FINAL YEAR PROJECT

CONTINUAL ASSESSMENT (CA-1) REPORT

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Introduction

With increasing power and decreasing cost of mobile devices a variety of interesting location based mobile applications have been developed. An interesting future of location based applications lies in unified global localization including outdoor as well as indoor localization. It could lead to new interesting business models like indoor advertising and discounts, location based remote monitoring, help in emergency rescue services or just enable us to play a life size version of the Pac-Man game in our offices. With increasing battery life, processor speed and number and type of sensors in today's smartphones, it is becoming easier to solve this problem and deploy a low cost scalable solution across the world. This project takes a similar approach to solve the problem of indoor localization by improving upon and combining existing technologies for indoor localization to give more accurate results. These technologies include Wifi fingerprinting, radio signal propagation, background sound sensing and accelerometer readings. We also try to explore new technologies such as barometer sensor equipped smartphones.

Motivation

Outdoor localization has already been tapped to its best potential and next natural step is moving indoors. The current outdoor localization technology (mainly GPS) does not extend to the indoors due to loss of GPS signal. This has called for a need to develop innovative indoor localization technologies. This need for indoor localization for pervasive mobile computing has led to a lot of interesting research in the past ten years. Some of the initial research included use of specialized emitters and sensors placed inside buildings to localize objects and people. This method though quite accurate is not scalable for commercial deployments and involves a certain overhead cost in installing and maintaining the additional infrastructure. Another popular method makes use of the existing infrastructure using wireless access points to

triangulate and localize using mobile devices. This method is quite accurate but it usually requires extensive surveying and training effort to build a radio frequency (RF) map of the building. There are also improvements to this method which reduce the efforts or eliminate them completely but at the cost of accuracy. With mobile technology becoming more powerful over the last few years, it is now embedded with more sensors which can improve the accuracy of the prediction by combining them with these earlier technologies. This is the motivation behind this project in trying to use fairly new methods such as accelerometer readings, acoustic background sound system and barometer readings in addition to wireless RF maps to increase the probability of predicted positions.

Objectives

Indoor localization as mentioned above is a research area that has attracted quite a lot of attention recently. A lot of work has been done on different innovative approaches to solve this problem. In this project I will analyze these technologies for advantages, disadvantages from a practical deployment point of view, and then implement a system combining the best and most practical technologies to increase the accuracy of location prediction. The goal is to bring together these technologies that currently exist in silos and create a working implementation.

I will be implementing these technologies on the Android platform creating an Android application that can localize a user in COM1 using just the phone itself. It should also be extensible to localize in other places as well.

COM1 building will be used as the test bed for testing the app. The results of this app will be compared to using the technologies used in silos to see how combining them affects the localization. I will also look into some possible simulation model to test out the app for different factors.

Related Work Analysis for use in the our system

A. Infrastructure Based methods

As mentioned before the earlier work in localization was mainly based on using pre-installed sensors. Active Badge (*Want et al., 1992)* is one such system that relies on specialized tags which emitted diffuse infrared pulses detected by ceiling-mounted sensors. Another technology, the Cricket Compass *(Priyantha et al., 2001)* used specialized ultrasound and radio frequency receivers to detect signals transmitted by fixed beacons. ARIADNE *(Bias et al., 2006)* deploys wireless sniffers at known locations and makes use of a sophisticated ray-tracing model based on detailed floor maps and uses simulated annealing to estimate radio propagation parameters.

These methods are not scalable so the focus shifted on using off the shelf technologies such as wireless routers, which were usually preinstalled, and measuring radio frequency signal for location discovery. Next we will discuss these methods.

