Fingerprinting Based Indoor Positioning System using RSSI Bluetooth

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Abstract— Positioning is basis for providing location information to mobile users, however, with the growth of wireless and mobile communications technologies. Mobile phones are equipped with several radio frequency technologies for driving the positioning information like GSM, Wi-Fi or Bluetooth etc. In this way, the objective of this thesis was to implement an indoor positioning system relying on Bluetooth Received Signal Strength (RSS) technology and it integrates into the Global Positioning Module (GPM) to provide precise information inside the building. In this project, we propose indoor positioning system based on RSS fingerprint and footprint architecture that smart phone users can get their position through the assistance collections of Bluetooth signals, confining RSSs by directions, and filtering burst noises that can overcome the server signal fluctuation problem inside the building. Meanwhile, this scheme can raise more accuracy in finding the position inside the building.

Keywords: Fingerprinting Technique, Indoor Localization, KNN Algorithm, RSSI (Received Signal Strength Indicator).

I. INTRODUCTION

The problem of locating a user is a fundamental problem in many research areas. In outdoor environments, the Global Positioning System (GPS) can provide good location estimates. However, the GPS solution cannot be used in indoor environments. In this kind of environment (which is typically called GPS denied environment) the GPS signal is very poor because of the lack of line of sight between satellites and the receiver.

Due to the large number of applications that can benefit from a location service in indoor Environments, indoor location systems have been an important research topic in recent years. The Bluetooth is devised as an open specification for low power, short range wireless data and voice Connections [1] and has been utilized in the communication and proximity market [2] for a long time. As widely supported by mobile devices, Bluetooth has more potential to become an alternative for indoor positioning [3]. There are two types of possible solutions for Bluetooth indoor positioning: connection based and inquiry-based [3]. In this paper, we are focusing on a practical inquiry-based Bluetooth indoor positioning approach via RSSI probability distributions.

We have organized the paper as follows. In the next section, section II, we point out propose system or motive of this paper. In section III, we point out some Basic information for Bluetooth. In the next section, section IV, there is system architecture. In section V, there is information of technique and algorithm Section VI shows result. Section VII and VIII shows conclusion and future work

II. PROPOSE SYSTEMS

As the goal of being a practical indoor positioning approach, the research intends to offer indoor positioning system based on Bluetooth RSS fingerprint and footprint architecture that smart phone users can get their position through the assistance collections of Bluetooth signals, confining RSSs by directions, and filtering burst noises that can overcome the server signal fluctuation problem inside the building. Meanwhile, this scheme can raise more accuracy in finding the position inside the building. Consider the Bluetooth standard limitations in procedures of inquiry, service discovery, authorization, connecting [3]. This paper mainly focuses on two aspects: (1) the suitable system architecture for Bluetooth positioning, and (2) the reasonable position estimation approach based on inquiry based Bluetooth RSSI.

III. BLUETOOTH AD-HOC NETWORK

Unlike other wireless communication, for example Wi-Fi, Bluetooth is a kind of a short range RF technology with low power consumption. It leads to the differences in the protocol and profiles during inquiry and connection phases. To establish a practical architecture, it is essential to look inside of the Bluetooth protocol and signal.

A. *Bluetooth Technology*

Bluetooth is a technology that allows electronic devices to communicate without wires. It was designed for low power consumption and is based on low-cost transceiver microchips. Bluetooth communicates using radio waves with frequencies between 2.402 GHz and 2.480 GHz, which is within the 2.4 GHz ISM frequency band, a frequency band that has been set aside for industrial, scientific and medical devices by international agreement. The Bluetooth specification was conceived in 1994 and is now managed by the Bluetooth Special Interest Group (SIG). Bluetooth is divided into three classes, each of which has a different range, as shown in table 3.1. This range can potentially be affected by the surrounding environment, as the signals are susceptible to propagation effects. This is especially true in an indoor environment. Although class 3 devices would be ideal for indoor

Class	Range
Class 1	100m
Class 2	10m
Class 3	5m

Table (1): Bluetooth range

Positioning purposes because of the small range, such devices are very uncommon and the vast majority of available devices are of class 2.[4]

B. Received Signal Strength Indicator (RSSI)

Generally, the RSSI is a measurement of the strength of an incoming radio signal. It is a relative indicator and its units are arbitrary, but the higher the value of the RSSI, the stronger is the signal. In Bluetooth, the RSSI is used to tell whether the received signal is within the Golden Receiver Power Range (GRPR), which is the name used to describe the ideal range of incoming signal strengths. The RSSI is measured in dB, and a signal strength within the GRPR results in an RSSI of zero dB. A positive or negative RSSI indicates that the signal strength is above or below the GRPR, respectively. The Bluetooth specification does not specify the upper or lower limit of the RSSI but simply states that it must be possible to tell whether the incoming signal is within, above or below the GRPR, hence this value is device specific. [4]

