"Building a Context-Aware Infrastructure using Bluetooth"

by

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Building a Context aware Infrastructure using Bluetooth

THESIS

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Jahnavi Kondragunta

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ABSTRACT OF THE THESIS

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Context Aware applications are applications that behave according to the context they are placed in. Infrastructures can be integrated with such applications to develop context awareness and modify their behavior according to the changes in the context. In this paper we present a core system that aids in developing such applications. The system estimates the location of people around the infrastructure by observing the bluetooth devices that they carry. The applications can then use this information as desired. To study the viability of bluetooth tracking and the efficiency of the system, an experimental system was implemented and deployed on the 5th floor of Donald Bren Hall at University of California, Irvine.

The experimental system was put on a trial run and the results obtained were analyzed. The results show that building a successful tracking system based on Bluetooth is complex and requires significant changes to user behavior.

1) INTRODUCTION

Context Awareness is an integral part of pervasive computing. In his founding paper on ubiquitous computing, Weiser envisioned a world in which computers are integral and invisible in people's life [1]. In this world small computers are present at every corner aiding humans in their day to day life. It is then hard to imagine these small computers functioning without any knowledge of the context that they are deployed in. It is not just difficult but impossible to develop a different application for every conceivable context.

A context aware infrastructure supports various context aware applications in behaving intelligently according to changing contexts. In this paper, we propose a system that aid's in developing a context aware infrastructure. It will help applications in keeping tab on people inside an infrastructure. This is done by observing the bluetooth devices that they carry. Many of the mobile devices in common use today have bluetooth capability and hence we expect a good number of people inside the infrastructure to carry a bluetooth device. In Section 2, we further illustrate how the system can help in building context aware systems, especially context aware infrastructures. Section 3 gives an overview of the system, the components involved and the principle behind the system. Section 4 describes a sample application we built using the hardware available in LUCI lab at University of California, Irvine. A series of experimental studies have been conducted on this trial application and Section 5 describes the results of these evaluation studies. Section 6 provides a quick comparison with similar systems and finally Section 7 provides the conclusion.

2) OUR SYSTEM'S ROLE IN CONTEXT AWARE INFRASTRUCTURE

A context represents the state of the surroundings. The surroundings can be location, identity and activity of the entities present nearby, physical surroundings, proximal computing environment etc [16]. Throughout this paper we focus mainly on the location of the people within the infrastructure. And hence, from here on a context should be interpreted to mean 'who is around'.

Context aware applications can be defined as applications that adapt according to the context they are placed in. For example, [2] developed virtual whiteboards that are reconfigured based on the people present in the room. If a project group is meeting then a project whiteboard is active.

Depending on the type of applications either a precise location is required or an approximate location would be sufficient. For example in the case of the virtual whiteboards, it is enough to know that the project group is in or very close to the meeting room, and not required to know which chair each person is sitting on, or at which end of the room they are etc. Stretching this, in some cases an even wider approximation like the person is in the building or in a certain section of the building would suffice. We target the applications where approximate location information is acceptable. The system we propose is aimed at helping to build context aware infrastructures using such type of applications. And will be seen in Section [6] the acceptability of approximate location reduces the complexity of the system and adapts more easily to different infrastructures.

The system is capable of handling any infrastructure as long as it has the three required components seen in Section 3. A floor plan of the infrastructure is taken as an input to the application and an approximate location of the person is calculated. This information can then be used as desired.

3) THE CORE SYSTEM

Key features of the System

This section outlines some of the key features of our system. Identifying the features of the system helps in understanding the design decisions of the system.

1) The system relies on imperceptible tracking of people using bluetooth devices. Imperceptible tracking can be described as resolving the location of a bluetooth device without explicitly letting the owner of the device know of the tracking.
2) Other than carrying a bluetooth capable device the system has no other expectations from the people. The infrastructure has no special relationship with the people. Hence, it is ideal to not have any special expectations from the users such as they should carry a special device or they should run a particular application on the device etc.
3) Since the people are only a temporary part of the infrastructure, the system only maintains minimal interaction and does not gather any extra information from the device.

4) The system provides an approximate, not precise, location of the people. As mentioned in the earlier section the target applications are the ones that do not require a precise location.

Overview of Bluetooth

The Bluetooth wireless technology is designed as a short-range connectivity solution for personal, portable and hand held electronic devices [14]. Bluetooth aims at replacing the connectivity cables required to connect devices while maintaining security. It defines a platform independent specification for devices to communicate in a wireless fashion. Any device that supports a bluetooth specification should communicate with any device that also supports a bluetooth specification irrespective of the type and manufacturer of the devices. The first bluetooth specification version 1.0 was introduced in July, 1999.

Bluetooth technology can operate over a range of 1m to 100m depending on the power class of the device. The three types of classes are:

1) Power class 1 - range 1m
2) Power class 2 - range 10m
3) Power class 3 - range 100m

Almost all bluetooth devices in common use today are class 2 devices. In this paper whenever we mention bluetooth devices, we refer to the class 2 devices.

Bluetooth signals travel in all directions and can penetrate non-metallic solid objects. Metals and water can block a bluetooth signal, though metals reflect the signal and water absorbs the signals. This means that Bluetooth can overcome obstacles like walls, tables, boards etc.

The bluetooth communication process consists of two procedures: an Inquiry procedure and a Paging procedure.

Inquiry procedure: An Inquiry procedure is used to discover other bluetooth devices within the range. When a bluetooth device wants to find devices within its range it sends inquiry requests. Any device that is set in discoverable mode listens for inquiry requests. When an inquiry request is heard it responds by replying to the requests. After Bluetooth Core Specification Version 2.1, the inquiry response consists of the discoverable device's active unique bluetooth address, and the bluetooth name (either default or as chosen by the owner of the device), RSSI (bluetooth signal strength), device class, list of services provided etc. The requesting device is called the inquiry device and the responding device is called the discoverable device. Any number of discoverable devices can answer to the requests by the inquiry device and also each discoverable device can answer to more than one inquiry device.

