EDIPS: An Easy To Deploy Indoor Positioning System to Support Loosely-Coupled Mobile Work

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Abstract Loosely-coupled mobile work is characterized by nomadic workers collaborating in sporadically and on-demand ways. Supporting nomadic workers' interactions requires knowing the location of the potential collaborator; therefore, indoor/outdoor positioning systems play a key role. Locating persons in outdoor environments is well addressed by Global Positioning Systems (GPS); however for the indoor scenario the solution is not so clear. Although several proposals for indoor positioning have been reported in the literature, most of them demand important setup efforts. This article presents the Easy to Deploy Indoor Positioning System (EDIPS), a WiFi-based system able to support the typical location requirements involved in loosely-coupled mobile work. EDIPS is aimed for fast deployment and real-time operations rather than for location accuracy. The system was preliminary evaluated as a support for locating medical interns' in a simulated hospital. The results obtained indicate the solution is able to locate nomadic workers in an indoor scenario, with enough accuracy to support loosely-coupled mobile work, while requiring minimal setup effort.

Keywords Indoor Positioning System, User Location Estimation, Loosely-Coupled Mobile Work, Nomadic Users.

1 Introduction

During the last years we have witnessed a revolution on mobile computing solutions. Advances in wireless communication technologies and mobile computing devices (from cellular phones to laptops) have allowed organizations, professionals, and individuals transfer part of their activities from desktop computers to these mobile devices [13]. Technological advances are also changing the work scenario and the human behavior and needs. Now, many persons are becoming "mobile workers" who want to be able to use any available time to continue working, independently of the place where they are located (e.g. at the office, a coffee shop, a plane or just walking) [5, 22].

Several researchers have shown that the computer-supported mobile work can improve the productivity of nomadic users in particular scenarios, such as healthcare [33], education [34], productive processes [28], mobile commerce [41] and emergency response processes [1].

Computer-supported mobile work includes various styles of work: *uncoupled work* (e.g. work done by mobile workers using only local resources), *loosely-coupled work* (e.g. a mobile worker interacting on-demand with servers and/or mobile workers during short periods of time) and *tightly-coupled work* (e.g. nomadic users working connected to servers/other mobile users) [17]. However, the most common mobile work style is loosely-coupled [29]. Since interactions between nomadic users doing loosely-coupled work are on-demand, positioning potential collaborators is a key issue for many activities; e.g., a nurse needing to find a physician to report changes in the health condition of a patient.

During the last years, positioning techniques and technologies have been strongly researched and developed. In particular, real-time positioning systems have generated strong attention given the high impact they might have on the broad spectrum of applications where ubiquitous information and services are predominant. Global Positioning System (GPS) is one of the most common and accepted technologies for outdoor positioning. Nevertheless, for indoors, GPS technology becomes infertile given its highly degraded or blocked satellite signal inside of buildings.

There are also several research works aimed at supporting mobile users' positioning in indoors. However, most of them require an important setup effort, which sometimes jeopardizes the feasibility of deploying a users positioning solution.

Key challenges for this type of indoor positioning systems are the capability of being deployed quickly and supporting real-time operations. These challenges set apart this type of positioning system from most of current technologies, which focus on higher accuracy achievements, a feature not mandatory for loosely-coupled mobile work.

This article presents the Easy to Deploy Indoor Positioning System (EDIPS), a WiFi-based system aimed for fast deployment and real-time operations rather than for high accuracy in positioning. The system is able to run in a broad range of mobile computing devices (from PDAs to tablet PCs) and interoperate in order to locate nomadic users by means of WiFi networks. Once deployed, the system is able to recognize the environment where the user is located, position other users on a map and react to changes on the user location.

This positioning system can be added as a service into other software applications to provide user positioning awareness. EDIPS has been preliminary tested in a

physical scenario simulating hospital facilities. Preliminary results indicate the system is easy to deploy and useful to position nomadic users performing loosely-coupled mobile work.

Next section presents the related work. Section 3 explains the positioning model used by EDIPS. Section 4 describes the EDIPS architecture, its main components and its user interface. Section 5 presents the evaluation process conducted to determine the accuracy of the EDIPS positioning system. Section 6 describes the evaluation conducted with medical interns in a simulated hospital scenario. Finally, Section 7 presents the conclusions and the future work.

2 Related work

Ample literature is available for real-time indoor positioning [4, 16, 23, 32]. Results describing partially successful efforts are available since at least a decade ago [3]. The existing proposals differ mainly in term of both, the method used to estimate the position of a resource and also the technology utilized to support the location process. These two elements typically establish several features of an Indoor Positioning System (IPS); e.g. its accuracy, deployment effort and coverage area. Next section presents the main strategies to estimate the position of indoor resources. Section 2.2 analyzes the technologies supporting IPS and some of the well-known implementations. Section 2.3 discusses various already implemented IPS, which could be used to support loosely-coupled work.