The RSSI of a Bluetooth device is obtained by starting the inquiry procedure from a second device. The RSSI will then be included in the first devices' response to the inquiry, meaning that it is not necessary for two devices to actually be connected or even be paired.[4]

C. Global Positioning Module

In this paper we seek to develop an indoor positioning system based on Bluetooth technology. This system will be integrated into the Global Positioning Module (GPM), software developed internally by the Institute of Service Science at the University of Geneva, and which provides the user with a geographical position by transparently selecting the technology, or position provider, that is the most appropriate in any context. The software did not have a Bluetooth provider, which is the reason why this project focuses on the Bluetooth technology. GPM is developed for the Android platform, which places certain restrictions on the system architecture since the positioning must take place on the Smartphone itself. In other words, it is the Smartphone that is responsible for detecting Bluetooth signals and estimating a position.

D. Bluetooth Provider

Bluetooth inquiries are initiated when the mobile phone detects movement, which is managed by the Motion Detector, a feature implemented in order to save battery power. It listens to the build-in accelerometer, and inquiries are then launched continuously until the Motion Detector notices that the mobile phone is no longer in motion. While the mobile phone is moving, Bluetooth starts asynchronous inquiries by calling the Bluetooth Scanner, which provides it with information about all the devices that are within range and in discovery mode. Once the asynchronous call terminates, Bluetooth calls the Position Finder in order to obtain a position estimate based on the returned devices. This class will use one of the positioning algorithms as well as the radio map stored in the database (not shown in the sequence diagram) in order to come up with an estimation, which is returned to Bluetooth.

The Bluetooth class has a similar role during the offline phase; however, each inquiry is explicitly initiated by the

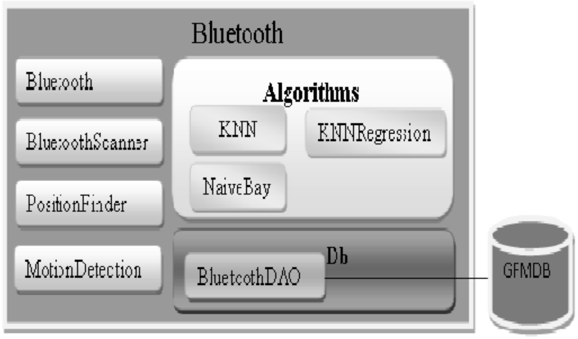

Fig. 1: Bluetooth Provider Architecture

user and not by the detection of movement. When an inquiry has finished, instead of running one of the positioning algorithms, the resulting fingerprint is stored directly in the database. Another important aspect of the provider was the selection of beacons. It is necessary to specify which beacons that are to be taken into account by the system in order to avoid those arbitrary devices, such as people's mobile phones, headsets, laptops etc. are included. Including such devices would break the radio map once the device is moved to a different location. The provider therefore takes this list into account during the position estimation and excludes any device which is not on the list.

IV. SYSTEM ARCHITECTURE

A general architecture for Inquiry-based Bluetooth indoor positioning system is presented.

A. Infrastructure

1) Data Flow

Before we continue to give the design details concerning the framework, we take a closer look at the data flow diagram in Fig.2 (a) that shows what happens when making a positioning request from a mobile device. The mobile device sends a positioning request, containing the captured measurements and the algorithm configurations, to the server component. The server then first configures the algorithm component based on the parameters in the request and then lets the algorithm calculate the position estimate. The algorithm component might also use some data from the data store for calculating the estimate. Once a position is calculated, it is returned to the client that made the request.

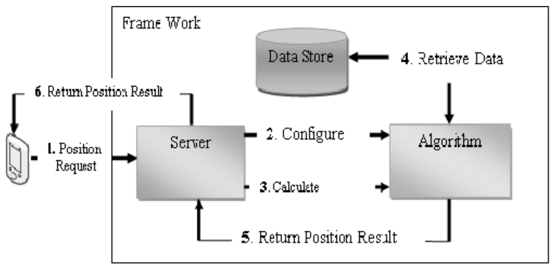

Fig. 2: Flow of positioning request

Fig 2 provides a top–level overview of the capturing of data and the following upload request with the data. Data is first captured on the mobile device and then exported to, for example, the user's laptop from where a request is sent to the server to upload the new data.

