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Bluetooth-WiFi based combined positioning algorithm, implementation and experimental evaluation.

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Autonomous Agents in Ambient Intelligence

Abstract

Positioning an individual with high accuracy is important since many location-based services rely on the position of the user to provide them with ubiquitous services. Despite the need for accuracy, no perfect solution has been proposed for the problem of accurately positioning an individual. A number of attempts to improve the accuracy has been made achieving an accuracy of about 2 meters using sophisticated techniques and the advances made in the mobile industry. In this paper we explain the methodology to get a propagation model suitable for Bluetooth in order to get a more accurate distance measurement, and also the algorithm to combine it with WiFi to position a user in an indoor environment. Firstly, we get measurements of distance related to a RSSI value obtained from the Bluetooth to get a propagation model, we compute a distance using the known propagation model from WiFi, and finally an algorithm to obtain the location of the receiver combinig Bluetooth and WiFi is presented.

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1. Introduction

Despite the vast amount of research, user positioning still remains an interesting topic due to the challenges faced when estimating the location of an individual. Although recent works have approximated user position with a higher degree of accuracy (about 2 meters in average), there is still work to be done.

As a consequence, a significant number of solutions, that were once considered feasible, have been proposed. For example, the use of geometric techniques [1], as well as other techniques that focus on non-radiolocalization technologies [2]. Indoor positioning is a challenging task that can not be solved using GPS systems since there is signal degradation in indoor environments [3]. Fortunately, the wide diffusion and availability of 802.11 WLAN infrastructure and Bluetooth technology have yield feasible solutions that are still under constant improvement and that offer a cost-effective solution [1].

Lateration techniques are implemented in this work since it is possible to implement a positioning method that does not require special infrastructure other than the existing one, and that the method does

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not necessarily require prior knowledge of the environment other than the position of the access points and beacons distributed in an indoor environment, in this case the ground floor of a house.

The aim of this paper is to present the methodology to obtain the propagation models as well as the implementation of an algorithm that uses WiFi and Bluethooth technologies for indoor position combinig the two types of signal to locate an individual in an indoor environment.

This paper is organized as follow. A review of some existing methods for location estimation using diferent sources is given in Section 2. In Section 3 we describe a methodology to obtain a Bluetooth propagation model based in RSSI readings. Section 4 presents the description of a WiFi propagation model. WiFi-Bluetooth based combined positioning algorithm is presented in Section 5. Section 6 contains the results using the obtained models as described in sections 3 and 4 for Bluetooth and WiFi respectively. Finally conclusions are given in section 7.

2. State of the art

Given the importance of indoor positioning, there is a number of works that bet on wireless technologies such as Bluetooth, WiFi, GPS and different approaches to tackle the problem depending on the transmitters.

For example, [4] presents an estimation based on Bluetooth trilateration but given the exclusive use of Bluetooth technology, it is a method that still carries high degrees of inaccuracy. Altini et al. [5] propose a method in which Bluetooth transmitters are placed according to a known distribution and a previously trained neural network is required to calculate the position. [6] proposes the use of RSSI information between several fixed wireless beacons to improve the reliability of a Bluetooth positioning systems by using this information to calibrate the sensors' responses.

Location fingerprinting schemes are feasible solutions for indoor positioning as described in [7] and [8]. These techniques are very promising since they can reach high levels of accuracy but they presuppose the existence of a radio map that was previously generated, therefore it tends to be impractical and time-consuming specially in a large scale implementation.

The approach proposed in [9] takes advantage of the wide availability of signals in the indoor environment from Bluetooth, WiFi, and GPS sensors. The method proposed is based on the prior existence of RSSI Bluetooth radio maps as well as WiFi radio maps. It also considers a pre-established distribution of Bluetooth and WiFi stations.