Paging procedure: A paging procedure is used for connecting two devices so they can continue further communication. The paging procedure consists of a paging device and a connectable device. As with the inquiry device in the inquiry procedure, the paging device sends page request packets. But unlike the inquiry requests which are open to all listening devices, the page request is specific to only one target device. For this purpose the page device has to have some knowledge of the target device. The target connectable device then responds to the page request and a connection is formed between the two devices.

It is important to understand the difference between the inquiry procedure and the paging procedure for our proposed system. Our system should be able to identify any device that is present within the infrastructure. This means that the system has no beforehand information about the device to be tracked. Also, the system should not gather any extra information from the devices. Hence, the inquiry procedure is used in our system. Inquiry procedure also ensures minimal interaction with the devices.

System Architecture

The core system we propose involves three basic components: A mobile bluetooth device, a static bluetooth reader and a server. Figure 1 illustrates the architecture of the system.

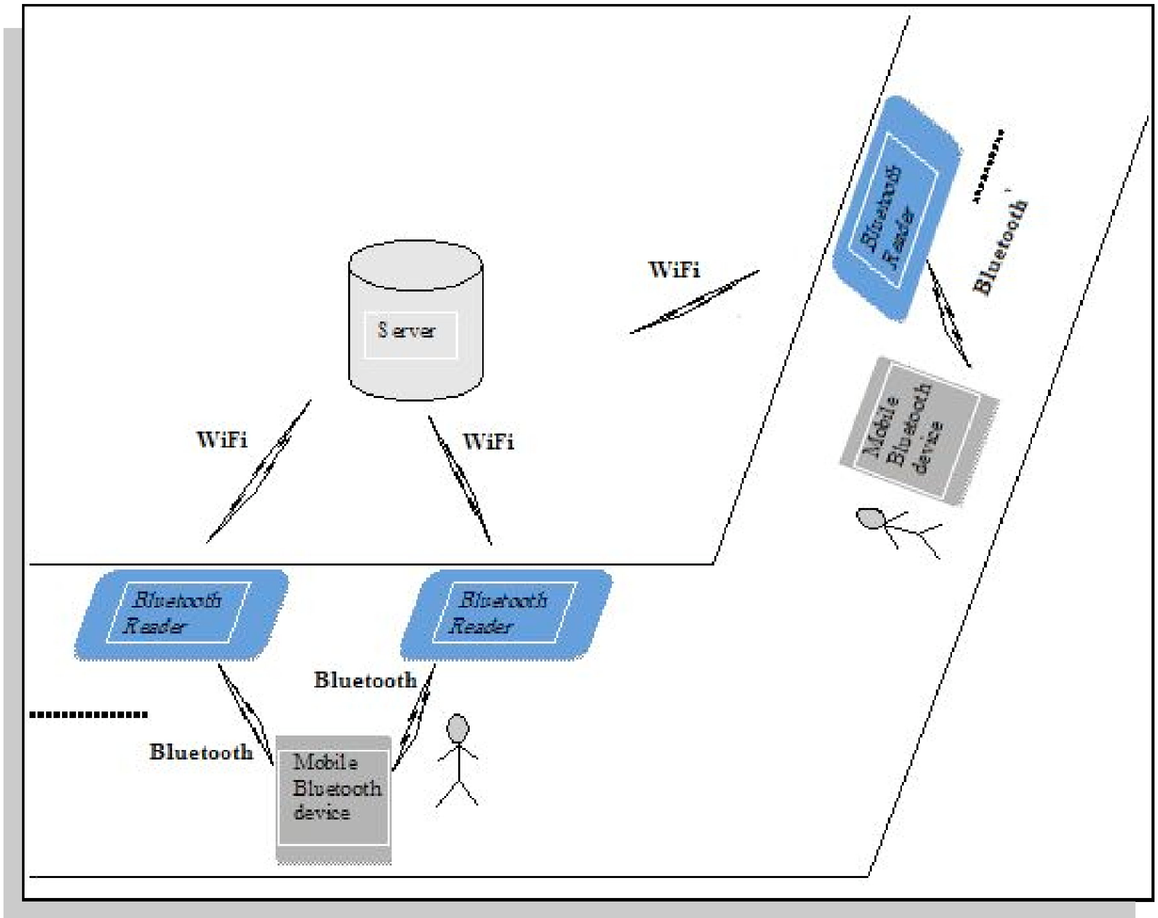

Figure 1: Architecture of the system

1) <u>Mobile bluetooth device:</u> The mobile bluetooth device provides its bluetooth information to any requesting device. A user would carry a mobile device of some sort which supports the bluetooth specification and has the ability to listen and respond to bluetooth inquiries by providing its information. The only expectation from this device is the capability to send its bluetooth information without any explicit knowledge of the receivers. Based on this information the system tries to keep track of the device as it moves along the infrastructure. Since bluetooth capable devices have become more common in the recent past, we assume that the

mobile devices are not required to run any special application to participate. This component acts as the discoverable device in the inquiry procedure.

2) Static bluetooth reader: A static bluetooth reader acts as the inquiry device with a fixed location. It inquires for bluetooth devices within its range and maintains a two way communication with the server. The infrastructure has the static bluetooth readers fixed at different points. Each device is capable of broadcasting the inquiry packets, receiving the responses and passing on the information to the server. For this purpose every reader runs a small application that can inquire for bluetooth devices automatically and communicate with the server. Each reader would also identify itself to the server when it sends the information. It may optionally receive a response from the server.

3) Server: The server is the central component which receives the information from the bluetooth readers and processes the information appropriately. The server is responsible for calculating the location information based on the readings from the bluetooth readers. It runs an application which receives information from the bluetooth readers about the bluetooth devices present that they can detect and processes this information to calculate the position of the bluetooth device inside the infrastructure. The input to the application is a floor plan of the infrastructure and the reader locations. The application then extracts a 2D graphic visualization from the input. Particle Filtering model [1, 2] is used for estimating the position of the device along this graph. Since the graph is a representation of the infrastructure, the position inside the infrastructure can be derived from this information.