2) Data upload to the server

Now that we have seen how the architecture looks like from a high level, we go more in depth by providing details on the design of the framework as seen in the Fig 3 below

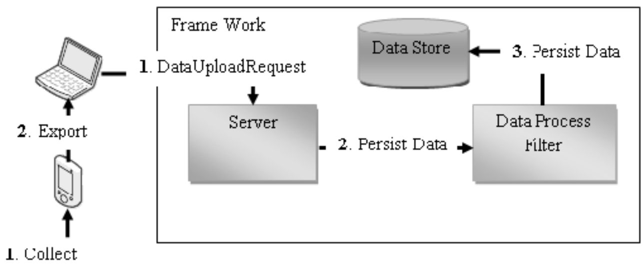

Fig. 3: flow of data upload request

We first begin by describing the data building blocks that are provided by the data store component and are used in most indoor positioning systems. After that we will see how the algorithms were made interchangeable and what the architecture of the server component looks like.

B. Data Entities and Manager:

In order for our framework to be generic, we have a number of basic data entities that are present and allow for implementing different types of indoor positioning systems, and can be expanded upon for other types of systems. The data entities that are available and provide the basic building blocks are:

1) Base Station: A device which can be uniquely identified and sends out some signal that can be captured and from which certain properties can be observed
2) Signal Measurement**:** A measurement of certain signal properties with the captured measurement values. For each property there can be a number of captured values since this allows us to for example take the average of the values or get other relevant information (Signal Measurement Values).
3) Measurement**:** Contains the different Signal measurements of certain Base stations.
4) Fingerprinting**:** A Measurement at a certain Position
5) Position**:** A simple 2-D position on a map where a Measurement can take place or that is returned as a position estimate by a positioning algorithm. It is defined by its X and Y coordinate on a map of an indoor location.

C. User Interface

In addition to adding the Bluetooth provider to GPM, the two other modules were also modified in order to provide a user interface that was consistent with the already existing providers. In terms of usage, the Bluetooth provider differs from the others in the way that it relies on the fingerprint had to implement a separate user interface for this purpose. This interface allows the user to select fingerprint locations on a floor plan and to easily create fingerprints that are automatically associated with the selected fingerprint location.

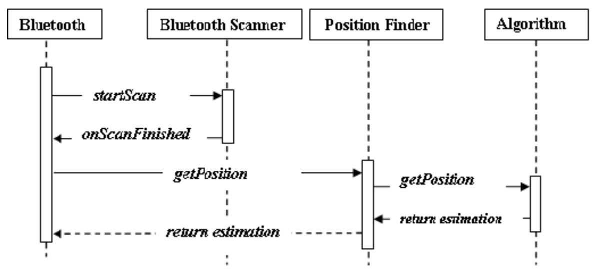

Fig. 4: Sequential Diagram position estimation using The Bluetooth

V. POSITION ESTIMATION

According to the observation data, we characterize the features of Bluetooth RSSI and create the fingerprint database relied on the features. Afterward, For Deterministic distance estimation approach we are going to use K nearest neighbor algorithm or K-means clustering algorithm using Euclidean distance formula and for probabilistic approach, we are going to use Naïve Bays Classifier.

The signal distance between the real-time RSS readings vector [s_1, s_2…, s_n] and the RSS vector in the database [S_1, S_2…,S_n] is computed by applying Eq. 1.

$$L_q = \left(\sum_{1}^{n} |s_i - S_i|^q\right)^{1/q} \quad (1)$$

The quantity Lq is a positive real value, where a lower value indicates a smaller difference between the two compared vectors. KNN algorithm ranks the list of RPs in ascending order by using the resulting Lq and then takes the direct average of the K-nearest neighbor coordinates. The average of the coordinates (x, y) can be used to estimate MU's location. [5]

A. K-Means Clustering Algorithm

In order to improve the KNN algorithm performance we deploy k-means clustering algorithm. K-means is one of the simplest learning algorithms that solve the well-known clustering problem.

K-Means Clustering Algorithm

1) Initialize K centroid points which represent initial group Centre point (centroid).
2) Calculate distances between RPs and centroids.
3) Assign each RP to a cluster that has the closest centroid.
4) When all RPs are assigned, recalculate clusters centroids.
5) Repeat step 2, 3 and 4 until there is no change for each cluster.