Reference [10] proposes a very simple approach that claims to achieve good position estimates using GPS as the main source of information. The authors present a possible solution that consists in solving a system of equations with at least 4 equations and one unknown. The four equations rely on the number of signals detected by the receiver and if the signals observed from the GPS are not enough to complete the system of equations, it is complemented with the signals that come from another source, in this case from WiFi. A similar methodology is used in our work in which the system of equations will be completed with signals that are available in the environment.

3. Generating a Model from Bluetooth RSSI

This section describes how to accurately generate a model by converting Bluetooth RSSI measures to a distance.

3.1. Approximation of RSSI measurements

Given the fact that the representation of Bluetooth RSSI values differ from manufacturer to manufacturer, we decided to create a model to correlate the distance between the transmitter and the receiver using the RSSI readings from the receiver. In this case, the receiver is the device we are trying to position in the environment. Technologies such as AzureWave AW-NH611 and CSR BC4-Ext were used for the transmitter and receiver respectively. The experiment took place in a house and consisted in placing the transmitter and receiver in a straight line in an open space, while the receiving device was held by a person using both hands.

Table 1. Mean and standard deviation of RSSI readings

Distance (m)	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0
Mean (m)	13.663	67.247	67.356	66.634	69.713	75.386	69.485	77.337	77.812	76.277	78.287
Standard Deviation	0.552	2.851	2.086	1.560	2.329	4.465	1.376	2.805	4.386	3.980	2.543

Table 2. Minimum and maximum mean RSSI readings

Distance (m)	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0
Maximum	14.769	72.949	71.529	69.754	74.372	84.317	72.236	82.946	86.583	84.238	83.373
Minimum	12.558	61.546	63.184	63.513	65.054	66.455	66.734	71.728	69.041	68.317	73.201

Both, the transmitter and the receiver, were placed at a distance of 5 meters divided in ten equally distributed parts 0.50 meters distance between each division since, being a model thought to work in interiors and expecting to find more than one transmitter in the environment, 5 meter distance fits well in the model given the fact that 0.50 meters is a distance smaller than that occupied in average by a standing person [11].

As part of the experimental setting, 100 samples were recorded for each division of the experimental space since using a smaller number of samples gave a standard deviation greater than 5, which theoretically, in a logarithmic model (since it is a propagation model), a standard deviation of 5 affects the measurements coupled with the fact that an overlap between the divisions of the experimental space was imminent.

As it is shown in Table 1, the mean was computed for each interval as well as its standard deviation, emphasizing that the standard deviation computed was lower than 4.5 for every interval of the experimental space. Once these results were obtained, we proceeded to search for a maximum and minimum mean values to be considered as the limits for each one of the divisions of the experimental space. To compute the minimum and maximum means, the mean that was computed previously was added or subtracted to twice the standard deviation, obtaining the results shown in Table 2. The results obtained in this experimental setting are required to generate other models as it will be described in the next section.

3.2. Deriving a RSSI Model

It is well known that precise and accurate estimates are required regardless of the type of problem we are trying to solve. Therefore, it is necessary to develop a model that allows us to approximate the position of the user with high accuracy. Recently, methods such as classical regression, neural networks, case-based reasoning and a wide variety of other methods are proposed. Nevertheless no conclusions can be drawn regarding which method is better than the rest since the best method depends on the phenomenon we want to model. In other words, the method is chosen depending on the phenomenon under study.

As it has been noted, radio-frequency propagation models follow a logarithmic behaviour, therefore the logarithmic regression given by (1) was implemented for this specific case, where

