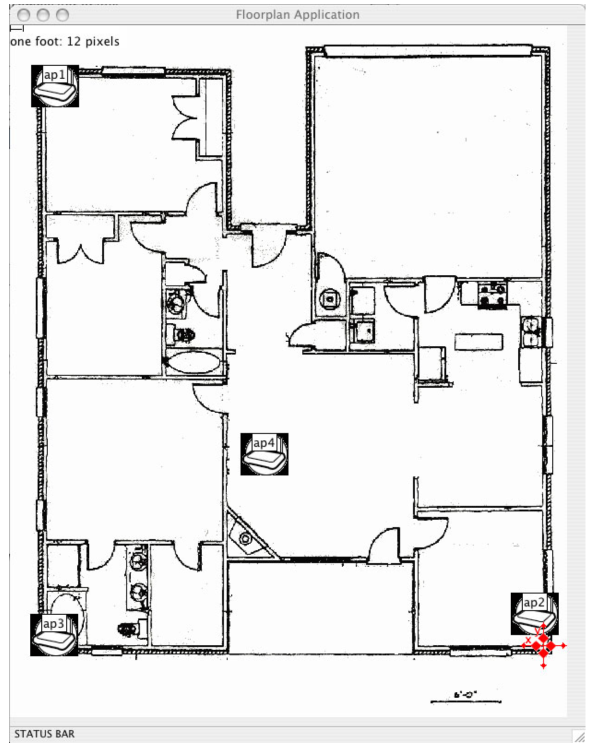

Figure 3. The floor plan in display

5 Research Results

We have used the location toolkit in our localization approaches. Specifically, we used two approaches in phase 1 and phase 2, namely probabilistic approach and geometric approach, whose general ideas are discussed in Section II.

5.1 Probabilistic Approach

This approach is based on the following observation: in an 802.11 network, as the distance between the mobile device and access point (AP) increases, the RF signal strength decreases. Different distances cause different signal strength values. If we allow multiple APs in the testing area, each location in the area has a distinct vector of distances to the APs, which cause a distinct vector of signal strength values that can serve as a ”signature” of the location. Based upon the idea of ”mapping relationship between location and signal strength vector”, our approach includes two phases. Phase 1 is the ”training” phase. A set of locations is selected in the physical space and signal strength values are taken at each location. These values form the training database. Phase 2 is the "observation" phase, where users move about the space and observed signal strength vectors are taken and processed against the database. In Phase 1, we set up four 802.11b APs (A, B, C, D) at the four corners of the experiment house that is 50 feet by 40 feet, as illustrated in Figure . We set one corner as the original point $(0, 0)$. Then we collect the sample signal strength vector $< A, B, C, D >$ at each training point (x, y) where x and y are product of 10 feet. We then group the signal strength values for each training point, and calculate the average value and standard deviation for each $< trainingpoint, AP >$ pair. In Phase 2, we collect signal strength at 13 locations scattered in the house. Then we calculate the likelihood between the observed data and any training data using the following formula:

$$value = \frac{e^{\frac{-(observation-training)^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}} \quad (1)$$

The training point that generates the maximum likelihood value is our estimate location. Therefore, this approach does not return the coordinate values of the observed location, but returns the most approximate training location instead. Using this approach, 60% observations end up with a valid estimation.

5.2 Geometric Approach

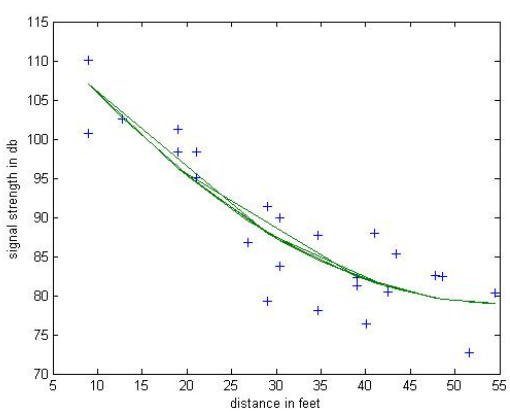

Figure 4. Signal strength VS. distance

This approach is based on the following idea: A distance value is associated with an signal strength value, therefore a signal strength value indicates a distance (assuming the mapping relationship is stable). Given multiple (at least 3) distances d_i, derived from signal strength values and the locations of the APs $O_i(i = 1, 2, ..., n; n \geq 3)$, we may derive the observe location by getting the intersection of circles (O_i, d_i). The geometric approach also includes the Phase 1 "training" and Phase 2 "observation". In Phase 1, after collecting the signal strength values in the training points, we identify the relationship between the distance and the signal strength. We use a reverse square formula to model this relationship. Each AP has its own distance-signal strength relationship formula. For instance, we used least-square regression approach and found the following formula for one AP, as shown in Figure 4 :