Particle Filtering Model

Observations from the bluetooth readers are noisy in the sense that a single device can be discovered by multiple readers or missed by a few readers. Then to estimate the location of the device efficiently, a suitable algorithm must be applied on the readings. For this purpose, we use the Particle filtering model which is an implementation of the Bayes filters. The remaining of this section explains Particle Filtering model and its application in our system.

Bayes filters provide a probabilistic model to estimate the state of a dynamic entity based on the noisy observations from the sensors interacting with the entity and the entity's previous state history [1]. For location estimation, the state of the entity is the location of the entity. In Bayes filter, at each point in time a probabilistic distribution of the location, called a '*belief*', is maintained. The beliefs estimate the location sequentially based on the sensor observation.

Particle filtering represents the belief as a sampled set of particles where each particle has a weight associated with it. When an observation is received a resampling algorithm is performed on the particles and a new sampled set is extracted.

The following Pseudo code explains the particle filtering algorithm:

```
At every time step,
   IF an observation is received
      Resample particles:
         Reweight the particles:
               Distance, d= distance of the particle from the notifying sensor
               New Weight, wn= (Observation range - d)/ Observation range
               IF wn is less than 0.01, wn= 0.01
         Choose the new sample set according to weighted distribution
   ELSE
      Re-estimate the location:
         Distance, d= avg human speed per time step
         Move the particle to by distance d
```

At any given instant t, the application maintains a set of samples, S{x_{ip}, w_{ip} : p = 1,2,......n}associated with it, where x is the location of the sample particle, w is the weight of the location particle and n is the number of particles in the sample set. The size of the sample set is fixed at 100 for our application. At every time step if an observation is received from any of the reader nodes the particles are resampled. If no observation is received the particles moved along the possible paths i.e, either x or w is varied.

Resampling: The resampling step involves reweighting the particles and choosing a new sample set based on the new weights. The particles are reweighted based on their distance from the sensor and the observation range of the sensor. Figure 2 shows the linear observation model of the particle weights as a function of the particle distance from the sensor node. The observation range for the bluetooth readers is around 30ft. Any particle that is within this range has a weight greater than zero. Farther the particle is from the reader node, the lesser weight it has. To avoid ending up with zero or negative values, the weight is always restricted to greater or equal to 0.01.

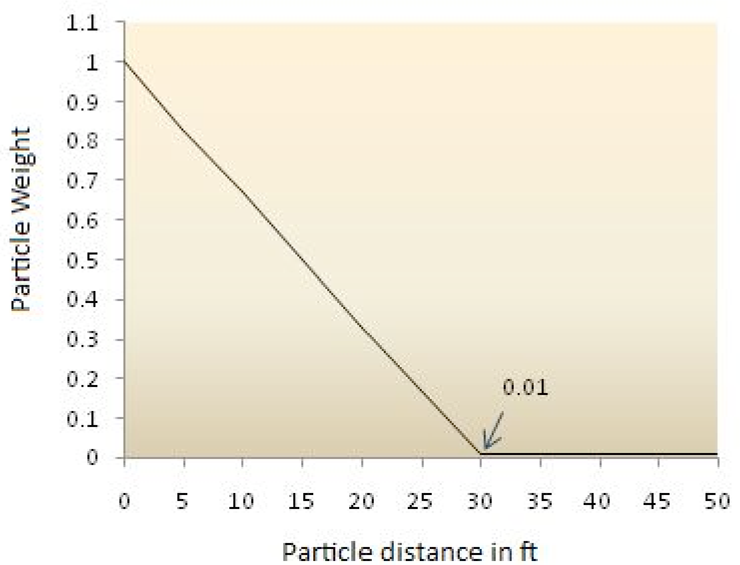

Figure 2: Observation Model for particle weights

<u>Re-estimation</u>: Re-estimation involves estimating the next position of each particle, provided that no sensor observation has been received. Since we are calculating the estimated location of people carrying the devices we predict the device to move a certain distance depending on the average human speed per the time step involved. The average human speed is adjusted by a Gaussian noise factor to account for difference in the speeds of the people.

4) EXPERIMENTAL SYSTEM

We developed an experimental context aware infrastructure using the core system discussed above to assess the viability and the efficiency of the system. First we will explain a scenario to better understand how the infrastructure responds. Then we explain the hardware used to correspond to the three components of the core system, which is followed by an explanation of how the three components work together.

Scenario

In this section we describe a hypothetical scenario illustrating a navigation system at a university building. A student, Dave, enters the building with the intent of meeting a Professor John. But Dave doesn't know where the professor's office is and he doesn't know the building very well either. He goes to a Kiosk near the entrance of the building and asks for directions to Prof. John's office. Then as he walks along the building displays on the walls that are nearer to him sense him and display the direction that he needs to follow to reach John's office.

Hardware

The hardware of our system consists of 12 Nokia N800 devices, a java webserver and the bluetooth devices that the users carry.

1) <u>Mobile devices</u>: These are the bluetooth devices that the people are assumed to carry. They are not required to be of any specific type. They are only required to have bluetooth capability, comply with the standard bluetooth protocol, and be

able to set the device in a discoverable mode. Cell phones are the most common devices that fall into this category. Though almost all phones have bluetooth capability, it depends on the type of cell phone and carrier for the device to have the capability to set it in discoverable mode. The location of the people is estimated by tracking these devices as they move along the infrastructure.

2) Nokia N800: We use Nokia N800 devices to serve as the bluetooth readers. The N800 is an internet tablet which can communicate with other devices via WiFi, bluetooth. It has touch screen capability and good display quality. It runs on Maemo which is a modified version of Debian GNU/Linux. A total of 12 N800's have been used to serve as the bluetooth readers. A python application is deployed on each N800. The application detects the bluetooth signals within the devices range and conveys the information to the server via WiFi. In turn it receives a response from the server and displays the information to the user. Currently the server responds with a dynamically generated image that contains the bluetooth name of the detected device. This image is displayed on the N800 screen. Figure 3 shows an N800 fixed on a wall near the LUCI lab, displaying the images containing the names. This N800 is displaying three names in the picture.