- y = dependent variable

- α = regression coefficient

- x = input variables

- β = error term

$$y = \alpha ln x + \beta \tag{1}$$

To evaluate the accuracy of the proposed model, it is necessary to apply not only quantitative but also qualitative tests to the model. The coefficient of determination (R^2) is proposed as a criteria to find the correlation between the real values of a variable and its approximating estimates. Values close to 1 indicate a better adjustment to the model [12].
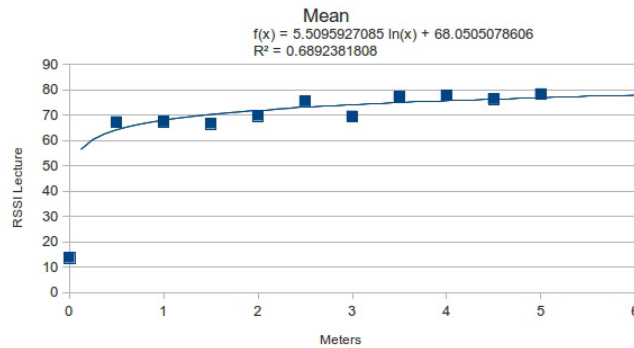

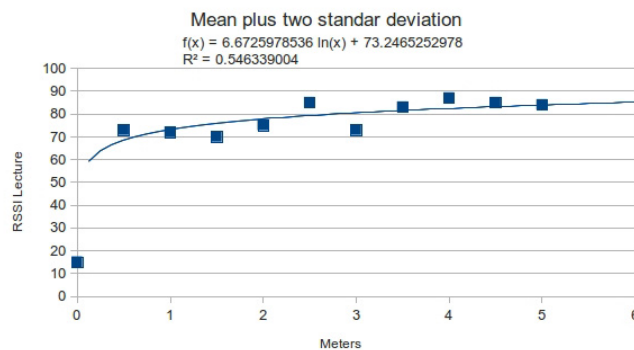Fig. 1. Logarithmic Regression Model obtained using the mean.

Fig. 2. Logarithmic Regression Model obtained using the maximum.

From the data previously collected, three models were acquired. The first model was obtained using the mean as it is shown in Figure 1, which has a R^2 of 0.68923 showing that the model is adjusted reasonably well to the data set. The second model shown in Figure 2 was obtained using the computed maxima, which relied on the standard deviation and the mean, having a R^2 of 0.546339. Finally, Figure 3 shows the model obtained using the computed minima with a R^2 value of 0.79071124, which, in fact, came out to be the model that better adjusts to the data.

Once the models were compared using the coefficients of determination of each model as an indicator of the model that best fits the data, we chose the third model given by 2 as the candidate to be implemented, where

- d = Computed distance based in RSSI readings (in meters)

- x = Receiver's RSSI readings

$$x = 4.5837524117 ln d + 62.7537263047 \qquad (2)$$
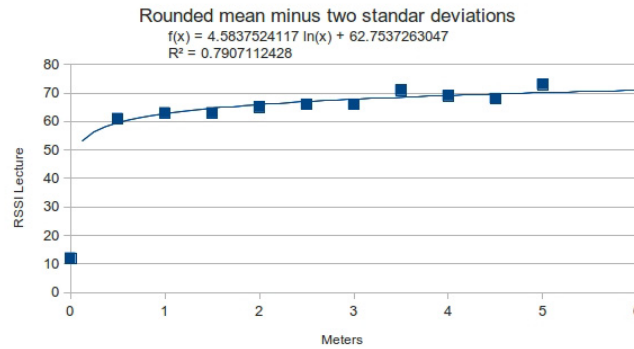
Fig. 3. Logarithmic Regression Model obtained using the minimum.

4. Model Used to Measure WiFi Stations

Among the vast amount of models and their equations, both empirical and non-empirical, for the propagation of radio-frequency, there exist models specifically designed for indoor environments such as Mootly-Keenan[13], the MWF model [14] and the Free-Space Path Loss (FSPL).