2.1 Indoor positioning location strategies

Indoor positioning strategies can be classified in four categories: triangulation, fingerprinting, proximity and vision analysis [19, 20]. These strategies can eventually be combined to enhance the positioning system.

Triangulation. This strategy takes advantage of the geometric properties of triangles in order to estimate the position of a resource. It considers a 2-D physical scenario. The estimation process uses three reference points with known geographical coordinates. Then, using the direction or length of the vector drawn between the location to be estimated (point A) and the reference points (B, C, D), it is possible to calculate the absolute position of point A [19]. This process is particularly known as tri-lateration. There are three methods typically used to calculate positions using triangulation: signal strength, time of arrival and angle of arrival [35]. The first two requires counting on three reference points to calculate a position, and the last one requires just two points. However, the angle of arrival method has accuracy problems when the target object to be located is far from the reference points [11]. The accuracy of the three methods improves when improve the number of reference points used for the estimation. An advantage of these methods is they involve just a small setup effort in order to start predicting the resources location.

Fingerprinting. This strategy calculates positions in a physical space by comparing current measurement of a given set of signals, with pre-measured data related to particular locations. Typically the strategy involves two phases: an offline training phase and an online estimation phase [20]. The goal of the offline phase is to collect samples of location related data (e.g. WiFi signals strength) for the whole physical space that is considered for the estimation process. The second phase uses such data to estimate the position of resources in such scenario. This method could be quite accurate, but it involves an important effort to collect samples during the offline phase.

Proximity. This strategy involves the use of detectors (e.g. RFID tags) that are located in known positions. When a target object is identified by a detector, the coordinates of such position are reported to a component in charge of mapping such data into a location in the physical scenario. The accuracy of this positioning strategy could be high, depending on the detection technology that is used. Such accuracy depends on the number of detectors deployed in the physical environment; the higher the density of detectors the higher the precision. This strategy is useful not only to position or track mobile users [6], but also to provide them personalized services [18] or support touch interactions [10]. RFID tags can be used to store data rather than only IDs [24]. A drawback of this strategy is the significant effort required for the setup process, which is usually high.

Vision Analysis. This positioning strategy analyzes images received from one or more capturing points (e.g. cameras located in the tracking area) [7], in order to try identifying a tracked object. Real-time analysis of images could be appropriate if the number of objects to be tracked is small. Otherwise, it is more efficient to combine this strategy with some of the previous ones, e.g. with triangulation, to reduce the number of images required for the analysis. IPS using this positioning strategy involve an important effort and cost during the setup phase.

2.2 Supporting technologies for IPS

There are several technologies that can be used to support the indoor positioning mechanisms [35, 19]. Among them are infrared, radio-frequency, Bluetooth, and sensor networks technologies.

Infrared systems need line-of-sight communication between transmitters and receivers without interference between the light source and the target [8]. Typically they operate based on target objects detection (i.e. proximity) with limited coverage. Some well known IPS using infrared are Active Badge [36], Firefly [12], and Optotrack [27].

Radio-frequency positioning systems use mainly triangulation and fingerprinting techniques [16]. Some of the radio-frequency technologies used by IPS are radio-frequency identification (RFID) and wireless local area network (WLAN). A well known IPS using RFID is WhereNet [38]. For the case of WLAN technology, some

well known IPS are RADAR [3], Ekahau [14], Compass [21] and Horus [40].

Bluetooth-based positioning systems mainly use proximity for resource positioning [30]. Typically, a Bluetooth-enabled device detects tags in indoor environments. Then, utilizing pre-loaded location information the mobile user's device can determine where the person is located. A well known Bluetooth-based IPS is Topaz [37].

Sensor-based positioning systems typically involve a large number of sensors, located in predefined indoor places, in order to determine the position of a person or a device [25, 26]. Positioning methods using sensor networks are usually complex and expensive. A well known sensor-based IPS is the ORP system [2].

The authors of this article consider, based on the above presented evidence, the most relevant supporting technologies seems to be radio-frequency; particularly the WLAN. The rationale behind this opinion is three-fold. First, it provides a suitable signal threshold. Second, it allows to deal with users' mobility in a gracefully manner. Third, it is anticipated this technology would involve a reduced deployment effort. Next section discusses more in depth some of the WLAN-based IPS, which could be used to support loosely-coupled mobile work.