1) Naive Bays Classifier

The Nave Bayes classifier is based on Bayes theorem, which gives us the probability of C given x:

$$P(C|x) = \frac{P(C)P(x|C)}{P(x)} \quad (2)$$

Where the different elements of the formula are denoted as follows:

$$posterior = prior * \frac{likelihood}{evidence} \quad (3)$$

In the case of the fingerprinting technique, this translates into the probability that fingerprint x belongs to class C, where the class is a position, described by its coordinates,

And x is a vector where each element contains an RSSI reading.
The classifier is called naive because it makes the assumption that the values in the input vector are all independent of each other. This makes it easy to calculate the conditional probability P (x|C), which simply becomes the product of the probability of each element in x given class C.

B. *Fingerprinting Technique*

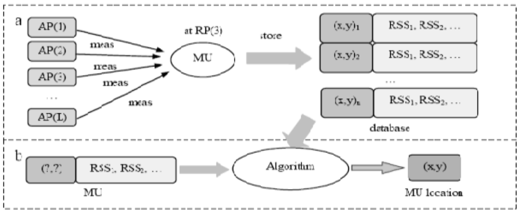

Fig. 5: Two phases of fingerprinting (a) training phase and (b) tracking phase

This technique is composed of two phases: Training (Offline) phase and Tracking (Online) phase. During the training phase (Fig.5(a)), signal strengths from APs are collected at pre-identified locations, which are called reference points (RPs). The objective of this operation is building the fingerprint database which will be used in the tracking phase. Because mobile user's location is determined based on the surrounding RPs, they should be distributed in the target area evenly and homogenously.

In the tracking phase (Fig 4(b)), MU's surrounding AP RSSs are compared with the RPs dataset collected in the training phase to identify the best matching RPs. The tracking phase could use deterministic and probabilistic algorithms to match real-time RSS readings with RPs signal data.

VI. RESULTS

A. *CheckGPM*

CheckGPM is a small Android application intended for developers only, which is bundled with GPM. This application was updated to include a user interface for the new provider,

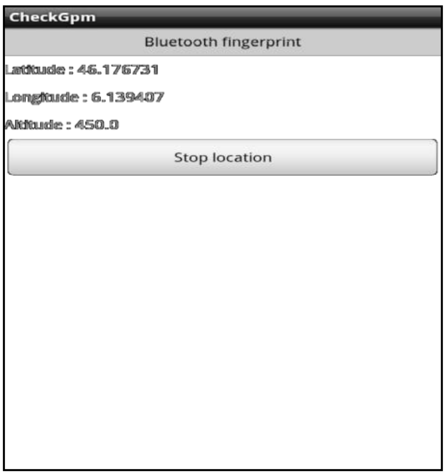

Fig. 6: Getting Location

similar to those of the other providers. Screen for the offline phase, where the user manually inputs the latitude, longitude and altitude of the fingerprint.

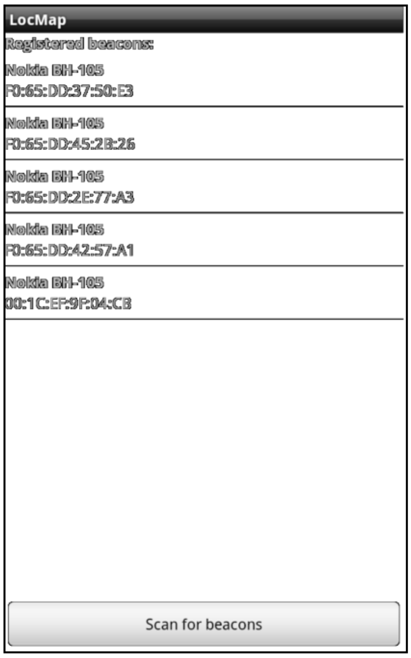

Fig. 7: Scan for Devices

Fig. 8: Positioning

B. *Preliminary Test*

The environments in the scenarios described above vary mainly by the size of the rooms. We therefore conducted a test to see if the size of a room has any effect on the variability of the RSSI. If this was the case, the experiments would have to be carried out in rooms of various sizes in order to evaluate all of the scenarios. Note that we do not care about differences in the RSSI itself, since the actual value is of no importance. The only thing that matters is to be able to reproduce similar signal strengths on the same locations, that is, a small standard deviation.