$$SignalStrength = 0.0132d^2 - 1.4545d + 119.1087 \quad (2)$$

Then in Phase 2, the observed signal strength vector $< AO, BO, CO, DO >$ is used to calculate the distances to the four APs $< d_A, d_B, d_C, d_D >$. As locations for APs A and B are known, we calculate the intersect points P_1 of circle (A, d_A) and circle (B, d_B). Similarly we can get three more intersect points P_2 out of d_B and d_C, P_3 out of $d_C$and d_D, P_4 out of d_D and d_A. Finally we can get the median point $\bar{P}$ of P_1, P_2,P_3,and P_4. This median point $\bar{P}$ is the estimated location. Using this approach, the average deviation (distance between the estimate location and the actual location) of the 13 observation is 10.41 feet.

6 Conclusion and Future Work

For both approaches, probabilistic and geometric, the results are not fine-grain enough to satisfy certain application requirements. But the results are encouraging, for we use the straight-forward algorithms, the basic hardware equipments (APs and mobile computers) and software system (the location toolkit and a third-party signal strength detecting system), without considering the other factors that affect signal strength, such as reflection, scattering and absorption. We are confident that we can improve our approach to provide more accurate and fine-grain location determination service. Our experiences find that the unstableness of the 802.11 RF signal strength is the largest barrier. To deal with the uncertainty, we will work in the following directions:

1. First, take the factors other than the distance into consideration. Apparently, distance is a key factor but not the only factor that affect the signal strength. The shape, size, layout of a room, the construction material, the furniture and people inside the room, the temperature and humidity, and the hardware devices will all play a role in twisting the signal strength. We will perform more experiments that control one factor each time to explore a more predicable location model.

2. Second, develop accurate and finer-grained observation data processing algorithms. Current algorithm requires signal strength values in 1.5 minutes, and uses

only the average signal strength value of it. Our new algorithm will consider the distribution of these values, and the variation patterns of them. We will borrow the idea of some "client-tracking" algorithm, which use the combination of the historical location value and the current signal strength value to derive the current location. Moreover, we will use more powerful statistic tool, such as Bayesian-filter, to facilitate the estimation.

3. Third, explore more reliable signal transmission media. 802.11 RF signal strength has some inherent uncertainty that is difficult to model. We consider another option for those most precise location estimation requirements: more reliable signal transmission media. At the same time we do not give up the idea of "performing without special-purpose hardware". We consider using the Ultra Wide Band (UWB) technology [23, 24]. UWB is defined as "radio technology having a spectrum that occupies a bandwidth greater than $1/4$ of the center frequency of a bandwidth greater than 500 MHz". A UWB signal is made up of signal bursts of extremely short duration, from tens of pico-seconds to tens of nano-seconds. The advantage of this feature in the location determination problem is: the burst duration is so short that in an indoor environment the signals arriving late due to multi-path propagation arrive at discrete intervals, so there is little or no signal loss due to fading, scattering and reflection. The subsequent and repeating bursts can be filtered out. UWB was adopted by the Bluetooth Special Interest Group for the physical layer of the Bluetooth specification. Therefore, this direction is a practical solution to deal with signal strength uncertainty.

4. Finally, we will expand our location toolkit, implement the new location service, and use the service in our other research projects related to pervasive computing.

References

[1] Mark Weiser. Some computer science issues in ubiquitous computing. *Commun. ACM*, 36(7):75–84, 1993.

[2] Stephen S. Yau, Fariaz Karim, Yu Wang, Bin Wang, and Sandeep K. S. Gupta. Reconfigurable context-sensitive middleware for pervasive computing. *IEEE Pervasive Computing*, 1(3):33–40, 2002.

[3] Mark Weiser. The world is not a desktop. *Interactions*, 1(1):7–8, 1994.