2.3 Indoor positioning systems for loosely-coupled mobile work

There is a significant number of WLAN-based IPS reported in the literature, being RADAR [3] one the oldest infrastructure-based systems. This system processes RF-derived distances to determine positioning, sharing several similarities with the system proposed in this article, but lacks the quick deployability feature. The bulk of the contribution of RADAR to this work is the use of a pre-stored RF-signal strength map built either by direct measurements or by using a propagation model. Interesting particular contributions are the following: (1) study of different signal propagation models, and (2) empirical analysis on how diverse factors impact measurement and prediction. In particular, factors such as the number of measurement points, the sampling rate, and the body orientation of the person carrying the monitored device.

Horus [40] is another system that can be seen as an evolution from RADAR which tries to reduce the prediction error. Horus uses a probabilistic approach instead of the deterministic one found in RADAR. Probabilistic approaches would deliver better results than deterministic ones, according to [39]. Similarly to RADAR, Horus uses a two-phase process: an off-line phase for sample gathering and calibration, and an on-line phase, the actual positioning estimation task.

Lastly, a very interesting work on the impact of movement behavior on positioning is presented by Castro and Favela [9]. Their work is framed in a hospital context and proposes the use of neural networks to tackle the problem generated by sudden movement of users. Their work highlight that movement behavior related to the monitored device has a significant impact on position estimations.

The above described initiatives emphasize the trade-off between effort/cost and performance. The more the accuracy and precision the system delivers the more the training/calibration, or additional technology, it takes. For the research presented in this article, an error in positioning up to 6 meters is considered acceptable, the system here proposed is envisioned to be used for human monitoring applications.

In terms of the role that Wi-Fi technology may have for positioning purposes, apparently there are strong limitations imposed by effort involved in deploying phases on the level of accuracy that can be achieved. For example, Ekahau Real Time Location System [14] exhibits moderate accuracy, using WiFi signal strength fingerprints, while demanding significant amount of time [15] and effort during system set up and calibration phases. For the system proposed in this article, the calibration and system setup time are in the order of minutes. Another key difference between Ekahau and the model here proposed is access to information; in opposition to dissemination policies used in academia, details on algorithms and signal propagation model are not of public domain for systems like Ekahau. The following paragraphs detail the model for positioning developed under this research initiative, highlighting the concepts both derived from and different to the mentioned related work.

3 EDIPS positioning model

The solution proposed in this document relies, as some of the systems mentioned in the previous section, on the building and use of a signal strength blueprint. The key differences between related work and the research here presented lie on the performance during the blueprint creation task; algorithms on using Wi-Fi signal strength reference points to derive position estimations; and on exhibiting the capability to use and share the same blueprint among devices, indistinctly of the specific Wi-Fi interface embedded in each device. As one could expect, the downside for having such features is lower accuracy. Nevertheless, as this system is designed for human tracking and perception level, accuracy degradation is not an issue as long as it does not increase more than a few meters.

3.1 Off-line phase – Infrastructure and calibration

During this phase, the signal strength blueprint is created and loaded into the device. Signal strengths are calculated for each reference point. Only signal source are utilized for these calculations, and radial decay is assumed for signal propagation. While it may not be the best assumption when complete information is available, we consider it a fair assumption given the limited information known or required a priori. Signal coverage for each signal is attenuated or amplified based on parameters related to each device, setting, or reference point. Signal propagation is modeled as adjusted by a constant parameter independent of the emitting source. Again, it is

a very basic model, enough to provide suitable accuracy while enabling faster setting and calibration phases.

In opposition to RADAR, where signal decay models include the effect of walls, this effort only requires to be aware of the physical dimensions of the 2D space containing the operations area. Details on the map and realism are not relevant, only scale is considered. On the map, positions of access points are registered (see Figure 1) as well as their MAC address. Then, the tasks described in the following paragraphs are conducted in an automated manner.
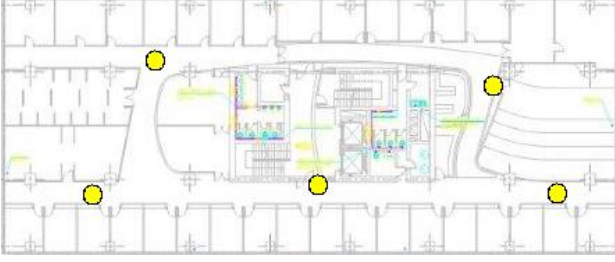

Fig. 1 2D map for the operations area showing the reference points (circles)