B. Infrastructure-less based methods

1) Location Fingerprinting methods using Wifi

Early Implementations

Radar (Bahl and Padmanabhan, 2000) was one of the early implementation of wireless *fingerprinting*[1] to approach the indoor localization problem. They used the RSS (received signal strength) measurements and user orientation as the input parameters for fingerprinting. Since they were recording signal strengths from direct signals received, user orientation was an important factor since the body of the user could dampen the signal too. Without using user orientation the accuracy of the system dropped by over 50%. Therefore for every position in the training phase four readings were taken for the four orientations. During the measurement phase[2] multiple readings are taken for each point and averaged. This average signal strength is

[1] Fingerprinting is a term repeatedly used in the report which refers to the mapping of the RF signals at different locations in the indoor environment, stored in a database to be used later to find the current location of the user. It may also be referred to as the empirical method.

[2] Fingerprinting technique works in two phases: the training phase which created the mapping and the measurement phase which is the actual testing of the implementation to calculate the location.

compared with the fingerprinted data. Radar uses the nearest neighbor in signal space (NNSS) method, computing the minimum distance between the measurements and the observation, to find the most accurate (nearest) location. They also mention that during the training phase taking readings closer than a threshold (two points should not be too near) reduces the accuracy of prediction and usually having three or more samples for a position increases accuracy.

A big limitation for scaling this method is that the training phase is very labor intensive, and recalibration is required if there is any relocation of wifi access points. Thus, they also propose a radio propagation model which tries to estimate the signal strength values over an area using the fact that radio waves weaken with the distance travelled and when passing through objects. They consider three popular radio propagation models and settle on the *Floor Attenuation Factor* propagation model *(Seidel and Rapport, 1992)* for its simplicity and accuracy. This model performed worse than the empirical method and also required empirical calculation of the wall attenuation factor (WAF). In practical use the WAF could be different for walls within the building and the real-time movement of people in the indoor environment might affect the calculations, which would affect the accuracy, so we decide not to use a propagation model for this project.

Location determination algorithms

Liu et al., 2007 does a survey of the current wireless indoor position systems and compares different techniques for various factors such as accuracy, precision, complexity, scalability, robustness, and cost. Brief overviews of the relevant algorithms from those discussed in the paper are as follows:

1) **Triangulation**: This method estimates location by measuring the distance of the mobile device from multiple reference points.
    a. **TOA**: time of arrival is used to measure the distance of the reference point emitting the signal, as it is directly proportional to the distance between them. All the transmitters and receivers need to be synchronized and timestamps need to be sent with the signals.

b. **TDOA**: time difference of arrival is used to measure the difference in arrival time of the signal at different positions. The intersection of the hyperbolic arcs to these positions gives the location of the receivers.

c. **RSS based**: measures RSS (Received Signal Strength) to use as a replacement for distance measures. It is better than TOA and TDOA as it takes into account multipath and shadowing effects. Pre-recording these values increases the accuracy.

2) **Angulation techniques**: uses the intersection of a pair of angle direction lines from the reference points to find the location. It works for 2-d localization with only 2 reference points, but needs extensive hardware for accurate measurements.

3) **Probabilistic methods**: A popular approach is the histogram approach which considers positioning as a classification problem and maximizing the likelihood of the predicted location. Another approach assumes the likelihood of each location candidate is a Gaussian distribution.

The paper further analyses and compares the current techniques for localization and suggests Horus *(Youssef and Agrawala, 2005)* to be the most accurate one.

Systems with higher accuracy

Horus system *(Youssef and Agrawala, 2005)* offers a joint clustering technique for location estimation, which uses probabilistic methods. Each location coordinate is regarded as a class or category. In order to minimize the distance error, location with the highest likelihood is chosen. They have shown that this technique can acquire an accuracy of more than 95% to within 2.1 m. Increasing the number of samples at each sampling location improves the accuracy, by improving the estimation for means and standard deviations of Gaussian distribution. The paper claims that according to their tests accuracy does not change with change in hardware.

After receiving a sequence of observations from each access point, the access points are sorted in the descending order of received signal strength. For the strongest signal access point, the probability of each location in the radio map is calculated. If the highest probability is significantly higher than the second one that value is returned, if not the same process is

repeated with the second highest signal strength access point with a smaller set of locations from the first access point.