[4] Stephen S. Yau, Yu Wang, and Fariaz Karim. Development of situation-aware application software for ubiquitous computing environment. In *COMPSAC '02: Proceedings of the 26th International Computer Software and Applications Conference on Prolonging Software Life: Development and Redevelopment*, pages 233–238, Washington, DC, USA, 2002. IEEE Computer Society.

[5] Yu Wang. An fsm model for situation-aware mobile application software systems. In *ACM-SE 42: Proceedings of the 42nd annual Southeast regional conference*, pages 52–57, New York, NY, USA, 2004. ACM Press.

[6] Himanshu Gupta, Samir R. Das, and Quinyi Gu. Connected sensor cover: Self-organization of sensor networks for efficient query execution. June 2003.

[7] Adam Harder, Lanlan Song, and Yu Wang. Towards an indoor location system using rf signal strength in ieee 802.11 networks. In *ITCC '05: Proceedings of the International Conference on Information Technology: Coding and Computing (ITCC'05) - Volume II*, pages 228–233, Washington, DC, USA, 2005. IEEE Computer Society.

[8] Jay A. Farrell. *The Global Positioning System and Inertial Navigation*. McGraw-Hill, 1998.

[9] J. Werb and C. Lanzl. Designing a positioning system for finding things and people indoors. *IEEE Spectrum*, 35(9):71–78, September 1998.

[10] A Ward, A Jones, and A Hopper. A new location technique for the active office. *IEEE Wireless Communications*, 4:42–47, Oct 1997.

[11] Roy Want, Andy Hopper, Veronica Falcão, and Jonathan Gibbons. The active badge location system. *ACM Trans. Inf. Syst.*, 10(1):91–102, 1992.

[12] Ping Tao, Algis Rudys, Andrew M. Ladd, and Dan S. Wallach. Wireless lan location-sensing for security applications. In *WiSe '03: Proceedings of the 2003 ACM workshop on Wireless security*, pages 11–20, New York, NY, USA, 2003. ACM Press.

[13] Nissanka B. Priyantha, Allen K.L. Miu, Hari Balakrishnan, and Seth Teller. The cricket compass for context-aware mobile applications. In *MobiCom '01: Proceedings of the 7th annual international conference on Mobile computing and networking*, pages 1–14, New York, NY, USA, 2001. ACM Press.

[14] A.M. Ladd, K.E.Bedris, G. Marceau, A. Rudys, D.S. Wallach, and L.E. Kavrake. Using wireless ethernet for localization. In *IEEE/RSJ International Conference on Intelligent Robots and System*, volume 1, pages 402– 408, 2002.

[15] Paramvir Bahl and Venkata N. Padmanabhan. Radar: An in-building rf-based user location and tracking system. In *Proceeding IEEE INFOCOM*, Mar 2000.

[16] E.S.Bhasker, S.W. Brown, and W.G. Griswold. Employing user feedback for fast, accurate, low-maintenance geolocationing. In *Proceedings of the Second IEEE Annual Conference on Pervasive Computing and Communications*.

[17] Andy Harter, Andy Hopper, Pete Steggles, Andy Ward, and Paul Webster. The anatomy of a context-aware application. *Wireless Networks*, 8(2 - 3), Mar.

[18] Improving the accuracy of wlan based location determination using kalman filter and multiple observers.

[19] Adam Harder. Master of software engineering project report, 2005.

[20] G. Dudek and C.Zhang. Vision-based robot localization without explicit object models. In *Proceedings IEEE International Conference on Robotics and Automation*, pages 76–82, April 1996.

[21] J. Hightower and G. Borriello. A survey and taxonomy of location systems for ubiquitous computing. 2001.

[22] Rachanee Ungrangsi, Ari Trachtenberg, and David Starobinski. *Lecture Notes in Computer Science*, volume 3283, chapter An Implementation of Indoor Location Detection Systems Based on Identifying Codes, pages 175–189. Springer, 2004.

[23] K. Siwiak. Ultra-wide band radio: Introducing a new technology. In *IEEE Vehicular Technology Conference*, volume 2, pages 1088–1093, 2001.

[24] R.A.Scholtz M.Z.Win. Ultra-wide bandwidth time-hopping spread-spectrum impulse radio forwireless multiple-access communications. *IEEE Transactions on Communications*, 48(4):679–689, Apr 2000.