After the blueprint has been created the discretization process of the physical space is performed (Figure 2). Equal size cells are defined and overlaid on the blueprint. Each cell is given an a priori expected signal strength value considering the reference points. The spirit of the segmentation approach is to have cells independently treated in case different conditions affect them. Nevertheless, at this step in the general process, all cells are treated in the same manner.
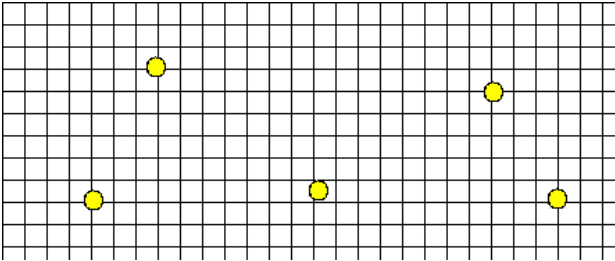
Fig. 2 Discrete cell model involving reference points (Wi-Fi access points)

Usually, signal decay modeling considers a large signal strength sample dataset gathered at many locations in the operations area. By doing this, system setup, calibration, and training are significantly impacted. In this work, system training step is completely removed; it favors quick deployment at a reasonable lack of accuracy. Figure 3 shows the signal strength landscape after all reference points' signals have been integrated into the operations area.
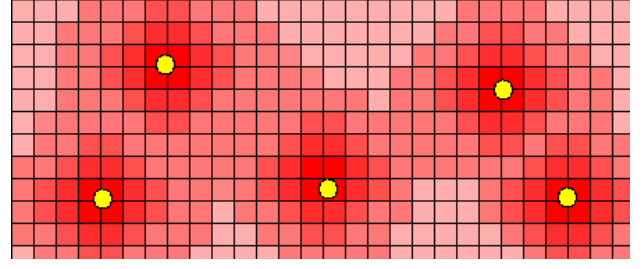
Fig. 3 Estimated signal propagation and decay model for the operations area

Regarding signal propagation and decay model, it is considered that a function $f(m)$ denoting the signal strength value at a distance m exists. Such function is used to determine the signal strength from source j detected at cell i as follows:

$$ SS\_Intensity_i = f(m) \times V_j \times K_D \times K_A $$

Where, m corresponds to the distance between cells i and j, V_j corresponds to a correction parameter for source j, K_D corresponds to a device correction parameter, and K_A is used to model environmental signal penetration. Unless these scalar correction parameters are specified by the user, they are given the unity value, i.e., 1.0.

In summary, input for off-line phase of the positioning system are: the 2D map of the operations area, and location and MAC address for each reference point. With this information a basic, but extremely fast, signal strength discrete landscape can be developed. The system allows the end user to decide which Wi-Fi signal propagation model to use. For example, the person setting up the system choose one among the ones already developed in some of the related work already described in the Introduction, or she can develop her own theoretical/empirical one.

3.2 On-line phase – Operations

The On-line phase aims to keep updated positioning information about devices being tracked. At every time step it updates the data used for position estimation and calculates the location. High variance in data sampled at this point does not allow raw data to be used directly, so signal strength data needs to be smoothed before used. By means of incorporating the last n signal strength readings from access points, weighting higher the recent ones than the older ones, positioning gets updated. Based on preliminary observations during the development of this system it seems that weighted average works better than standard average. From now on signal strength will refer to the weighted average of signal strength.

The positioning model tries to find the cells that minimize the error between the theoretical and sampled signal strengths. So, each cell from the grid is processed determining what place minimizes the error, including all other places given an error range. At the end of this iterative process the system holds a set of candidates pro the location of the device. The worst case happens when the set of candidates are distributed in a non-continuous region in the grid. Currently, the position is determined by

calculating the corresponding center of mass from the set of candidates.

3.3 Error weighting algorithm

This algorithm delivers a score (error) for each cell in the grid. The cells having the lowest scores are the ones considered as the ones where the monitored device most likely is located.

Let us have U representing the set of all the signal sources used as reference points, and U' the subset of cells containing the strongest signals. For each X in U' we call Xm the sampled signal from source X and Xi the corresponding theoretical signal for source X at position i. Then, the following formula is used to calculate the error for cell i:

$$Error_i = \sum_{X \in U'} (Xm - X_i)^2 \times f(Xm, X_i)$$

Given signal precision decays as it gets weaker, the calculation uses set U' instead of set U. Also, the quadratic error is weighted by a function f that favors stronger signals over the weaker ones. Quadratic error was chosen because it provides better treatment of variance in the sample.

The above described process can be improved with problem domain restrictions/knowledge. For example, people carrying/wearing the monitored device cannot displace over certain value in a given period of time. Consequently, error related to cells far from the current/last cell can also be weighted, and impractical further locations can be ignored. Finally, there is always space for introducing movement behavior models to include movement patterns, frequent trajectories, etc. It is out of the scope of this article and is part of future work.