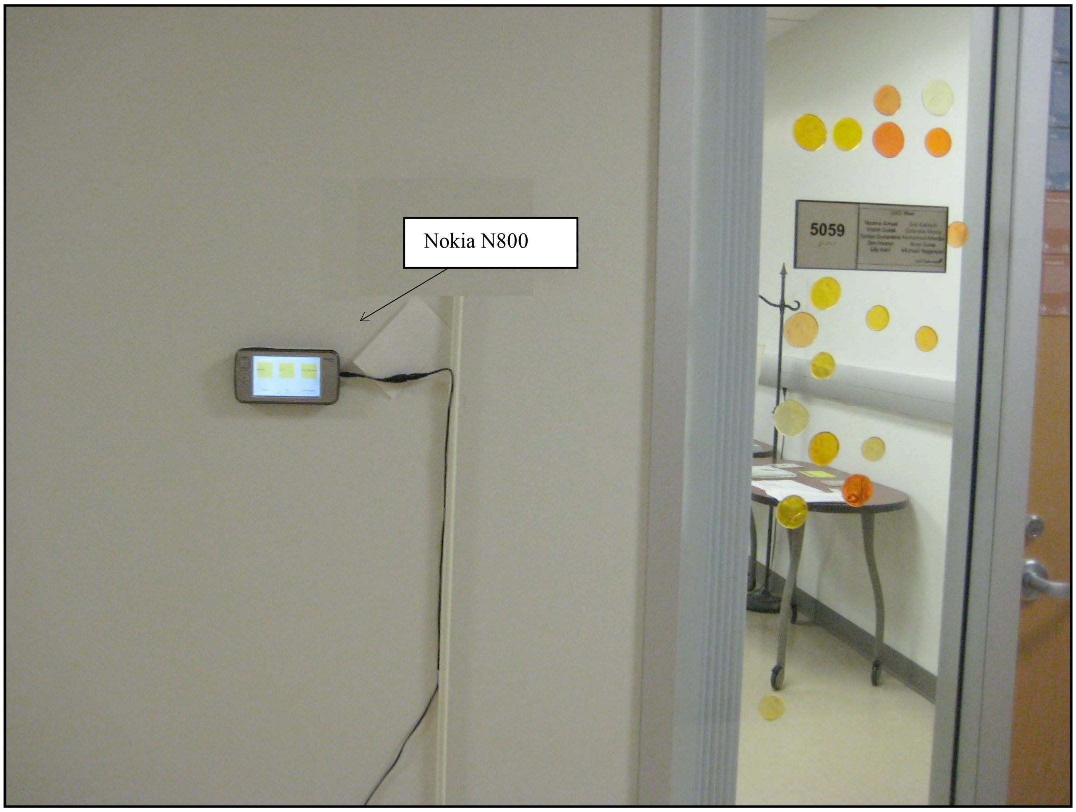

Figure 3: A N800 fixed near the LUCI lab, at UCI

3) <u>Java Webserver:</u> The server is a java webserver which runs an application for the location calculation. The application consists of a graph of the infrastructure derived from the input of the floor plan, the physically possible paths within the infrastructure and the location of the static bluetooth devices on the graph. Figure 4 shows a partial graph visualization of the DBH hall. The bluetooth readers are represented as the nodes in the graph and the edges represent the physically possible paths between the readers. Pseudo nodes can be added if the sensors are too far apart and to represent corners and other structural elements. Whenever a reading is notified by one of the readers it is interpreted as an observation from

the associated node and the location on the graph is calculated based on this. Particle filtering model explained in Section 3, is used for the location estimation.

