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RobustPathFinder: Handling Uncertainty in Indoor Positioning Techniques

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Abstract

Indoor navigation technologies rely on accurately determining the position of a moving person or robot to guide her actively through the building. This cannot be done using GPS because it is indoors. We have been dealing with this problem in the context of designing and building a system for helping blind people navigate in public buildings. However, indoor localization based on RSSI is not very accurate, since the quality of the signal is influenced by many factors that include, for instance, wall reflections or people passing by. The fact that the person is moving also introduces several degrees of uncertainty, including a changing number and placement of beacons in-range. The challenge is therefore to develop mechanisms to handle uncertainty. In this paper we propose and evaluate uncertainty-handling mechanisms.

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Keywords: Indoor Positioning, Location, Positioning Algorithms, Wireless Sensors, Beacons, RSSI;

1. Introduction

Knowledge of user location is very important in many applications. The contextual knowledge of the current position of people and objects helps realize the vision of the Internet-of-Things, since it becomes possible to know where the person or object is at a certain instant in time, and to make contextual decisions based on that.

Determination of user location indoors is based on calculations from beacons signal strength. However, the accuracy of such readings is a well-known issue that needs to be taken into account. More accuracy is obtained with

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beacons of short range, thus requiring a greater amount to cover the whole environment. Lower cost of deployment can be obtained with beacons of longer ranges, decreasing the quantity required, increasing however the probability of errors in the calculation of location.

The location algorithm should also take into account dynamic conditions, transient inconsistent RSSI readings and other factors to produce a robust solution. The positioning algorithms should include several conditions that enable estimation of user's position even without appropriate number of beacons in the range of the user. An example of these conditions is predicting the user's position based on previous positions.

We were confronted with these issues in a very practical context. We developed a system with the aim of increasing the autonomy of blind and partially sighted people in their day-to-day lives. The proposed system – RobustPathFinder – provides a mechanism for navigation within public buildings. Since a blind person does not have access to the information common in visual cues, the system adds an application to the smartphone to allow guided and assisted navigation inside public buildings. The system needs to determine the user location continuously, calculate routes and identify areas in the vicinity of the user. Locating beacon technology for the system may be for instance Bluetooth or Wi-Fi based. In this context, we wanted to reduce the number of beacons that would be needed, in order to lower the costs and inconvenience of the system when deployed in any building.

2. State of the Art

Indoor positioning is a complex area whose main objective is to estimate or determine specific positions indoor. Outdoor positioning is already performed, although with the known error of a few meters, by GPS. GPS cannot be used indoors due to signal attenuation through walls and structures, and due to the required accuracy. Indoor positioning systems are used in various applications, such as location-aware services, tourism or military infantry.

The main focus of this paper is to develop a simple, low cost and easy-deployable system to determine positions of people in a building that handles uncertainty as well as possible. In this section we briefly review works on the issue of indoor positioning.

Works such as [1, 2, 3] describe algorithms and methods to determine the position of robots and/or people. We emphasize [2] which divides indoor positioning into three sections: fingerprinting (mapping the environment with RSSI values), triangulation (mathematical operation used to find the location of a user based on three known points and the angles between the known points and the user location) and proximity. The basis of proximity approaches is the proximity beacons, this beacons have very short range, so when they are detected the user is near the beacon.

The work in [4] presents an evaluation of various indoor positioning systems, including infrared, ultrasounds, radio frequency, magnetic, vision and audible sound based (those technologies are thoroughly exposed in [5]). That study evaluates systems in terms of accuracy, performance, robustness, deployment cost, security and privacy.

Several studies on indoor positioning are based on Bluetooth technology [6, 7, 8]. Works in [9] and [10] present an approach using Bluetooth technology, where Bluetooth beacons on the environment have the active function of detecting user's device (the device to be positioned). The advantage of this approach is that the user's device does not have to install any specific software to be positioned. Authors of [11] show that the accuracy obtained with Bluetooth signal is not enough for use triangulation algorithms that are required for Bluetooth indoor positioning based systems, and therefore fingerprinting is more adequate.