4 Implemented indoor positioning system

EDIPS has a layered and fully distributed architecture. Each mobile device running this positioning system is autonomous and does not need the support of any other component to perform the positioning estimation process. The system may operate in a variety of devices, such as PDAs, smartphones, tablet PCs, and notebooks, supporting interactions among them, as well. Next subsections explain the role and components of each layer of the EDIPS architecture.
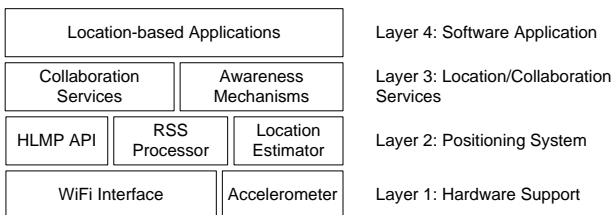
Fig. 4 EDIPS architecture

4.1 Hardware support

Since EDIPS uses WiFi not only to support the location process but also the communication/interactions among mobile workers, the WiFi interface becomes a crucial component. The positioning process must consider that WiFi antennas of different devices have different power. It means the signal emitted by an access point may be perceived differently by different devices, like smartphones and notebooks. Clearly, this situation affects the accuracy of the position estimation process. In order to deal with this issue EDIPS assigns a baseline signal strength for each type of device. The baseline signal strengths were established empirically based on several tests conducted by the authors using an important number of different devices. For example, the signal strength perceived by a smartphone is approximately the 70% of the signal strength perceived by a notebook located in the same place. On the other hand, signal strength differences among devices of the same type, even they do exist, they are not relevant in the position estimation process.

If the user wants to improve the accuracy of the positioning prediction process of his/her device, the system allows the users to tune the signal strength perceived through a correction coefficient that is particular for each device. No particular setting of WiFi interfaces is required to use the system.

If the device has an accelerometer, EDIPS is able to use it to enrich the awareness mechanisms deployed through the user interface; e.g. indicating that a nomadic worker is stationary or on the move. The accelerometer does not affect the accuracy of the location prediction process, and it is an optional component.

4.2 Positioning system

The positioning system involves mainly two components; a received signal strength (RSS) processor and a location estimator. These components are in charge of performing the estimation process described in section 3. However, there is a third component named HLMP API [31] that contributes to extend coverage area of the positioning system and eases the mobile workers discovery process. Next we present a brief explanation of such components.

RSS Processor. During the offline phase this component is in charge of establishing the reference points in the operations area. This component also enables users to do tune the signal strength perceived by the antenna of each mobile device. During the online phase the RSS processor retrieves, adjusts, records and informs the signal strengths perceived from the reference points (i.e. the access points). This information is then used by the location estimator component to predict the position of a resource (e.g. a mobile worker).

Location Estimator. During the offline phase this component performs the discretization of the physical space and characterizes the signal strengths for each cell of the map. Such information is stored in a XML file, which can be eventually shared among mobile users. During the online phase this component determines the most probable position of a target object depending on

the set of signals strength currently received by the mobile device. This functionality is useful not only to position resources but also to identify the physical scenario where the user is located (e.g. the 3rd floor of a particular building).

HLMP API. This component allows mobile workers keep connected and interoperate through a Mobile Ad hoc Network (MANET). Such infrastructure provides most communication services required by nomadic users when performing loosely-coupled work [31]; e.g. automatic formation of a MANET, automatic detection of users, automatic inclusion/exclusion of users, messages routing, and data synchronization. Since this infrastructure provides messages routing, the positioning system's coverage area could be extended over the limits of the WiFi communication range. For example, a mobile worker located in the 3rd floor of a building could know the position of a partner located in a contiguous floor. Since HLMP does not utilizes the access points or centralized components, the use of this infrastructure allows keeping the fully distribution paradigm proposed in the design of EDIPS. HLMP also helps to implement awareness mechanisms that are required to perform loosely-coupled work, such as users presence, users roles and public/private resources.

4.3 Location/collaboration services

This layer involves two components: (1) the collaboration services that support the loosely-coupled work and (2) the awareness mechanisms that allow nomadic users become aware of peers. Most collaboration services are based on services provided by HLMP API. Examples of such collaboration services are work sessions management, file transfer and floor control. These components partially support the indoor positioning systems. To exemplify a situation where collaboration services support the IPS, let us suppose the following work scenario. User A detects the presence of user B in an indoor environment through a service provided by HLMP API. However user A is not able to know the location of B, because A does not count on the information of the physical environment where s/he is located (i.e. the signals strength map and the blueprint of the physical environment). In such case, EDIPS running in the user A's device utilizes the file transfer service to obtain such information from B. Such information is dynamically loaded and thus user A is now able to locate user B.