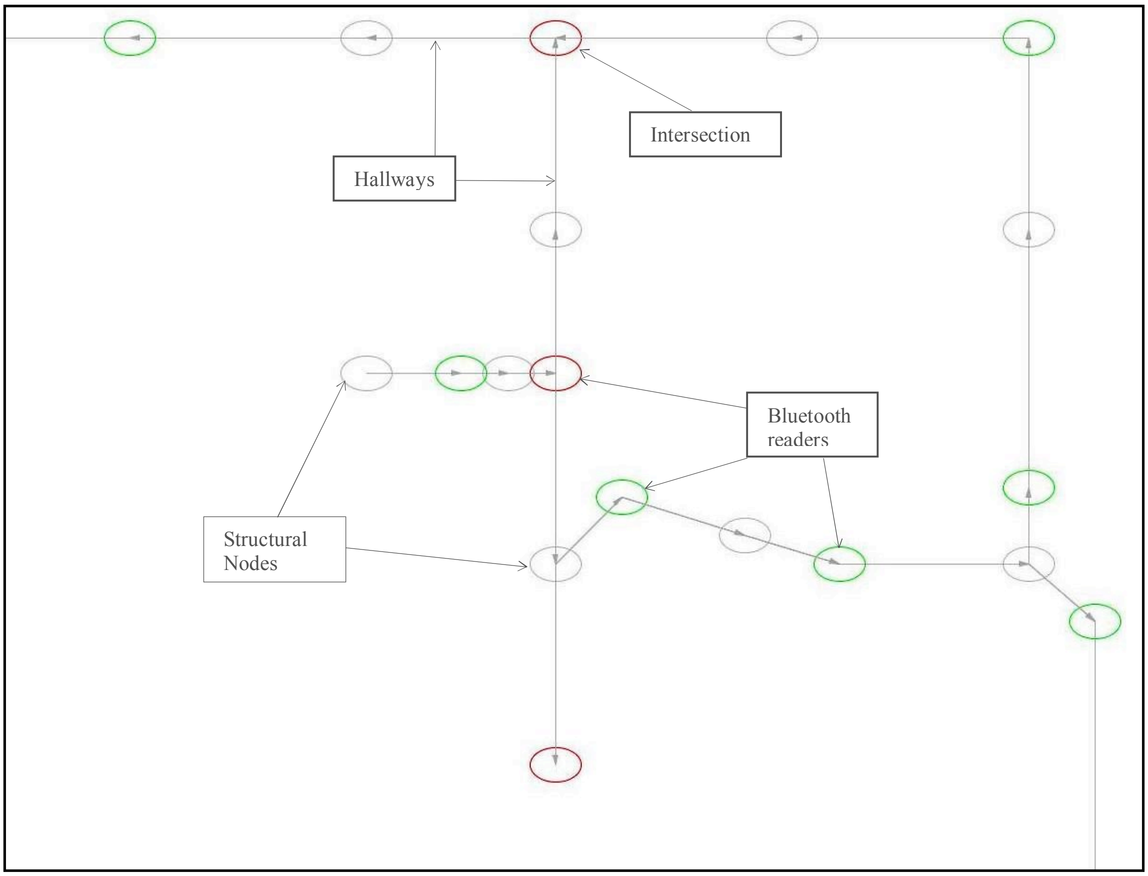

Figure 4: Graph Visualization of the DBH floor plan

Component Interaction

In this section we explain how the different components interact with each other to determine the location of the person. The experimental system was deployed on the 5th floor of the Donald Bren Hall. 12 Nokia N800 devices have been fixed at 12 different locations. Each N800 continuously runs the inquiry process which is implemented using the python bluetooth module. A small java webserver that runs the tracking application is deployed on the server. The application accepts a map of the infrastructure and converts it into a graphic visualization. For the test run, the map of the 5th floor of the Donald Bren Hall is given as an input to the application. Once the application creates the graph visualization, it waits for readings from the Nokia N800 devices. When a user enters the range with a discoverable bluetooth device, the device receives the inquiry packets from the reachable N800's and responds. When the client application on the N800 receives the response, it in turn relays it to the server. Having received the information, the server first creates a sample set for this particular device, marks the location of the sample set based on the location of the reading device and starts predicating where the user might be at each time step. From now on as the device moves along the map, different inquiry devices pick up its presence at different points and relay the information to the server. The server then proceeds to reweight the sample set based on these readings. Figures 4, 5, 6 and 7 show a part of the graph visualization at different instances of time. The dots on the graph represent the particles in the sample set. Figure 4 shows the visualization at t=0, when the first reading for a device is just received from a static bluetooth reader A. Figure 5 represents the state at t = 15, when no readings have been received between t = 0 and t = 15. The particles wander in different directions. Figure 6 represents the state at t = 16 when an observation is received from reader D. Figure 7 represents the state at t = 17, and is presented to show that the particles nearer to D got sampled more and the farther particles became sparse during the resampling. Thus based on the weights of the sample at a location, the approximate location of the device can be achieved.