Another system *(Haeberlen et al., 2004)* uses a topological map instead of a geometric one to increase accuracy. They decrease the granularity of the search space by dividing the floor space into rooms and hallways into segments instead of mapping cells which are smaller in area. Large rooms were broken up into segments too. This makes the system more robust and less error prone. Moreover the fingerprinting time required for each segment is about a minute, which helps makes the process much less intensive and results in 95% accuracy. When the wireless access point density was reduced to half, accuracy dropped to 90% and with the movements of people inside the office the accuracy dropped to less than 70%. Therefore, despite of this interesting new approach, this method does not seem very practical for actual deployment.

Android Implementations

Martin et al., 2010 show an Android application implementation using the wifi fingerprinting approach and claim to have an accuracy of up to 1.5 meters. The accuracy drops quite a lot with less than three available wifi access points available. They have used the Nearest Neighbor in signal space and Access Point averages approach to calculate the most probable location. Our proposed application will be similar to this implementation, trying to be more accurate and less labor intensive for fingerprinting. The training and experimentation was carried out in very controlled conditions for this application, which may not be very scalable. There is not much detail available about the implementation and testing about this application.

Another Android application called "Locate Me"*(Pereira, 2011)* also attempts to solve this problem combining three methods: 1)Fingerprint localization using wifi access points 2)Location using geo-referenced access points which stores GPS values with the fingerprint values 3) Localization using geo-referenced mobile base stations, which performs quite badly, but might be the only available method sometimes. This is the only smart phone app available for indoor localization but it doesn't really let the user localize his space. It also does not show GPS and cell values.

Previous years project (CS4274 Mobile and Multimedia networking):

A group of SoC students have approached indoor localization in the CS4274 project. Their implementation is based on wifi fingerprinting storing the difference in signal strength values for different Access Points. The project however does not mention how accurate the system is due to lack of time for extensive testing. The implementation is on the Android platform fingerprinting two floors of COM1. This work can certainly be reused in our implementation, keeping in mind extensibility of the system to accommodate alternate methods of localization discussed later.

Disadvantages of fingerprinting

As discussed earlier, most of the present indoor localization techniques use the location fingerprinting method which requires an 'offline phase' or training phase to build a detailed RF map for a target area. There are three major problems with fingerprinting:

1. The devices used in the 'offline phase' may differ from the actual device used in the 'online phase' to take measurements.
2. The 'offline phase' has been described to be very labor intensive, taking samples in all the locations and possibly in different orientations.
3. These static models built during the 'offline phase' do not take into account the time varying nature of the wireless signals. It has been observed that the signal strength varies with movement, occupancy and surroundings.

Methods to tackle disadvantages of Fingerprinting

Now we discuss methods which try to tackle these problems.

One of the fundamental problems in location fingerprinting is the differences in received signal strengths in different clients. This usually happens due to different hardware, software and lack of standardization. Current methods try to do some kind of mapping between these different devices and some approaches even do separate measurements for each device. *Hyperbolic Location Fingerprinting (Kjaergaard and Munk, 2008)* approaches to tackle this problem by recording signal strength ratios between two pairs of base stations instead of recording the absolute signal strength. HLF was evaluated with two popular fingerprinting

techniques –*Nearest Neighbour* and *Bayesian Inference*. The signal strength ratios were also shown to be more stable and less variant over time. Another improvement proposed in this paper was to tackle highly sensitive antennas by using the K-strongest filter, which only takes ratios of the K strongest values. This small improvement increased the efficiency by over 15% in the Bayesian Inference model.