Indoor positioning systems based on Wi-Fi have the great advantage of buildings already being provided with Wi-Fi networks. The work in [12] presents an indoor positioning system based on Wi-Fi used by a robot for navigation. Other positioning systems based on Wi-Fi were presented in [13, 14, 15]. K. Arai and H. Tolle [16] present a fingerprinting method for Wi-Fi environments that reduces calibration effort while creating the fingerprinted map.

Some systems based in RFID are presented in [17, 18, 19]. The work reported in [20] is related to an indoor positioning system that does not require the definition of maps. The system stores and matches radio and compass signatures to record paths traversed by people, thus self-creating a map of the environment.

The works referred intend to provide indoor positioning systems that work in ideal conditions, on the contrary our work intends to propose an approach that can handle under-ideal situations and uncertainty.

3. RobustPathFinder Approach

Since a robust location algorithm must take into account dynamic conditions, transient inconsistent RSSI readings and other environmental factors, in this section we propose the RobustPathFinder. It provides mechanisms for navigation inside public buildings and includes conditions that enable estimation of user's position even without appropriate number of beacons in the range of the user.

RobustPathFinder aims to increase the autonomy of blind and partially sighted people in their day-to-day lives.

In the remaining of this section, methods and algorithms used to build the RobustPathFinder are described. The first subsection presents the requirements of the setup. The second subsection describes methods and mechanisms used to handle uncertainty issues, while the third subsection presents algorithms used and the relation between all parts of RobustPathFinder.

3.1. Requirements

In order to enable positioning in every point of the environment, it is necessary to load information to the system. This information is related with building layouts and beacons. The building layouts information comprises corridors, walls, rooms, and wherever there are obstacles limiting possible positions for people, while the beacons information comprises information such as position, ID and fingerprinting information. This information will be used to compute possible user's positions. The fingerprinting information is an empirical relation between RSSI's measures and distances to/from beacons. To obtain this information, several RSSI measurements are taken at different distances from the beacon.

RSSI relation to distance from the emitter is a complex issue under study [21]–[23]. Therefore as the issue of this paper is how to deal with uncertainty, we considered a reliable relation between RSSI and distance. Table 1 presents an example of the input we defined.

Table 1. Example of RSSI measurements for a beacon.

Distance (m)	0	5	10	15	20	25
RSSI (dBm)	-45	-60	-68	-80	-90	-95

When an RSSI value is found between known values, a linear interpolation is used to infer the correct distance to the signal source.

3.2. Handling Uncertainty

Here are discussed the uncertainty issues that we intend to overcome with the RobustPathFinder. The main strength of our approach is its ability to handle the under-ideal situations that may be found.

3.2.1. Walking Dynamics

Since beacons have limited range, during a trajectory followed by a person, beacons in range, as well as the number of beacons available are constantly changing. The position of the user is computed after each scan for beacon signals in reach, so the problem that may happen is the insufficient number of beacons. We introduced information of build layouts and history information (positions correctly computed in the past) to limit the possible user positions. When there is not any beacon in range, the historic information is used to predict current position.

3.2.2. Imprecision

Our approach was designed to perform positioning of persons indoor, therefore the precision of the position obtained can have a variability that is due to several factors that include reflections and obstacles. Our approach uses redundant beacon readings (readings from multiple beacons and voting) to reduce the effects of this kind of uncertainty. Tests proved that our algorithm computes positions of persons with less error than a meter, even under highly uncertain conditions.

3.2.3. Proximity Beacons and Beacons

The information uploaded prior to the system enables the utilization of proximity beacons and beacons. The utilization of proximity beacons has the great advantage of precision. When a proximity beacon is detected, the user must be near of the beacon. However, long range beacons enable to use less beacons to cover the area, decreasing the cost of deployment. RobustPathFinder is enabled to compute location with both beacon types, since the information of beacons is loaded in the beginning of the procedure.

3.2.4. Reflections and Fingerprinting

Reflections are inevitable when using beacons and wireless sensors, those reflections have to be taken into account when using signal strength values. Fingerprinting is a technique used to partially overcome this problem. It requires the measurement of RSSI values in any position in the building, creating an RSSI map of the building. This technique, although more reliable than to use the standard relation between RSSI and distance, is very complex and may fail with people passing by and thus reflecting the signals randomly.