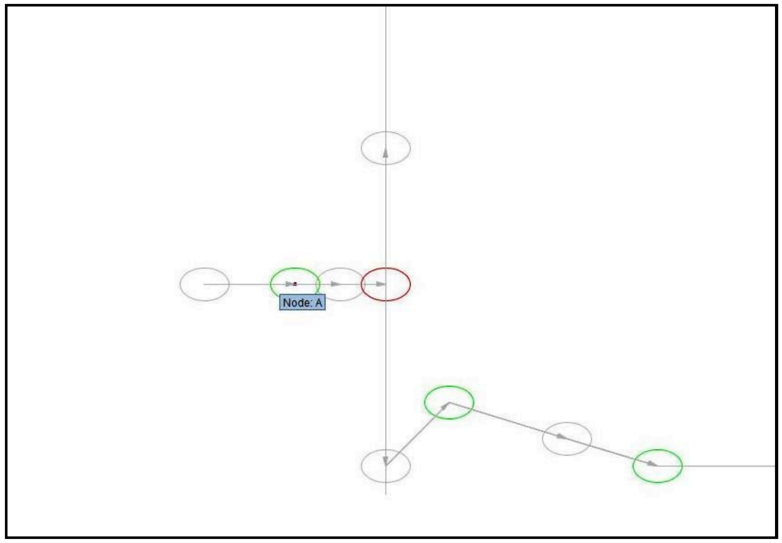

Figure 5: Sample set distribution at t=0

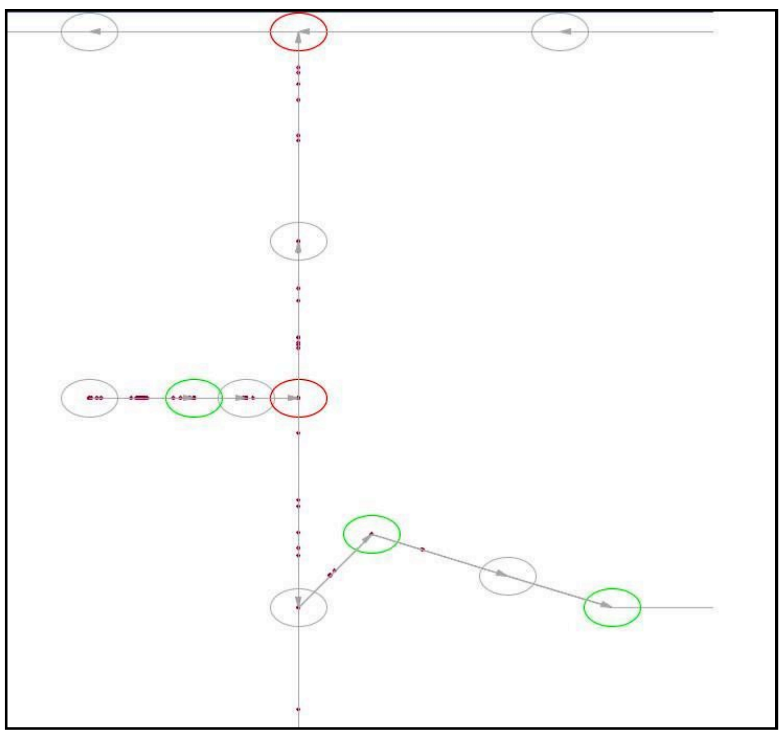

Figure 6: Sample set distribution at t=15

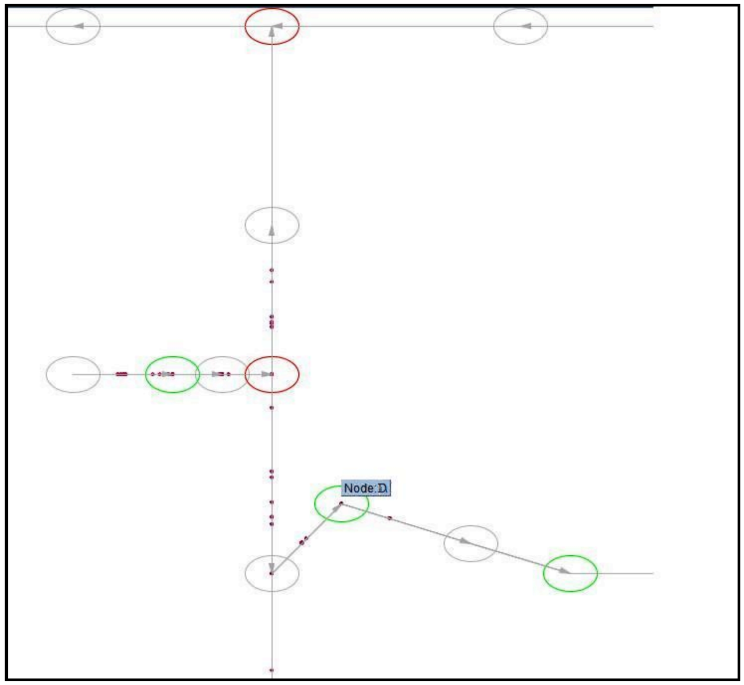

Figure 7: Sample set distribution after resampling, at t=16

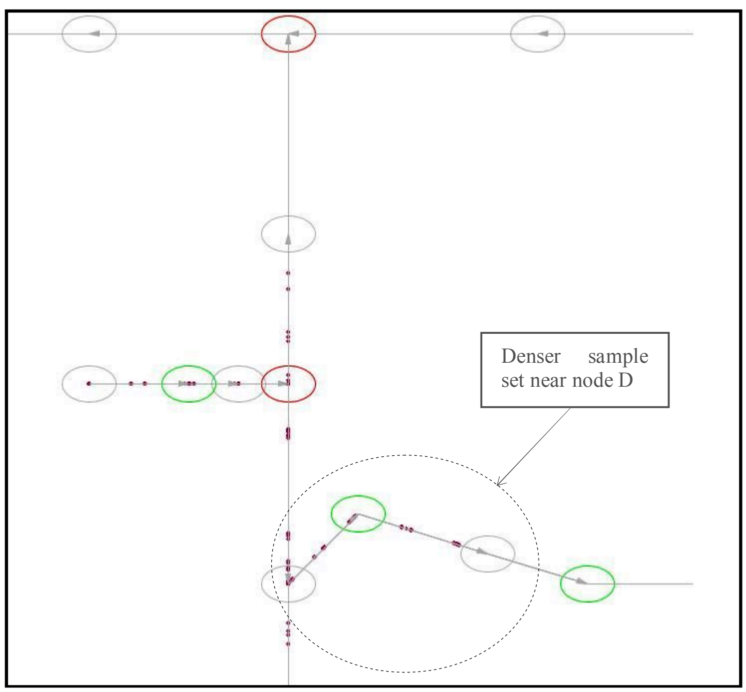

Figure 8: Sample set distribution, at t=17

5) EVALUATION

A series of experiments were conducted to evaluate the concept of imperceptible bluetooth tracking and the efficiency of the system in doing so. Five factors that need to be analyzed have been identified.

Factor 1: Discoverable bluetooth devices

One of the key features of our system is imperceptible bluetooth tracking and hence a few experiments have been conducted to evaluate its viability. Since people are not explicitly requested to participate, it is assumed that they carry some sort of a discoverable device that can be tracked. And hence the viability of this assumption needs to be analyzed.

For this analysis we conducted the experiments by setting up one bluetooth reader at a specific location and logging the devices that were discovered by the reader. The author, acting as an experiment conductor, would sit at the same location and count the number of people within the bluetooth range. This way a ratio of the number of discovered devices versus the actual number of people is achieved. The non-discovered population would consist of:

a) People not carrying bluetooth devices
b) People carrying the devices lacking the ability to be discoverable
c) People carrying devices that were set in invisible (non-discoverable) mode
d) People carrying discoverable bluetooth devices, but moving out of range before being discovered.

Three experiments as described above were conducted for this analysis. The first study was conducted at the entrance of the Donald Bren Hall at University of California, Irvine. The second study was conducted at a Starbucks location. The third study was conducted in a seminar hall during a seminar at University of California, Irvine. Table 1 summarizes the results:

Table 1: Number of people discovered Vs Actual number of people

Experiment Location	Number of people discovered	Actual number of people	Discoverable percentage
Donald Bren Hall, UCI	31	600	5.16%
Starbucks	17	130	13.07%
Seminar Hall	10	38	26.31%

The inconsistency in the ratios may be explained due to a number of factors. Let's start with the seminar hall where the ratio seems to be the highest. In the seminar hall, where the discoverable percentage is the highest, people tend to have their laptops open and most of the laptops have more bluetooth capabilities set in discoverable mode. Also since the devices would be within the range throughout the course of the seminar they have a very high chance of being picked up. In the case of Starbucks the target demographic possibly consists of an older and richer population who could afford more technologically savvy devices. Also with the new driving laws more people would tend to have cell phones that can support bluetooth head sets. Another factor would again be the length of time a person would be within the range. Since the person would be ordering something, the device would be in the range for a longer period of time and consequently has more chances of being picked up. The third factor is the Starbucks being closer to other food establishments. There might be people invisible to the experiment conductor but visible to the bluetooth device since the bluetooth signals can penetrate walls. In case of Bren Hall, the experiment was conducted at the entrance. This means that the devices move quickly out of the range as people continue towards their destinations.

