Bluepass: an Indoor Bluetooth-based Localization System for Mobile Applications

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***Abstract*—Location-Based Services have become quite popular in mobile computing. However, these services are often not effective when devices are in indoor environments. This paper presents an indoor room-level Bluetooth-based localization system. Fixed stations distributed throughout the environment get the RSSI from user devices. With these data, we compute the distance between the device and the stations, based on the signal propagation. In this paper, we propose a room localization method, based on a voting scheme, that eliminates cells close to a base station detecting devices with a weak signal. Another contribution of this paper is the empirical evaluation of the methods within a real environment.**

I. Introduction

Location Based Services (LBS) are mobile device applications that have attracted much interest [1]. Location Based Services are accessible via networked devices and uses information related to their geographic locations.

Some of these services, such as those using the Global Positioning System (GPS), were designed to solve the outdoors localization problem [1], [2]. They present a poor performance in indoor environments, where the signal is under a high attenuation level [3].

Recent works have addressed the indoor localization problem by exploiting pervasive wireless communication technologies, such as WLAN [4], [5] and Bluetooth [6], [7]. Some of these systems are fingerprint-based [1], [8]. However, these methods require high cost maintenance caused by the constant measurements in the environment [9], which is ineffective for covering wide areas, like universities.

In order to develop a system suitable for different indoor environments, in this paper, we propose a Bluetooth-based system (because Bluetooth is a low cost, low power and popular technology among the mobile devices [10]) called Bluepass (Bluetooth Compass). Fixed stations distributed throughout the environment are responsible for collecting the Received Signal Strength Indicator (RSSI) broadcasted by mobile devices found in the neighborhood. Then, they transmit these data to central computers that compute and store the device locations in a database.

This paper is organized as follows. Sections II presents the theoretical background for this work. In section III, we present the details of the Bluepass system architecture. In Section IV, we describe our empirical study. Section V presents the experimental results. Finally, section VI contains the conclusions and future work.

II. Background

A. Trilateration and Multilateration

Trilateration is a method that computes a node position by intersecting 3 circles. To estimate its position, a node needs to know the position of three reference nodes and its distance to each of them. Multilateration is similar to trilateration, but more than 3 references nodes are required [11].

Inaccurate distance estimation, as well as inaccurate position information of the reference nodes, make it difficult to compute the position [11].

B. Indoor propagation models

Indoor radio channel differs from traditional mobile radio in two aspects: communication range is smaller, and environmental dynamics are greater. It has been observed that propagation within buildings is strongly influenced by specific features such as the layout of the building, the construction materials, and the building type [3].

C. The ITU indoor propagation model

The ITU (International Telecommunication Union) model is a radio propagation model that estimates the path loss inside a room or a closed area inside a building delimited by walls of any form [12]. The model is defined by

$$L = 20 \cdot log(F) + N \cdot log(d) + Pf(n) - 28 \qquad (1)$$

in which L is the total path loss in decibels; F is the transmission frequency, in megahertz, ranging from 900MHz to 5.2GHz; d indicates the distance in meters (up to 1 km); N is the empirical distance power loss coefficient; Pf(n) is the floor loss penetration factor (n is the number of floors).

D. Related Works

Current solutions aim at solving the indoor localization by calculating the distance between mobile device and fixed stations based on RSSI [4], [6], [13]. There are also techniques that use the response rate (RR) [1] and RFID [14]. Location systems that use RFID need special hardware, such as readers and transponders, increasing the system installation cost. The RR, as some tests show, begins to vary significantly only after a certain distance. This fact made impossible to use RR within the environment where the Bluepass experiment were performed. However, the RSSI vary considerably as the distance between a fixed station and a device increase, which enables one to infer distance from RSSI signal level.

Among the wireless communication technologies, the most widely used are Bluetooth [6], [8] and WLAN [7]. In this work only the Bluetooth technology was used.

To estimate the device position, the most frequently used techniques are trilateration [13], [15] and fingerprint [1], [4]. In the fingerprint method, we need to create a database with measurements of the environment network properties. The main drawback of this method is the inability to automatically model new obstacles or changes in the infrastructure, affecting significantly the location results. To overcome that problem, many periodic measurements would be necessary to maintain the system accuracy. Thus, if the system area were too large or too crowded, it would be difficult to deploy the system and handle its maintenance. Feldmann et al. [13] combine RSSI measurements with the trilateration method, which is the strategy used in our solution.