The second component, i.e. the component that implements awareness mechanisms, provides feedback about the surrounding ambient and its composition through the device screen. Some of the awareness mechanisms already implemented in EDIPS are the users' presence and location, the map of the physical area where the user is located, and the mobility status of each user (i.e. if the user is stationary or on the move). The current implementation of the system updates this awareness information almost in real time. In order to shown more clearly these awareness components, next section presents the user interface that brings by default EDIPS.

4.4 Location-based software application

A simple location-based application was developed at EDIPS's upper layer in order to evaluate the positioning services provided by this system. The application supports the offline and online phases of the location process. During the offline phase it is possible to load a blueprint of the area and mark the position of the access point(s). Such activity represents the deployment of the system and it takes (depending on the physical scenario) a few minutes.

During the online phase the system presents the user interface shown in figure 5. There, it is possible to see the blueprint of the area in which the user is located and also the presence of other three nomadic users. The icon labeled as "me" is the local user, which is colored different to the rest of the participants. The user icon's shape also changes depending on mobility status of the user. For example, (in Fig. 5) the local user and "user 1" are stationary, and the other two users are on the move. "User 2" appears over an arrow; it means such user is out of the screen portion visualized by the local users. Shall the local user want to find "user 2", s/he has to walk in the direction indicated by the arrow.

EDIPS also has an icons bar and a menu. The icons bar allows the users to perform quick commands on the user interface; particularly the first icon centers the blueprint image in the upper left corner. The second icon centers the image in the local user. The third icon shows users that are around, but not visible in the portion of the blueprint shown on the screen. The last icon hides all icons except the local user icon.
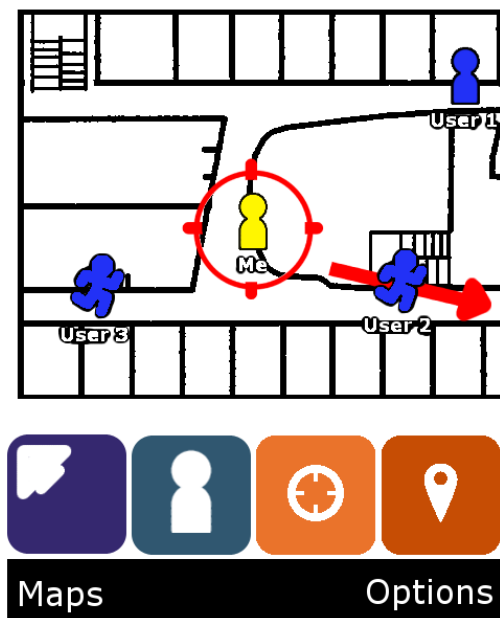

Fig. 5 EDIPS main user interface

The "maps" option in the EDIPS menu allows a person to access functionality related to blueprint and signals strength maps; e.g. to select the resolution of the blueprint shown on the screen or to obtain the signals strength map of a nomadic user near her. The option "options" in the menu allows configuring the visibility of

a user as a member of the physical environment. For example, a nomadic user could prefer to be invisible during some time periods because s/he wants to avoid interruptions from other users. HLMP API provides several visibility services, and this menu option allows the user to active/deactivate such services.

This application was used in two evaluation scenarios. The first one was focused on determining the accuracy of the proposed indoor positioning model, in addition to measure the effort required to deploy the system. The second scenario involved medical interns and had two goals: (1) to verify the effort required in the deployment process, and (2) to determine suitability of the application in supporting loosely-coupled work conducted by medical interns in a hospital setting.

5 Evaluation scenario I

The test of the system was conducted at the 3rd floor of the Computer Science Department of the University of Chile, in Santiago, Chile. This test was fourfold. First, the error in meters was calculated for certain points of interest. A Wi-Fi enabled device was used for both determining the signal strength propagation model and testing the performance of the system at the points of interest. No correction parameters were utilized, i.e., they all had value 1.0. Second, the performance of the system was observed while varying the device to be monitored. Third, correction capability of the model and signal quality were studied while more reference points were added. Finally, the fourth is same as the third, except this time the signal strength landscape was improved based on "patching" weak signal spots detected through the ongoing sampling.
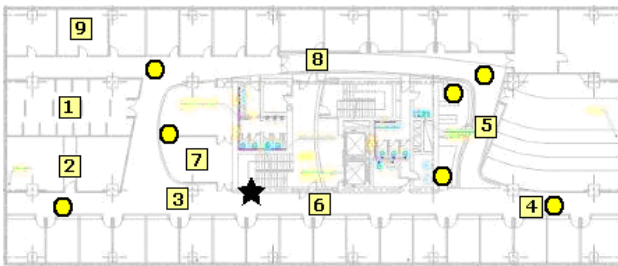
Fig. 6 Floor plan for testing operations area showing locations were different elements were placed

At the testing place there were already seven access points covering an area of approximately 55 x 24 square meters. Figure 6 presents the dimensions and the location of the elements utilized for this testing task. Numbered squares represent locations were measurements were conducted. The black star represents an additional reference point added during the second part of the test. Circles represent the locations of reference points, i.e., access points. Given the estimated position for the monitored device may not the same for different sampling, about 20 samples were averaged for every measurement point.