Our approach uses multiple calculations (when more than three beacons are available) to compute the correct position and the information about proximity beacons (that are less contaminated, as their range is lower), this way minimizing the influence of signal strength contaminations.

3.3. Algorithms

Once defined the necessary requirements, methods and mechanisms used to handle uncertainty, in this sub-section we define the algorithms to calculate the user's position. Different situations were defined to predict different scenarios. All calculations are based on the conversion from RSSI values to distances (in Table 1). Figure 1 presents the flow chart of proposed algorithm.

Initially, information about the building and beacons available is loaded to the system (functionalities B and C) and the positioning device (PD) scans the vicinity for beacons signals (functionality A), then the information collected by the PD is matched with the information loaded (step 1) to find which signals scanned are known and which can be used. Afterwards the algorithm follows to one of the options 1A to 1E, according to the number of beacons in reach (signals matched).

If three or more beacons in reach (1A and 1B), triangulation is used to compute position. Selecting three beacons, knowing their location and the distance from the user (PD) to each beacon (information in Table 1 is used), three imaginary circumferences with center in beacons and radius equals to the distance of the PD to each beacon are draw in order to identify the user's position. The intersection of the three circumferences gives the PD's position. This method is called triangulation.

In the case of having more than three beacons, a voting is also used to compute the position more accurately. Groups of three beacons signals are created (each one with three RSSI values, resulting from the combination of three beacons signals) are used to determine a possible position (by triangulation). All the possible positions are used to vote the more likely to be position.

The voting approach used consists on an analytical average of the positions calculated from combinations. According to the number of positions, the farthest positions are discarded (considered outliers) in order to decrease the voting variance. This allows calculating the user's position with more accuracy.

When only two beacons matched (that is, found by PD and whose information is stored in the system – 1C), analytical conditions are used to find the intersection points of the two circumferences formed by the two distances. In this situation, building layouts are used to invalidate one of the two possible solutions when possible. If none is invalidated, the beacon with best signal strength (lowest value - 6) is used to check the proximity to the beacon. This condition is also used in the case of having just one beacon available (1D).

The proximity condition checks if the distance to the beacon is greater than a defined value (α). If the distance is greater than α, the position cannot be known, if the distance is lower, the position assumed is the position of the beacon. At this moment, we define α as two meters, considering that the approach is intended to identify positions of persons.

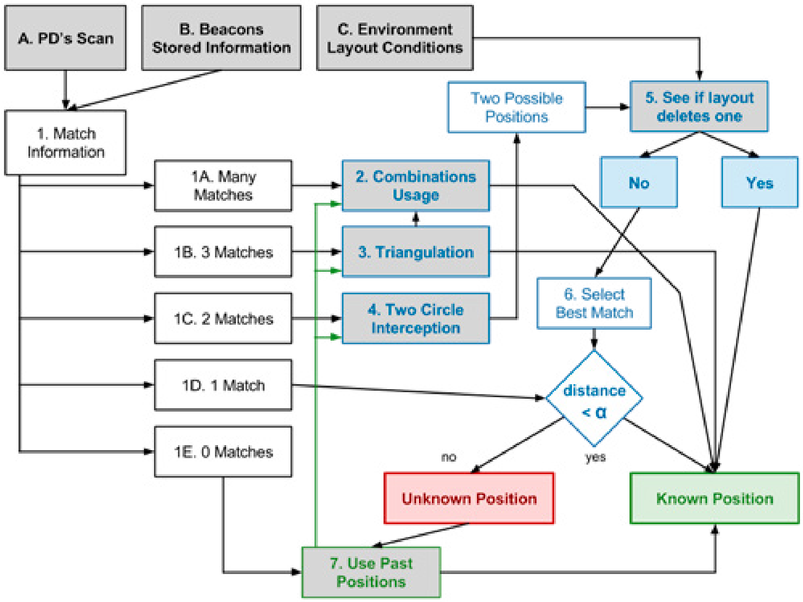

Fig. 1. RobustPathFinder approach.

When past information is available (step 7), it is used to support other calculation means, for example, in voting, the position estimated with past positions is used as an extra possible position. This information uses the previous positions identified and the corresponding timestamp to estimate where the user may or may not be. If there are none beacons in the range, this information is used to estimate user position. Past information is not used repeatedly, avoiding an error increasingly large.