Equation 3 describes the Free-Space Path Loss model used for our purposes. This model represents the loss in signal strength of an electromagnetic wave that would result from a line-of-sight (LOS) path. There is no reflection or diffraction. As can be seen, FSPL is the function of frequency and distance between transmitter and receiver[15], where

- f = is the signal frequency (in hertz)

- d = is the distance from the transmitter (in meters)

- c = is the speed of light in a vacuum

This equations allows us to obtain an approximate distance from the decibels acquired by the receiver as well as the frequency of the transmitter. On the other hand, FSPL does not need to know any prior data from the environment in which the transmitter is located, offering more flexibility and adaptability in any indoor environments.

$$FSPL(dB) = 10log_{10}((\frac{4\pi}{c}df)^2) \tag{3}$$

This distance similarly to the one obtained by the Bluetooth, considers a line of sight, resulting in significant variations, but it is useful to complete the system of equations in case there is not enough Bluetooths available at the moment.

5. WiFi-Bluetooth based combined positioning algorithm

In [16] we proposed an algorithm to fuse the distance information collected from Bluetooth and WiFi, which regardless of its simplicity, showed a considerable improvement in the accuracy compared to that of multilateration.

The proposed algorithm relies on multilateration and to estimate the position of the individual only requires the coordinates of at least 3 devices near the receiver with respect to an origin that can be randomly chosen (e.g. the entry door of the house) as well as the frequency of the WiFi stations.

Figure 4 shows the flowchart of the proposed algorithm that was implemented in this work. The models obtained for Bluetooth and WiFi in sections 3 and 4 respectively were used to compute the distance from

the receiver to each of the available transmitting devices. After the distances were computed, an equation that looks like 4 was generated for each of the transmitters, where

- x_n : X-Coordinate of the receiver n(in meters)

- y_n : Y-Coordinate of the transmitter n(in meters)

- d_n : distance calculated by the corresponding model of the transmitter n(in meters)

- x : unknown X-Coordinate of the receiver

- y : unknown Y-Coordinate of the receiver
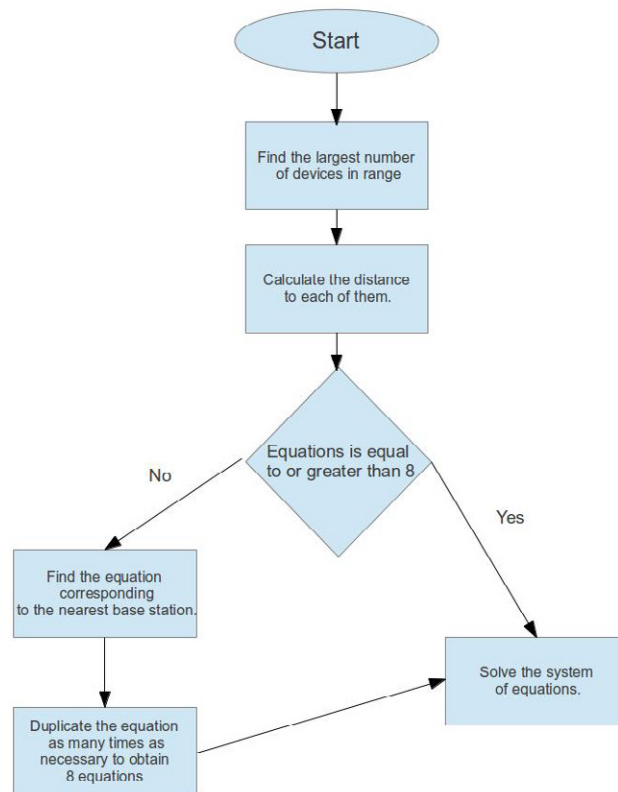

Fig. 4. WiFi-Bluetooth based combined positioning algorithm flowchart.

$$d_n^2 = (x - x_n)^2 + (y - y_n)^2 \qquad (4)$$

Following the proposed algorithm, a non-linear overdetermined system of equations was generated with 8 equations and two unknowns, which was also simplified, leaving a linear overdetermined system of equations with 7 equations and 2 unknowns. This was accomplished by using the method proposed by Dan

Kalman in [17]. The obtained linear overdetermined system of equations was solved using the Least Squares method given by 5 where,

- $\tilde{x}$: vector of unknowns corresponding to the X-coordinate and Y-Coordinate of the receiver

- A, b : System of equations in matrix form

$$\tilde{x} = (A^T A)^{-1} A^T b \tag{5}$$

Given this, x and y values, corresponding to the coordinates of the receiver, are estimated with the minimum amount of error.