Feldmann et al. [13] consider a test methodology very similar to the used in this paper performing the tests within a single room of 46 m^2, and using 3 fixed stations. In our evaluation, we have considered a 195 m^2 area with 4 rooms. Three of these rooms contain a single station each (section IV-A), allowing a realistic evaluation of an indoor location system (circulation areas separated by several walls). We also show the difference between the behavior of a method applied in a single room and the behavior of the same method applied in the entire environment.

III. Bluepass architecture and operation

Bluepass is an indoor Bluetooth-based localization system that relies on the RSSI. The system main goal is to allow users in a given environment to locate and be located by other users through their mobile devices.

The client-server architecture was chosen due the fact that a mobile device can only be detected if there is a fixed infrastructure, with static reference points. The system is distributed and consists of 4 main components: the central server, the local server, the Bluetooth devices detection program and the mobile application.

Bluepass users are considered in active state while they are accessing the system through the mobile application and inactive when they are not. A user connected to the system, is associated with the current mobile device, so the user can choose which device will be located.

In Bluepass, a map corresponds to the facility floor plan. The map is divided into smaller parts, corresponding to the buildings of such facility, each one composed of spots (rooms, hallways).

For each map, there is a single local server and a set of Bluetooth-device-detection programs running on static stations in the facility, covering the entire perimeter (except the areas where system is not desired). A user within the area covered by the system is considered to be in the corresponding map.

The server was split into two parts (central and local), because the structure of the system has been designed to work with physically distant maps. A user does not need to register in each local server to be located, because his account is stored in the main server database, not in the local servers. Thus, a user with the same account can access the system from any map. However, in a simpler case, considering a single mapped facility for example, these two components can be merged in a single server.

A. Bluetooth devices detection program

The program that detects Bluetooth devices in its range runs on a PC with a class 1 (100m range) USB Bluetooth adapter (fixed station). This program must be connected to an active local server in order to run. During its execution, the program can be in two states: active or inactive. The inactive state corresponds to: (a) the period after the program has connected to a local server, waiting to be activated for the first time; or (b) the period immediately after the program has been temporarily disabled, waiting to be reactivated.

During the active state period, the program continuously performs a scan (detecting active devices) followed by a stand-by time, both with a fixed duration. Data received from the detected Bluetooth devices during the scan are stored in a hash using the Bluetooth address as the hash key. The program does not distinguish between the devices associated to a user from the ones that are not.

During the stand-by time, the stored data are processed and an RSSI average is calculated for each of the detected devices. These averages, along with the Bluetooth addresses, the fixed station position in the 2D map.

B. Local server

The local server runs on a PC. It is responsible for processing the data obtained through the detection programs that cover the local server map in order to locate all active users within the map.

Once the fixed stations are connected to their respective local server, it sets the duration of the scan and stand-by time, and activates them. Once they are activated, the local server continuously receives lists containing the data of all devices found by each program. However, it processes only data corresponding to currently active users.

The local server waits for data related to one device for a minimum time. When this time expires, the local server estimates the location of a user with data from at least 3 different stations. Otherwise, the data is considered outdated, being discarded, and a new waiting period begins.

Location estimation consists of two steps. First, the local server estimates the distance between the user device and each fixed station that sent data related to the device. We estimate the distance by using a linear regression model based on data collected according to section IV-C. As it will be shown in section V, the choice of this model is due to better results when compared with other models. In a second step, to estimate the room where the device is located, the distances obtained through the chosen propagation model are applied in two distinct methods: the multilateration and the signal coverage density method (SCDM). The multilateration estimates a point in the plane where the mobile device is located, based on the distances obtained by the fixed stations (section II-A). Once it is estimated, the system determines the spot where the point belongs.

The local server can also disable the detection programs connected to it. The programs (and the data transmitted by them) will always be synchronized, considering the fact that the local server is the only one that can determine when the programs are activated or deactivated.

C. Signal Coverage Density Method (SCDM)

The SCDM uses the propagation model to determine the room where the user is probably located, without calculating the users coordinates. First it creates a matrix, whose size matches the environment in which the system is deployed. This matrix is a computational representation of the grid mentioned in section IV-A, with its cells initialized with 0 (zero). After a fixed station had detected a device, it is estimated the distance between them by using the RSSI. However, unlike the trilateration method, which considers a circle around the fixed station, the SCDM considers a square whose side is equal to twice the estimated distance.