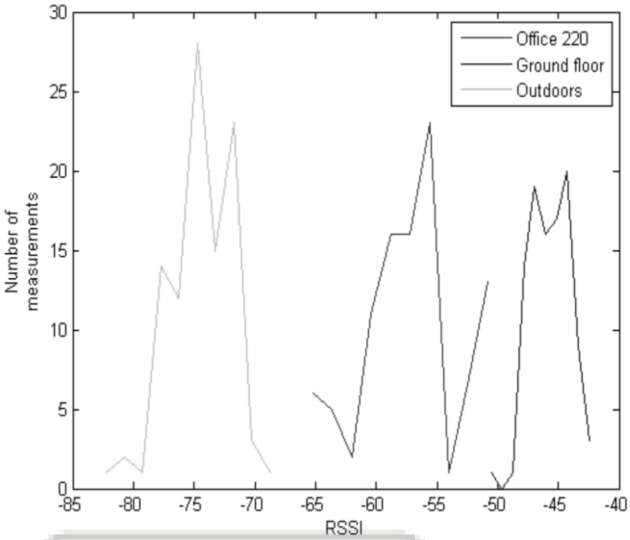

Fig. 6: The results of the preliminary test to evaluate signal variation in rooms of varying sizes.

C. *Precision and Accuracy of Positioning Graphs*

In this experiment we evaluated the precision and accuracy of the system for each of the positioning algorithms.

Separate software was used for the calculation of the accuracy and the precision. The calculation was done using cross validation on the radio map. Since the data set (the radio map) is quite small, leave-one-out cross validation was chosen instead of the more commonly used k-fold cross validation. Leave-one-out, as the name suggests, uses a single data sample as the validation data, and the rest of the set as the training data. This is repeated for every single sample; hence it is computationally heavy but gives a more thorough validation than the often used 10-fold validation.

The positioning system uses latitude and longitude, expressed as decimal degrees with an accuracy of 6 decimal places, to denote locations. In order to calculate the distance between two points, in this case the distance between the location of the validation sample and the locations of each of the training samples, the distance had to be converted to the metric system. The accuracy of such a conversion depends both on how many decimals that are being used, and on the distance from equator1. Due to the curvature of the Earth, the accuracy of the longitude increases with the distance from equator, whereas the accuracy of the latitude remains similar. At equator, a coordinate with an accuracy of 6 decimal places is accurate to 0.111 m.

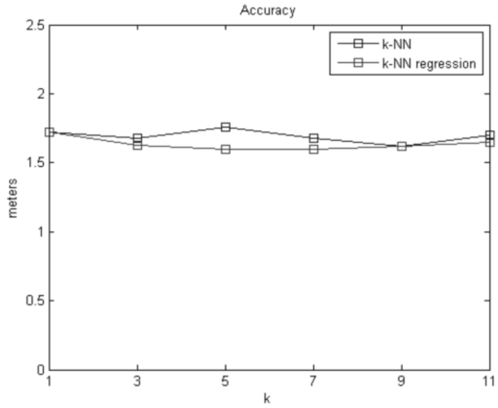

Fig. 7: Accuracy

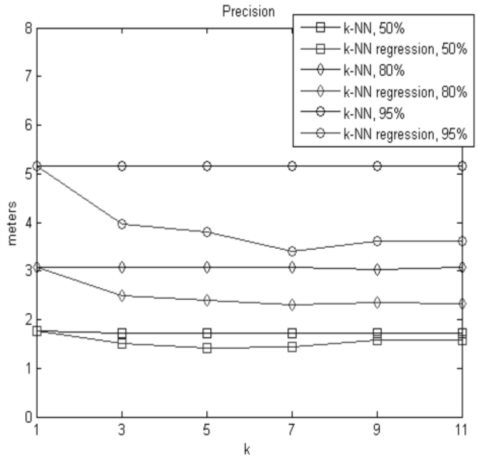

Fig. 8: Precision

VII. CONCLUSION

The general overview of this thesis was to design and implement a system capable of performing indoor positioning with Bluetooth signal as well as current Techniques being used for find out users' localization with respect to positioning techniques and Bluetooth signals.

The design implementation has been carried out in two phases, first the simple method: mobile application which is to run in mobile device and server for positioning scenario The implementation methods that we utilize for the measurements to find the position using the fingerprinting technique that have been described.

In order to estimate the position we used three algorithms that are frequently used on the basis of, positioning system: Naive Bayes' Classifier, k-NN and a variation on k-NN that uses regression.

FUTURE WORK

Due to the low power consumption protocol, Bluetooth positioning has a significant bottle neck: the updating frequency. In our future research plan, we are going to improve the positioning performance from two aspects. Firstly, optimizing the system architecture is one way to reduce the time consumption in each positioning epoch. Secondly, without timely update, more intelligent position Estimation algorithms are necessary for reasonable location prediction.

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