The problem of intensive 'offline phase' has been approached in an interesting and novel way at Microsoft Research India *(Chinalapudi et al., 2010)*. They come up with a service called EZ which does not require any intensive fingerprinting efforts and has an accuracy of 2m and 7m respectively in a small and large building. EZ works on a set of assumptions:

- There are enough wireless Access Points to provide good coverage throughout the building.
- Users always carry smartphones or other such devices equipped with Wifi.
- Occasionally such a device would be able to attain a GPS lock at the edges of the building like windows or entrances.

Using EZ users do not need to report their true locations even during the training phase and it does not require any extra training time, as the training is done by normal daily movement of the user in the building. This method exploits the fact that for location determinitation we require at least three known positions, which it obtains through the occasional GPS locks. Since the method is irrespective of other nodes a single user can build a detailed RF map over time. Though there is a loss of accuracy for this system as compared to Radar *(Bahl and Padmanabhan, 2000)* or Horus *(Youssef and Agrawala, 2005*), EZ is more robust to change in device (hardware) and measurements over different times, due to the variety and large samples of data collected. EZ uses the long distance path model (LDPL) to predict RSS at various locations in an indoor environment.

EZ has the following limitations:

- GPS lock received might not be accurate especially around tall buildings, which is the most like deployment place of such an indoor positioning system. GPS antenna might

receive signals which are reflected from other buildings which affect the accuracy of such location determination.

- Each unknown location requires at least 3 APs to find a solution to the LDPL equations.
- Keeping Wifi and GPS functionality always on will drain the battery of the user's device.
- The outdoor movement of the user cannot be differentiated from his indoor movement which might corrupt the data in the training phase.
- Less accurate than manual fingerprinting methods.

Due to these limitations and the fact that the accuracy readings received by this method was in controlled conditions, we would not be taking this approach for our deployment as we think it requires further research and more detailed experimentation to tackle these limitations.

2) Using Accelerometer

Most of the indoor localization methods focus on single floor implementations. Methods such as Wifi fingerprinting might not always work to determine floors when the Wifi signal is not strong enough to reach other floors. FTrack *(Haibo et al., 2012)* is an alternative way of determining which floor the user is based on the only accelerometer values. Ideally we can calculate the user location indoors by double integrating the acceleration, but the accelerometer readings are usually very noisy. **FTrack** proposes using the signatures in human walking patterns (the nature up and down bounce) to obtain the current floor information for the user. Taking stairs and using the elevator have been identified as the two main ways of changing the floor value and the time spent in changing the floors is recorded.

While taking the stairs it can be figured out based on the number of peaks in the acceleration time graph that how many steps were taken and in what direction (up or down). Similarly for taking the elevator time to go to different floors is recorded. The acceleration and deceleration at the start and end of the elevator ride is used to the figure out the time taken and direction of these values is used to figure out the direction of the movement. This information is stored in two states: S<*UserID, StartTime, EndTime, Encounters*> which is when

the user is on a particular floor and M<*UserID, Duration, ActionT ype, Direction*>, while the user is changing floors.

The fingerprinting is done by several people changing floors over a period of time. It also makes use of Bluetooth technology during fingerprinting to record any encounters (coming in close proximity) between different users. These encounters are later used to verify the predicted floor information. For example, if two users travel the same period of time and in the same direction (up or down), and end up on the same floor and encounter each other, they must come from the same floor. 97% accuracy was achieved after 3 hours of data collection and it was observed that a higher number of encounters positively affected the results.

There is a prime limitation of this method. Taking an escalator (which has become an everyday alternative to stairs and elevators) is not accounted for in this experiment. Readings similar to an elevator can be expected if the person does not move. If the person also climbs the escalator stairs at the same time, it would be difficult to figure out the time taken. The sudden acceleration and deceleration when a person gets on and get off an escalator might still produce a spike in the graph good enough to distinct the time taken, but then again it would differ every time the user takes an escalator as he is free to climb it faster if there is less traffic present.