On the SCDM, once a square representing the fixed station signal range is created (around each fixed station according to the RSSI), the cells within that square are incremented in the matrix. Thus, the intersection of the squares will create areas with a higher signal density, i.e., areas in which the device is more likely to be located. When the signal is too weak, the areas near the station are not incremented, because it is known that the device is not near the station. To do so it is considered a new square with the same center and half the original side, whose cells are not increased.

The room where the user is probably located is the one with the highest signal concentration, i.e., the room with the higher number of cells with the highest values. Cells of lesser value will be considered until there is no longer a tie.

D. Central Server

The central server is responsible for the system database and was designed to run on a desktop to allow the connection of several local servers and clients, while serving as a bridge between these two components. The database stores users data and maps, with their buildings and spots. When the central server receives a connection request from a local server, the data of this local server map, as well as the data of this map spots and buildings, are sent to the local server.

Figure 1. Bluepass login screen and main screen (digital map).

When a user connects to the central server, it first validates the username and password in the database. If there is a user account and the user is inactive, begins a period of user detection, in which the central server sends the users data, along with the Bluetooth address of the mobile device to all the local servers to attempt to detect it.

When a local server detects the user, it informs the central server, which sends the map data related to where the user was detected, including his location and the other active users on the map location as well, finally allowing the user access. Then, the remaining local servers are informed by the central server to stop tracking that user, since a user cannot be in multiple maps at the same time.

When the user decides to terminate his activities in the system, the central server also warns the local server (responsible for that map) to stop estimating its location, since the user is inactive.

E. Mobile application

The application runs on any Bluetooth enabled device with wireless access and Linux OS. The main location service provided to the user by the application is a dynamic digital map of the facility (Figure 1). This 2D map, which shows the facility floor plan, is displayed in the user mobile device after its detection by the system. In this map, the color of each spot indicates its type (room, hallway) and in the middle of each one there is the number of users located in the spot. The users currently in the spot can be viewed in a detailed list, when a spot is selected.

The map is updated at fixed intervals. Since the current application focus is only to show the users location at room-level, and not his exact position in a room, a real-time update would not result in benefits.

IV. Experimentation

A. Infrastructure

The Bluepass system was deployed in an area of approximately 13m x 15m. This area consists of 4 rooms (3 of them are computer labs) and two hallways. The considered indoor area was covered by a defined 2D map and 3 fixed stations were distributed at the corners of the map among 3 of the 4 rooms. As the system was intended to cover the area with the least amount of fixed stations, it was not used a fourth one, because 3 were enough. Each fixed station consists of a Linux desktop equipped with a class 1 USB Bluetooth adapter running a Bluetooth devices detection program (section III-A). The local (section III-B) and central (section III-D) servers are also running on a Linux desktop located in one of the computer labs.

The area where the system has been deployed has been split into a grid of $1m^2$ cells to ease data collection, which will be explained in section IV-C.

B. Propagation Models

To calculate the distance between a device and a fixed station based on the RSSI, it is necessary to use a propagation model that best fits the device's environment.

The ITU model was one of the considered models for the test. This model uses an attenuation constant N (section II-C) based on the signal frequency and type of environment where it is working. Despite the fact that several constants are proposed in a table in [12], there is no constant set to the Bluetooth operation frequency (2.4 GHz). During the initial tests, we adopted the constant for the frequency of 1.8 GHz and for the environment of an office (N = 30 in [12]), because this was the one that closely matched the Bluetooth frequency and the test area environment.

Besides the ITU model, other ones were created to simulate the scenario where the system was deployed using different types of regression using the collected data set (section IV-C). Initially, only the set of data collected in the same room where the station was settled was applied in the models. Then, all the data were applied in the models. Thus, it was possible to choose the model that best represented the environment, comparing the behave of a same model used in the whole environment and used in only one room.

C. Data Collection

The data collection consists of storing the RSSI measurements of a specific device into several positions of the plane according to one of the stations. This process was repeated 50 times at each point where the device was located.

Once the measurements were completed it was calculated the RSSI average at each point, matching each average with the distance between the mobile device and the fixed station.

This procedure was performed in 134 of the 195 grid's cells. The points that were not measured correspond to inaccessible points (bathrooms or restricted areas) or to areas not covered by the station's signal due to intense degradation. The mobile device was placed in the center of each cell by the time needed to complete the all the 50 measurements. The behavior of the signal at the test area will be shown in section V.