The device used during the first part of the testing was a HTC Diamond Touch, from now on referred to as HD1.

Table 1 presents the results for this part of the test. The measurements obtained at two points presented in this table are interesting. First, point 4 shows a small error, not surprisingly given its proximity to a reference point/access point. Second, at point 6 the error is large given increased distance to reference points. This point is a candidate for the third part of this test.

For the second the phase of the test a different Wi-Fi enabled cell phone was used. HTC Diamond Touch 2, from now on HD2, was selected. Among the results for this component of the test it was observed that for a given measurement point there was a difference of about 10dB between readings obtained with HD1 and HD2. This fact suggested that the model should be adjusted.

Table 1 Errors obtained for the different measurement points utilizing HD1 during the first face of the test

Point	Device	Average Error (m)	Standard Dev (m)
1	HD1	4,61	0,61
2	HD1	2,79	0,21
3	HD1	8,74	1,38
4	HD1	1,11	0,00
5	HD1	3,26	0,64
6	HD1	22,05	6,01
7	HD1	4,44	0,40
8	HD1	9,17	0,79
9	HD1	7,99	4,23

In the case of EDIPS, the propagation model is corrected by a constant modeled as intrinsic to the device, which tends to balance factors like having antennas with different gain among devices. HD2 received about 0.85 of the signals strength received by HD1, so the correction propagation model correction constant KD was adjusted accordingly. Table 2 presents the results for error calculation for the different measurement points.

Table 2 Errors obtained for the different measurement points using HD2 during the second face of the test

Point	Device	Average Error (m)	Standard Dev (m)
1	HD2	4,60	1,39
2	HD2	2,38	0,45
3	HD2	5,31	1,93
4	HD2	1,00	0,00
5	HD2	2,89	0,83
6	HD2	10,16	3,64
7	HD2	5,51	1,01
8	HD2	6,50	1,25
9	HD2	30,96	7,98

Given the results obtained at point 6 from the two previous measurement sets a new reference point was added nearby, represented by the black star icon in Figure 6. After that new measurements were taken at point 6 drawing the results shown in Table 3. These results highlight a positive correlation between error and distance to reference points.

Table 3 New measurements obtained at point 6 after reference point added nearby

Point	Device	Average Error (m)	Standard Dev (m)
6*	HD1	5,26	0,82
6*	HD2	5,92	1,49

The last part of the test is similar to the previous one, but it involves a different type of model correction. Point 9 exhibits a large error in previous sampling; even the signal strength received at that point is not weak. It leads us to think the issue was at the model level. After several samples were taken, the source correction parameter for the corresponding source was adjusted. Results after such adjustment improved significantly for HD1, but not for HD2 (see Table 4). We conjecture it was due to lack of reception of at least three strong enough signals at that point.

Table 4 New measurements obtained at point 9 after source correction calibration

Point	Device	Average Error (m)	Standard Dev (m)
9*	HD1	0,95	0,72
9*	HD2	6,04	2,63

6 Evaluation scenario II

A second evaluation scenario involved the 3rd and 4th floors from the Computer Science Department of the University of Chile (each floor having 1320 square meters). The building hosting these floors is similar to a hospital in terms of space distribution and materials used in its construction. The EDIPS deployment process took 12 minutes for the 3rd floor and 15 minutes for the 4th floor, involving only one person in such process. This is a minor deployment effort compared to the effort required by other IPS using fingerprinting, proximity or even triangulation.

The goals for this evaluation were twofold: (1) to verify the results obtained in the first experimentation phase and (2) to determine if the application could be useful to support the loosely-coupled work performed by medical interns in a hospital.

This experience involved three medical interns. Each medical intern had to find a target object (e.g., a person playing a medical specialist role) which was located in either the 3rd or 4th floor of the building. This activity is proper of a situation where the intern requires the opinion from a medical specialist in order to confirm a diagnosis. Three stationary and three mobile target objects were deployed in the evaluation scenario. To find the targets, each intern conducted six searching trials relying only on the EDIPS system, while an external observer monitored the interns' activities at all times registering how long it took them to accomplish the searching tasks.