If the position cannot be identified, the algorithm awaits for the next scan to identify a new position.

4. Experimental Results and Discussion

In order to test the developed algorithm, we designed a test scenario and predefined a route for a person's movement, which comprises the positions to be calculated. We also divided the algorithm into different phases of integration: from Baseline to Phase A4. The increments added with each phase of the algorithm are detailed in Table 2.

The baseline (B) includes simple association between collected RSSI values and the RSSI values recorded in fingerprinting (the distance to the beacon is approximated to one of the measured values, interpolation is not performed), positions are calculated with triangulation (only when there are at least three beacons in reach) and proximity to beacons.

For all except phase A4, when there are more than three beacons available, the best three signal strength are used to compute the user's position. This computation is done by using the triangulation method.

The scenario designed includes some wall conditions and the variation of the number of beacons in the range of the person. There were also defined different configurations for the scenario: ranging from a configuration with very few beacons (where almost every position has just one beacon in range), to a configuration with abundant beacons (where the positions can be calculated with more than three beacons). Four different configurations were created, from C1, with a low number of beacons, to C4, with high density of beacons. Figure 2 presents the scenario designed, and the beacons are identified with the number of the configuration where they were added to the scenario. The scenario has 135 meters in length and 75 in width.

Table 2. Increments of algorithm test phases.

Phase	Approach added
B	Baseline
A1	Interpolation of distances to beacons
A2	Algorithms for one and two beacons, building layouts
A3	Inclusion of past information
A4	Combination of sources and voting

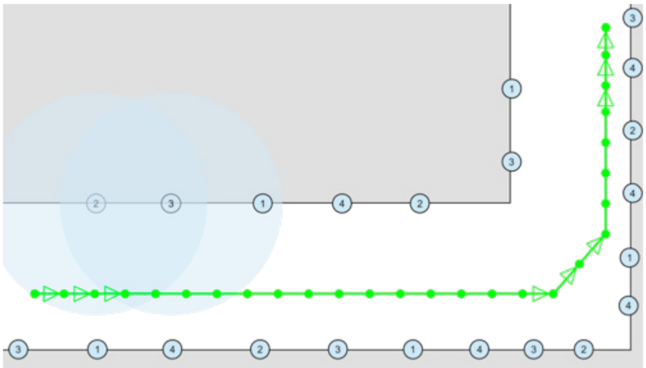

Fig. 2. Scenario designed to test the algorithm.

The blue circumferences on the figure show the beacons range. At this moment every beacon has the same range. The green line in the figure represents the route defined for the person and the green dots in the route are the positions where the algorithm must determine location (a total of 30 positions). For each precise location the RSSI values corresponding to each beacon in range is calculated with the fingerprinting information and the distance to each one (by interpolation). Then, in each position the algorithm receives just the RSSI value and ID of each beacon in range.

In order to evaluate the accuracy and performance of RobustPathFinder in different situation/configuration, the percentage of positions identified (PPC, %), the time of computation (Time, seconds) and the average error (Error, meters) between the computed position and the real position were registered. The time of computation measured corresponds to the time needed to calculate all thirty positions defined. These results are shown in Fig. 3.

The results show that the number of beacons available is a very important factor, since the positioning is based in their signal strength. It is very clear that the capacity of the system to find positions is strongly related to the number of beacons in the environment. In the configuration 1 (C1), where there is just one beacon in reach for almost every position, the approach cannot identify any in the simulation (since the designed route does not include passing a beacon closer to two meters, only beacons with number 1 are used in C1).

When more beacons are introduced in the simulation, the capacity of the algorithm is highly increased, in any of its phases. As expected, phase A4 (the most complete) can achieve the highest performance for every configuration (C2 to C4). The phase B of the algorithm is able to identify positions in C3 and C4. In fact it achieves a percentage of positions computed similar to A4, because the number of beacons in reach at any position is at least three. The baseline phase only uses triangulation to compute positions, so when there are three beacons available, positions can be delivered. Phase B does not include any limitations of building layouts, therefore some calculated positions may does not even be available. In fact, the average error for phase B in C3 or C4 is high, showing low accuracy of measurements.