D. Mobile device position estimation

Once a propagation model is chosen, the device location is estimated using the information obtained from at least 3 base stations. To calculate this location two methods were used: trilateration and the SCDM. The use of trilateration instead of multilateration is due to the configuration of the test area (section IV-A), which is limited to 3 base stations.

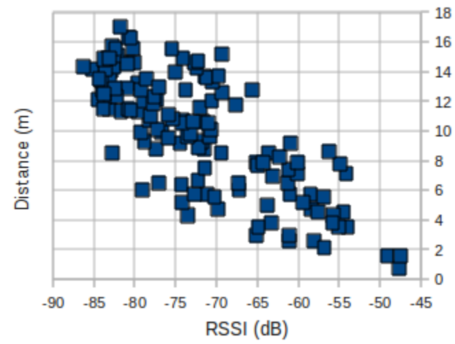

Figure 2. Distance x RSSI of a mobile device according to a station.

The trilateration method is explained in section II-A. However, it is important to highlight that one of the biggest drawbacks of this method is the inability to use only the most reliable information. Moreover in some cases trilateration returns points outside the 2D map (negative coordinates), making it impossible to determine the device's room.

The negative coordinate correction consists in transform the negative coordinate into a positive one close to zero. One of the advantages of the SCDM is the natural treatment of this type of error, because SCDM only considers the behavior of the signal within the test area.

E. Comparison of results and error measurement

To compare the results it was used the mean squared error (MSE). It was chosen this method to calculate the error because the use of an arithmetic mean of the errors lead to bad results, since the same errors in opposite directions from the fixed station are not considered during the sum. Using the MSE the error is preserved regardless of it direction, providing greater reliability in the final results.

V. Results

The measurements results along the test area are shown in Figures 2 and 3. Once we collected the data, we applied the ITU model to them to determine the compatibility of the adopted constant (section IV-B) with the environment where the system was deployed. We achieved an average error of 4.56m, using the data from a single room, and 8.39m, using the data collected in the whole area. These results show the incompatibility of this constant with real environments.

To determine the best constant, values between 1 and 100 were applied in the ITU model, computing the MSE according to the real data. Figure 3 shows that small constant values lead to high errors, and after the error reaches the lowest point, i.e., the point that defines the best constant (N = 37), it tends to increase as the constant increases. This

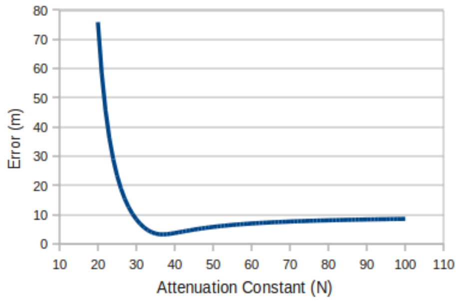

Figure 3. Distance estimation error in meters according to the ITU attenuation constant (N).

Table I
ERRORS IN THE DISTANCE ESTIMATION BY MODEL

Model	Error in a single room	Error in the whole area
Linear	3.27m	3.15m
Exponential	4.16m	3.75m
ITU (N = 30)	4.56m	8.39m
ITU (N = 37)	2.33m	3.23m

shows the incompatibility of very high constants with the used environment.

In addition to the finding of the best constant for the ITU model, two types of regression were computed, using the real data, to verify the possibility of finding a better representation for the environment.

According to Table I, ITU model presents the smallest error when estimating the distance in the same room, but the error increases about 1m when applied to an environment with several rooms, showing the inability of the method to represent obstacles. Feldmann et al. [13] do not show such a comparison, limiting the testing to only one room.

The formula generated by the linear model was chosen as the system propagation model, because it presented the smallest error considering the whole environment. The two models that better estimate the distance in the whole test area according to Table I were chosen to test the results of the system. A new data collection was performed, consisting of 100 RSSI values of a mobile device collected by 3 fixed stations in different rooms at the same time.

This procedure was repeated at 9 points, 3 in each room. The 3 chosen points within each room were chosen as follows. The first was about 0.5m from the fixed station. The second was located in the middle of the room. Finally, the last was about 0.5m from the door. These 3 points in each room were chosen to determine the error at each location.

The data set was divided into two groups composed of 30% and 70% of the total set of values. This division was used to verify whether the results obtained in a small group of data are maintained with a larger group of data.