However even considering the largest ratio, 26% is still too low for imperceptible tracking to be effective. This would indicate that imperceptible tracking of bluetooth is probably not viable under most circumstances. So unless the applications explicitly request the users to participate, the results may not be satisfactory.

Factor 2: Latency of Discovery

Latency of discovery is the average amount of time taken per reading to discover the bluetooth devices. As explained above, a person might not be discovered by a bluetooth reader if he quickly moves in and out of its range. Though the chance of a discoverable device being missed by every reader is highly improbable, every missed observation effects the location estimation. Since the discovery process is sequential, the amount of time for each bluetooth reading effects the number of such missed observations. Hence, if the latency is higher there is a higher chance that more number of devices would cross the reader range before the next reading process begins.

It has to be recalled that the bluetooth reading process, the inquiry procedure, consists of broadcasting the inquiry packets and collecting the responses from the listening devices. The larger the number of devices around, the larger the number of responses and hence the longer it takes to collect the responses. Thus, it can be concluded that the average time to discover a device depends on the number of devices within the range.

During our trial run the number of devices discovered in each bluetooth reading averaged to 5 and the latency in discovery averaged to 25.81 seconds. At the average human walking speed of 1.3 meters per second, a person can walk 1.3 * 25.81 = 33.55 meters between two readings. Since the bluetooth range for commonly used class 2 devices is 10 meters, this implies that some observations are bound to be missed. To improve the efficiency of the system, methods to decrease the latency of the system should be researched.

Factor 3: Accuracy of the system

As explained in Section 2, our system is aimed at applications where an approximate location estimate is acceptable. However, the level of approximation needs to be defined to be able to determine if the system is suitable enough to be used in an application.

To determine the accuracy of the system, a person holding a bluetooth device was asked to walk along pre determined paths and make a note of the time he is at each bluetooth reader. This data is then compared to the logs obtained from our tracking application to determine the accuracy percentage. The logs show the probability of the location along an edge.

The logs are analyzed on three levels of granularity to determine the accuracy of the system. For the first level of accuracy the number of times the application estimated the location of the device to be on the same edge as its actual location. In the second level, any estimation on the same edge or on the edge directly reachable from the actual location edge is considered to be accurate enough. We included a dummy node that represents structural elements like corners, hallways etc, between every two sensor nodes. This means that one physical edge between two sensor nodes is represented as at least two edges in the graph. Hence, for the third level we consider any estimation on the edges reachable in one edge hop from the actual location edge, to be accurate enough. Table 2 shows the results of the analysis.

Table 2: Accuracy of the system at varying granularity

Level	Granularity	Accuracy Percentage
1	Same edge	27.4%
2	Same edge , Directly reachable edges	36.5%
3	Same edge , Directly reachable edges , Edges reachable in one hop	67.77%

A number of factors that affect the accuracy of the system can be identified. The most important factor is the granularity of the sensor infrastructure being much lower than the bluetooth range. This means that the bluetooth readers that are quite a few edge hops away from the actual location of the device would record an observation on the device, thus affecting the probability distribution. Thus the number and the location of the static readers should be chosen carefully considering the infrastructure. A further research is warranted on this.

Another important factor is the latency in discovering the devices. If the latency is low more number of readings can be received thus making the system more accurate. As will be seen in Section 6, a higher level of accuracy can be obtained using a combination of

RSSI and particle filtering or triangulation. But this requires finger printing while deploying at different infrastructures and adds more complexity to the system. Hence based on the accuracy and the granularity of the accuracy required, the implementations should decide if the proposed system is suitable or not for their application.

Factor 4: Reliability of the system

Initial requirements identified in setting up the system are security and power requirements for the bluetooth readers.

<u>Security:</u> The infrastructure setup should take steps to ensure the security of the bluetooth readers so that they are not stolen or moved out of place. Moving the bluetooth readers out of place would invalidate the initial input of the sensor locations to the application.

<u>Power requirements:</u> The bluetooth readers continuously inquire for discoverable devices and hence require enough power to be always active. This typically means having to be plugged in for most of the time.

A similar issue was found with the mobile devices that are being tracked. The mobile devices respond to the inquiries from the bluetooth readers. Since the inquiry packets are sent continuously this means that the listening devices also respond continuously. This seems to cause a strain on the power levels of the devices. In some cases this also interferes with the device's functionality.

In 38 hours that the system was up, 87 devices were discovered and estimated with an accuracy factor described earlier. After the initial bugs in the test run were fixed, the system was able to hold up for the scheduled time without any issues. Since inactive devices are cleaned up and a limited effort is made to identify stationary devices and ignore them, memory is managed effectively. The system test was run on a simple laptop with no special configurations. This proves the application is simple, small, and has no special requirements.

Factor 5: Mobile vs Stationary

The purpose of the system is to track people as they move along the infrastructure. Though tracking stationary devices would not affect the accuracy of the system, it is inefficient to track them. As mentioned earlier the bluetooth inquiry process drains the power levels on the listening devices. This is a higher concern with the stationary devices since they would always be present within the infrastructure and continuously try to respond to the inquiries. Hence it is necessary to understand the number of mobile devices versus the stationary devices identified.

Using the logs obtained from the trial run of the system, we tried to distinguish the number of mobile devices identified and the number of stationary devices identified. The logs were used for identifying the nature of the device. In most cases the name of the bluetooth device can reveal the type of the device. For example, a bluetooth name for a Mac device defaults to <username>'s Mac or <username>'s Mac Book like John's Mac. A device is also considered stationary if it is identified by the same readers for a long period of time or if it was identified for more than 2 hours and doesn't vary much in the readers identifying it. Out of the 87 devices identified, 33 devices were recognized to be stationary. Figure 8 illustrates the percentage breakdown of mobile and stationary devices identified.