AAMPL (Accelerometer Augmented Mobile Phone Localization) is another technology which makes use of accelerometers to find the position of a person indoors. It tries to find a correlation between accelerometer readings taken while being in different kind of business stores. It tries to measure the time spent standing or sitting and maps it to the type of business *(Ofstad et al., 2008)*. For example, you are more likely to be standing more at a supermarket than a restaurant. It finds your location, retrieves the businesses around you and then filters them by business type based on your accelerometer readings patterns.

3) Using background sound

Another interesting approach is based on a new ambient sound fingerprint called the Acoustic Background Spectrum (ABS) to figure out the room a person is in. This system has a surprisingly good accuracy and is easily computed, compact and resistant to transient sounds. *(Tarzia et al., 2011)*. According to the field of architectural acoustics *(Kuttruff, 1973)*, the rooms geometry and furnishings give it a distinctive background sound.

After recording an audio sample of a set length using the microphone present on the phone, it is divided into fixed length frames. The frames are in turn multiplied by a window function vector, which reduces the signal magnitudes near the frame boundary and then the power spectrum for each frame is calculated. After this the frequency band of interest is filtered out. This value is normalized to be expressed in decibels. To filter out the transient sounds that may corrupt the data we choose the 5th percentile (lower value) for each frequency from the data.

ABS is completely independent of the Wifi fingerprinting method and even the errors of ABS are completely different from Wifi fingerprinting. Usually Wifi fingerprinting is not able to distinguish between adjacent rooms, which is quite accurately done by ABS. ABS fingerprinting can be done simultaneously with the usual Wifi fingerprinting procedure. They have also released an iPhone app called Batphone which is freely available and implements a milder form of the technique but also comes up with amazing results. For a full set of 33 rooms in the experimentation, the accuracy of prediction was 69% and a pair of rooms was distinguished with 92% accuracy. Therefore this method can be used as an assistive method with a prime measurement method such as Wifi fingerprinting.

4) Using new indoor mapping techniques

Another piece of the indoor localization is indoor mapping and navigation. Most of the research and implementations use floor plans to map the indoors and have internal methods to tag different components of the indoor floor plan. Open Street Maps is an open source organization which uses crowdsourcing to map roads, building, trees, signs etc. They have a schema (like a geo markup language) used to tag things by using key-value pairs as nodes, ways,

closed ways and relations. Nodes are like points on the maps which represent points of interest. Ways are roads or waterways, marked by straight lines between a series of nodes. Closed ways are ways with the same starting and ending node, and are used to mark buildings, parks etc. Relations are used to tag commonalties between not directly associated objects.

Some work has been done to extend this technology to the indoors, known as **IndoorOSM** *(Goetz and Zipf, 2011)*. They propose a schema, which is simple enough for OSM community to learn and start mapping the indoors. A building is associated with the outdoors using a relation and has certain attributes and levels. Each level has certain attributes and building parts which could be rooms, passages, vertical passages, doors, windows, movable and immovable objects. Starting with a floor plan and converting it into a tagged OSM map does not take very long if you are acquainted with the building. Using this schema a building was modeled and the 2-d and 3-d models can be found on the OSM website. The application also provides routes from one room on the building to any other room including one at different levels.

We believe this model is quite extensible and can be extended to include wireless access points and tags which have ids of the fingerprint information. Looking forward this would be very scalable as well, as the OSM community for mapping is already quite big and active. If implemented properly indoor mapping, localization, and navigation could be a technology easily implementable and used freely by anyone.

Comparative study

In the following table we compare strengths and weaknesses of all the systems mentioned above:

Localization Technique	Advantages	Disadvantages	Fit for use in our system
Infrastructure	• High Accuracy.	• Costly installation.	• No

based methods		• Not scalable.	
Wifi Fingerprinting	• High Accuracy. • No extra installation is required. • Scalable and deployable	• Depends on existing infrastructure • Labor intensive • Time varying nature of wifi signals • Hardware/software change might affect the results.	• Yes
Radar	• Takes into account user-orientation	• Low Accuracy • Labor Intensive	• No
Horus	• High Accuracy • Complimentary to ABS	• Labor intensive	• Yes
Haeberlen et al., 2004	• Robust • High Accuracy	• Needs a sufficient number of wifi signals • Low granularity	• Yes (Maybe to increase performance)
Locate Me	• Implemented on Android working on low processing power	• Low accuracy • Experimentation done in controlled conditions	• No
HLF	• Robust • Increased Accuracy	• A single AP node not working will affect the system.	Yes (Maybe with another technology)
EZ	• No labor required for system setup	• Low accuracy • Battery draining • Requires at least 3 APs • Cannot automatically	No

		differentiate indoor and outdoor	
FTrack	• Complimentary to fingerprinting	• Does not work for escalator movements • Labor intensive fingerprinting	Yes (With fingerprinting if required)
AAMPL	•	• Low Accuracy • It is only used to detect presence inside a building	No
ABS	• Complimentary to wifi fingerprinting, with different errors and same method for fingerprinting • Increases accuracy of other methods	• Requires Fingerprinting	Yes
IndoorOSM	• Generalized • Scalable	• Requires more research and implantation required	No

Properties of a good Localization system

1. Should be light enough to run locally on the phone.
2. Should require minimum effort in setting up (fingerprinting).
3. Should be stable with variation of time.
4. Should be robust to changes in the environment.
5. Should work equally well with any measurement device (any mobile phone)

6. Should be accurate enough to predict the room the user is in.

Limitations

1. Unexpected interference in actual deployment which was not present while fingerprinting.
2. Keeping wifi and GPS on all the time might be draining on the battery.
3. Location of Wifi access points may not be known in places like offices and malls where the deployment is done by external parties.
4. Floor plans might not be publically available.
5. Security in case of privacy breach might be an issue.

Techniques to be used in the proposed system

Based on the analysis of the current methods of indoor localization these are some interesting techniques that can be used in our implementation.

Wifi fingerprinting: As discussed before since location fingerprinting has proved to be the most accurate method with over 95% accuracy we will use the Horus model for indoor localization.

ABS: Since this method acts as a compliment to the wifi fingerprinting method and gives surprisingly good results we combine it with the wifi fingerprinting.

Floor determination: The wifi fingerprinting can be used for floor determination but most research done on wifi fingerprinting does not focus on it, so here are two alternate methods in case wifi fingerprinting does not prove to be an accurate method for floor prediction.

Floor determination using accelerometer: FTrack technology discussed before.

Barometer: Preferably we will use this technology which is becoming more common recently and has not been used for the purpose of localization currently to our best knowledge.

Time based finger printing: This is an interesting approach that we can explore in the experimentation and training phases, where we can fingerprint at different times of the day to and store it as separate data sets to deal with the environment and time variant factors.

Coarse grained localization (room level instead of cells): This can also be explored as an alternate finger printing method, using coarser grained values based on the whole room area rather than smaller cells. This may be quite complimentary to the ABS system.

User feedback system: A user feedback system can also be implemented, so that the user corrects any wrong predictions and the system can record such errors and recalibrate the system.

Integration with COALITION middleware of ELF_SPACE

This indoor localization project is part of the service oriented context-aware technology called ELF_SPACE that enables highly personalized services which will lift the user experience to a new height well beyond the current mobile computing and applications could hope to achieve. The technology also facilitates the development of smart city, smart home and smart living spaces in general. Such technology, a kind of ubiquitous computing, is expected to change the way we communicate and interact with others and the surrounding, be more efficient in the utilization of resources, and to influence the way we live, work and socialize. An important aspect of this service is to be able to figure out the exact indoor location of a mobile user to deliver ads, emergency services or just lifestyle enhancing applications. The Location service on this device will be connected to the Coalition middleware *(Zhu et al., 2010)* through a simple API call to gain the knowledge of location of the mobile user. The middleware uses this location and other context data to feed to a query system which figures out the response to this query.

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