Two types of error were considered at this stage. The first is the error, in meters, between the estimated coordinates and the actual position of the mobile device. This error is computed only for the trilateration method, because SCDM does not estimate the coordinates for the device.

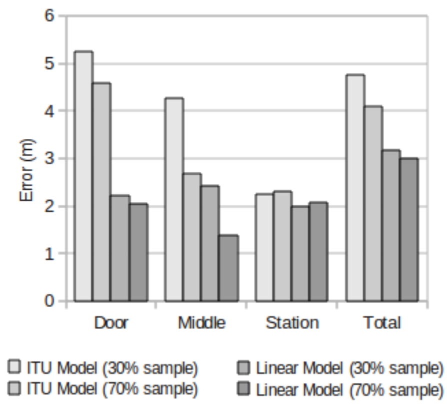

Figure 4. Trilateration coordinates error in meters.

The second error type corresponds to the number of times (in percentage) that the method correctly estimated the room-level location. This error was computed for both methods: trilateration and SCDM.

According to Figure 5, the error in meters is smaller in all cases when we use the linear model, validating its use as a propagation model for the Bluepass system. The smallest erroroccurs when the mobile device is near the fixed station.

The results obtained by applying the data collected in the trilateration method without using the negative coordinates correction method (section IV-D) can be seen in Figure 5(a). By applying the correction method it is possible to realize a significant increase in the percentage of correct room-level location, as shown in Figure 5(b). Considering the room-level accuracy, the SCDM results are almost the same regardless the propagation model.

In addition, the greater accuracy in the SCDM (100%) occurs when the mobile device is located near the fixed station and not in the middle of the room. Similar behavior is observed for trilateration method.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, we presented an indoor Bluetooth-based localization system that allows the evaluation of path loss methods in a real scenario, demonstrating their feasibility. Also a methodology for estimating the best attenuation constant of a certain environment for the ITU model is defined. This methodology can be replicated to other models.

The signal coverage density method (SCDM) makes a better use of the information obtained by each fixed station. For example, when a fixed station detects a mobile device with a very high RSSI, there is a high probability that this device is in the same room of the station. A method such as trilateration does not detect this type of situation, because it only computes the intersection of geographical

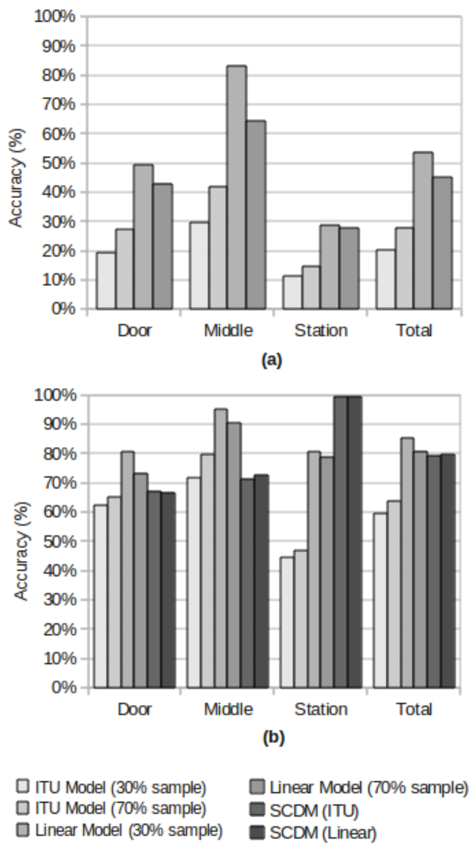

Figure 5. (a) Trilateration room-level accuracy without the negative coordinates correction. (b) Trilateration accuracy with the negative coordinates correction and SCDM room-level accuracy.

circles, without using all the relevant information obtained by the stations. Thus, results achieved by using trilateration depend entirely of the accuracy of the path loss model to be able to determine the coordinates of the device. According to the obtained results (Table I and Figure 5(b)), a 0.10m error difference between the ITU and the Linear model will increase the error in the coordinates, computed by using trilateration, in 1.6m, affecting the room-level location in 23%. However, the same propagation models applied on the SCDM did not affect the room-level location significantly. Thus, the SCDM is more stable when the propagation model is not very accurate.

Interesting directions for future research include: (a) analyzing the impact caused by the change of the fixed stations position on the system, in terms of performance; (b) combining trilateration and SCDM results to improve the room-level and the coordinates accuracy; and (c) deploying the system in different indoor environments to complement the experimental results.

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