6. Results using Obtained Models

Once the propagation models for the devices that serve as transmitters were obtained and using the algorithm previously described, a series of tests were implemented in real physical environments with a distribution as shown in Figure 5. For this specific case, only the ground floor of the house was considered since there is a sufficient amount of transmitters, as it is shown in Figure 6, to do the necessary calculations. The following transmitters were used, 2 AzureWave AW-NH611, 1 CSR BC4-Ext, 1 WX8196C22 Wireless router and the following receiver, 1 CSR BC4-Ext.

a)   b)
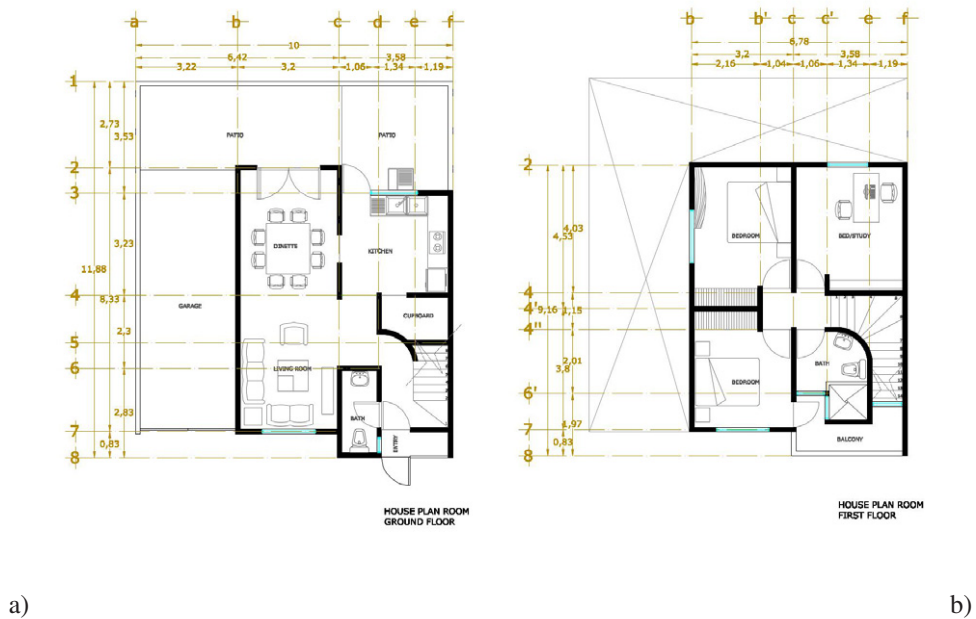
Fig. 5. House plans with furniture, (a) ground floor; (b) first floor

The measurements were taken in 3 different location points of the ground floor. They were arranged in such a way that different results could be obtained since we were trying to diversify the characteristics that surround the individual and that can affect the signals that travel from the transmitters to the receiver. The first point corresponds to a location with 3 transmitting devices without obstacles interfering and 1 surrounded by furniture commonly found in interiors (e.g. chairs, tables, etc.) The second position is located between all the transmitters without obstacles interfering, coupled with similar distance with respect

Table 3. X and Y measurements mean

Location ID	Real X	Real Y	X Measured	Y Measured	X error	Y error	Total error
1	1.8	2.4	0.97523	2.31188	0.82477	0.42514	1.01126
2	3.0	5.0	1.06560	4.27490	1.93440	0.93207	2.32628
3	1.65	5.2	0.82643	5.14091	0.82357	0.22153	0.86909

to all the transmitting devices. Lastly, the third point described in the experimentation was located in the coordinates in which furniture was placed; this location is of special importance since it is surrounded by furniture avoiding direct line of sight except for one of the transmitters as it is shown in Figure 6 (a).