Concerning to the average error in positioning calculated with the knowledge of precise positions previously defined, it is clear that there is an improvement (the error is low) with the increments on the algorithm (see Table 2). It is also shown that the number of beacons in reach affects the accuracy of the positions calculated. Taking into account the similar amount of positions computed (in C3 and C4), the average error is decreased in the C4. This behavior is more noticeable for the baseline phase.

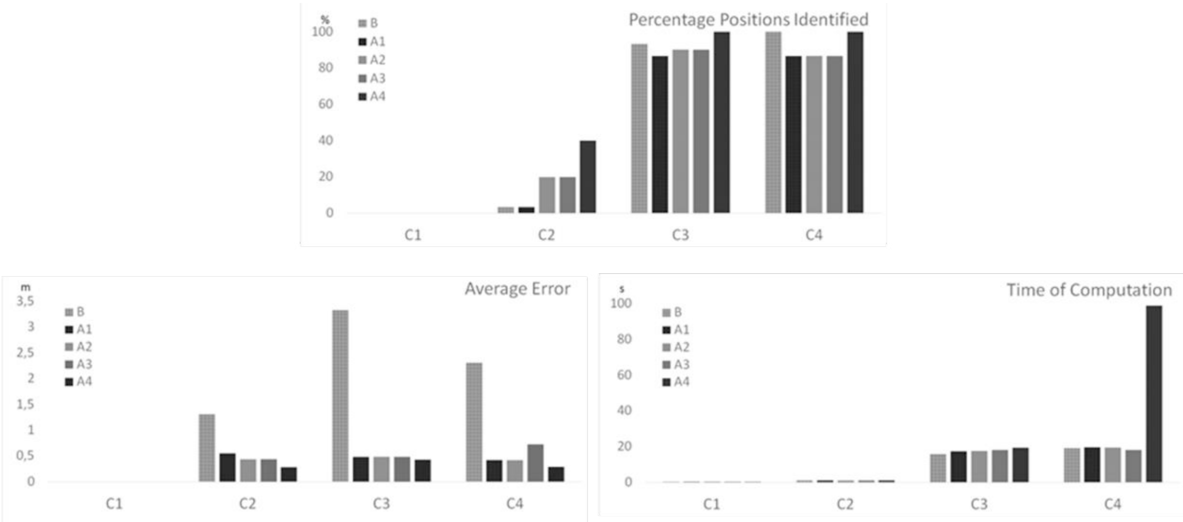

Fig. 3. Results of tests to evaluate RobustPathFinder.

Concerning to computation time, the maximum computation time achieved was 98.79 seconds for all 30 positions, which results in 3.293 seconds per position (average). Considering an ordinary walking speed, three seconds to identify a position may be too much. However, in a real situation the environment will have less beacons deployed, and a situation similar to configuration 4 (C4) is probably barely found.

A high number of beacons increases, in average, five times the computation time in phase 4, where voting and combinations methods were introduced. For a low number of beacons, the computation time is neglected.

5. CONCLUSION

Regarding the importance of location aware systems, in this work we proposed an easy indoor positioning system that locates persons in any location inside the building. We proposed mechanisms to handle the effects of location uncertainty. The algorithm was designed to handle several situations that may occur during the navigation inside the buildings. The system developed is able to determine positions under uncertainty conditions, including different layouts of buildings or different beacons in reach at any instant.

The proposed system is supported by beacons deployed in the environment and a device carried by the person to sense those beacons. It relies on signal strength measures.

In order to evaluate the proposal, a simulation environment was designed including every uncertainty situation that may be found in a real context. The tests performed evaluate the performance of different levels of complexity and show that the proposed approach mitigates the uncertainty issues present in indoor navigation systems. We also tested the influence of the number of beacons in the building, by placing more or less beacons in the simulation environment.

After the testing phase, we can conclude that the approach proposed can deal with several conditions, ranging from the lack of sufficient number of beacons in range to the existence of many beacons that can be used to vote the adequate readings and eliminate erroneous readings. Our approach also relies on the past positions to help better support determination of a new position.

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