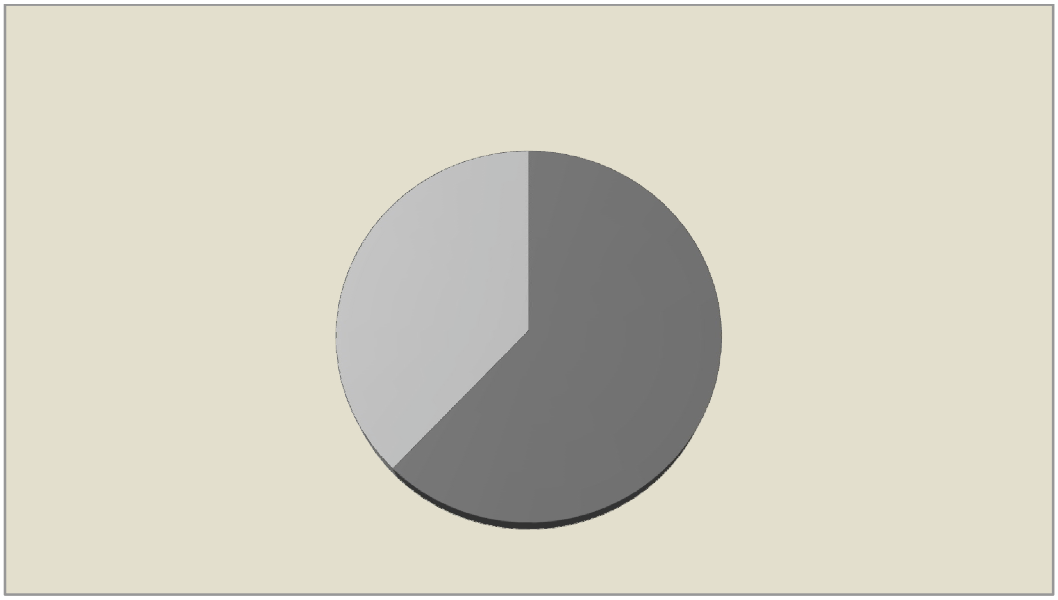

Figure 9: Percentage of mobile vs. stationary devices identified

6) COMPARISON WITH SIMILAR SYSTEMS

Quite an amount of research has been published on bluetooth tracking systems. [9,10,11,12,15] are examples of few such systems. As can be noted all these applications focus on resolving the location of the device, on which the application is running, i.e, they are meant for smart devices that can locate themselves within an infrastructure. Our system focuses on building a smarter infrastructure and implements imperceptible tracking of the devices. That is the mobile devices are not explicitly required to do any additional tasks to participate. In fact the mobile devices are not even required to be notified of the application.

SmartMoveX[15] and Locadio[9] are similar systems that use Hidden Markov Model in location estimation which is also the basis for particle Filtering principle used in our system. SmartMoveX also uses a graph of the physically possible paths and estimates the location along the edges of this graph. SmartMoveX requires people to carry specialized devices and requires an initial configuration of the infrastructure. While the cost of the devices to carry is low, it still means an explicit relationship between the subjects and the infrastructure. But we envision the infrastructure to be aware of any person who is around without requiring the person to perform any extra actions. Hence, our system only has a minimal expectation from the subjects. The only requirement is for the people to carry some sort of a discoverable bluetooth device.

Locadio[9] uses WiFi signal strengths and the probabilistic model similar to the one used in our system to estimate a users location. The average error of the system is 1.53 meters which provides a higher accuracy than our system. But using WiFi Signal strengths means that the system requires an initial 'Finger Printing' to gather the signal strengths at various locations whenever the system has to be redeployed in a new infrastructure.

[10, 12] are similar systems with bluetooth that use bluetooth signal strengths (RSSI) and triangulation method to estimate the location. As with Locadio, using signal strengths means an initial configuration of the system by gathering the signal strengths at various points in the infrastructure. As the size of the infrastructure and the number of the bluetooth sensors (WiFi access points for Locadio) grow this becomes a tedious task. Though using the signal strengths provides the location estimation on a finer granularity, we focus on applications where a wider range of estimation is acceptable. In such cases, our system proves to be less complex and efficient enough for the purpose.

The BIPS [11] system requires the users to explicitly pair with the master application, which may not be very secure. Our system involves minimal interaction from the participating device. As mentioned earlier the people do not or are not required to share a special relationship with the infrastructure. In such a scenario minimal interaction is ideal.

7) CONCLUSION

We have introduced a core system for indoor location estimation that can be customized for individual applications to build a context aware infrastructure. We have shown an experimental application that is built using this system. A trial run was performed on the application and the results were analyzed for different factors that need to be considered. Based on the analysis of the trial a few limitations have been found with the system.

A key issue is the latency in discovering the devices. [8] proposes a technique for reducing the latency by modifying the inquiry procedure. The suggestion involves modifying both inquiry request process and inquiry scan process. Since imperceptible tracking and minimal interaction with the system are key features of our system, modifying the inquiry scan is not viable. However, modifying the inquiry request might be worth digging deeper into.

An interesting side effect was found on the stationary devices where the system drained the power levels and interfered with other bluetooth profiles of the devices. An ideal solution is to interfere as little as possible with the stationary bluetooth devices. But stationary bluetooth devices can be considered a part of the infrastructure and hence it might be possible to interfere with their bluetooth modules. They can be not set in ‘discoverable’ mode when possible. When not possible other mechanisms to restrict the module from not answering to the requests should be investigated upon.

Setting up the bluetooth readers too sparse or too dense may affect the system, but such a study is out of our scope. More research needs to be done on the relationship between the size of the infrastructure and the optimum number and location of the bluetooth readers.

Based on the issues we found during the trial run of the system, it can be concluded that our initial assumption of imperceptible tracking of bluetooth devices is not completely viable. A number of caveats have to be added to the system, making it more complex, to address all the issues seen above and to increase the efficiency. The decision to use the system must be made after a careful consideration of the requirements for simplicity, accuracy, acceptable interaction with the devices to be tracked, etc.

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