a)   b)
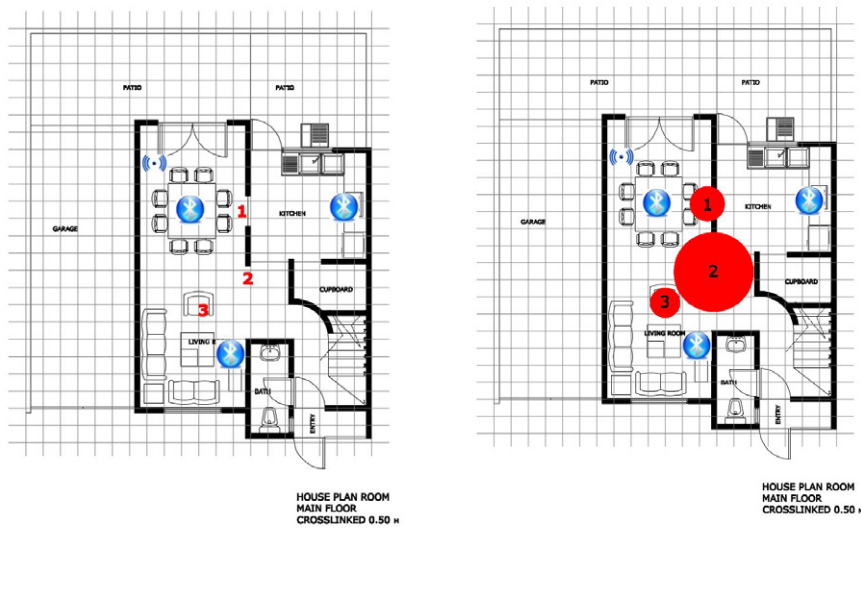
Fig. 6. Different location points, (a) transmitters distribution; (b) measurements average

Table 3 was constructed after doing a series of experiments that consisted of 30 measurements for each of the 3 locations. After the measurements were made, an average of the 30 trials was computed leading to the results of the table.

As it can be observed from the second location with coordinates 3.0 in X and 5.0 in Y in Table 3, this location presented the highest average error even though, as it is observed in Figure 6 (b), it is located in an open space free from immediate obstacles for the receiver. On the other hand, the third location with coordinates 1.65 for X and 5.2 for Y, which was expected to have the poorest approximation due to the significant amount of obstacles given that the person was sitting at a couch, shows the lowest total error with an amount of error of 0.87 meters. This value offers an insight of the significant results achieved using our model compared to the best approximation reported by other methods that utilized similar devices and more complex algorithms to estimate the location of a user in an indoor environment, as it is shown in Table 4.

An error of 0.87 meters was obtained. It is also important to mention that, if we consider that the physical space occupied by a person can not be represented by one point in particular, coupled with the fact that in average a measurement from shoulder-to-shoulder is 0.54 meters [11], the error is considerably reduced.

Table 4. Comparison of different approaches

Approach	Error (in m)
WiFi GPS based Combined	19
Bluepass	3.15
Trilateration	2.45
Dynamic Calibration	1.01
Our Approach	0.87

7. Conclusions

Indoor positioning is gaining importance given the amount of services that rely on it to offer customized services. Wireless technologies such as WiFi and Bluetooth make it an attractive solution due to their availability. This work focused on the use of these technologies to develop a positioning method that does not require high computing resources or previous knowledge or modifications of the indoor environment. A methodology to obtain a propagation model for Bluetooth was proposed as well as a model for WiFi and also an algorithm that estimates the position by combining them. The results show that the models obtained with this methodology, and using the proposed algorithm, our method outperformed the 4 methods with which it was compared.

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