The average error of the positioning system was 4-5 meters approximately, which is similar to the values obtained from the first evaluation process, described in the previous section. All target objects were found in the first try; i.e., the EDIPS system provided a direct access to the searched resources. Table 5 shows average and standard deviation values for the time spent during the resources searching process

Table 5 Time spent in searching for target resources

	Search Duration (Average)	Standard Deviation
Stationary target 1	1′30″	25″
Stationary target 2	2′15″	34″
Stationary target 3	1′57″	20″
Mobile target 1	2′24″	23″
Mobile target 2	1′58″	18″
Mobile target 3	2′37″	27″

Analyzing the results from each searching task we can appreciate from Table 5 that the standard deviation ranges from 15% to 27%. We interpret these results as a confirmation that the functionality provided by the EDIPS system is appropriate to conduct the searching process, and therefore the users do not require using additional personal capabilities (e.g. sense of orientation) to carry out such process. The variance for the time each intern spent on the searching trials may be explained as a consequence from the fact that walking speeds and routes followed to reach target objects may vary from intern to intern.

Fig. 7 and 8 correspond to the test labeled as "stationary target 2" in Table 5, where the intern looks for the medical specialist who is located in a hospital room doing personal work. Fig. 7 shows the EDIPS interface at the moment when User 1 (i.e. the intern) finds User 2 or "Me" (i.e. the medical specialist). Fig. 8 shows the same situation, but in the corresponding physical scenario.
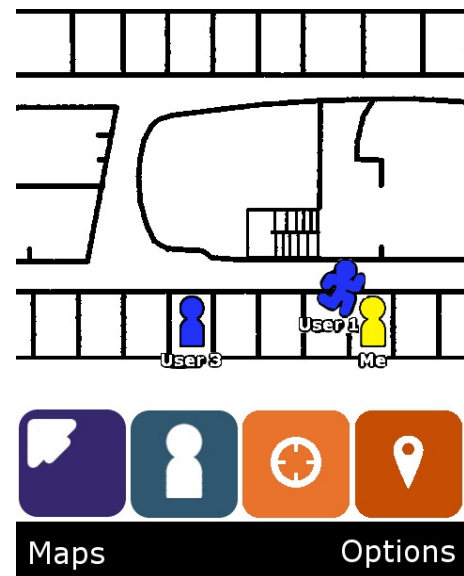
Fig. 7 Encounter between two users using EDIPS

Fig. 8 Encounter in the physical scenario

Once this experimentation process concluded, the interns were interviewed to gather their feedback on the usability and usefulness of this application. The responses from the interns were totally aligned with the feedback provided by the person monitoring the interns' activities: the EDIPS system is useful and usable to locate persons within the domain of application conditioned by its restrictions. While current results are still insufficient to make sound conclusions, the authors consider there is ample space to make the results improve significantly with further work.

7   Conclusions and future work

An encouraging development of an indoor positioning system is presented in this article. The key characteristics of this system are the following:

1. Quick building and setting up of this model. By setting a preliminary estimation for signal strength propagation much of the implementation effort can be reduced. Walls and more complicate signal propagation model utilized in other solutions are not considered here, improving performance for system start up. Nevertheless, the model proposed can be extended with as much detail as the user may need/desire, making this solution a very flexible one.

2. A great advantage of the system proposed is that it is very flexible regarding the signal strength blueprint; it can be built on theoretical or empirical data, or a combination of both.

3. Accuracy in positioning can be improved in an on demand basis, minimizing the efforts involved in such activity. In the results obtained during experimentation it has been shown that error is within a few meters. If error becomes greater than expected, the system provides calibration mechanisms to reduce it.

The system proposed in this article has mechanisms to deal with the variety of antennas that can be found in different Wi-Fi interfaces. This design feature is crucial to avoid ending up with a model tied to specific devices being monitored.

In terms of accuracy, the granularity level exhibited by the system developed may not allow tracking of objects inside a room, but it is adequate enough for people positioning and awareness. For example, it can be used for proximity awareness, people position tracking and monitoring, and situational awareness, among others.

Lastly, the work presented here opens encouraging paths for further research and development. Some examples are: continue research on error reduction strategies and methods; improve the model based on few initial measurements; develop a method to estimate the intrinsic constant associated to a device's signal decay and propagation; explore the impact of varying grid/cells dimension, also for memory and processing optimization; investigate the incorporation of inertial measurement units or inertial navigation systems, or a combination of multiple navigation sensors. All the previous ideas framed within the goals of this initiative: to have a system that is quickly deployable, easy to modify and adapt, while still delivering enough accuracy for indoor people tracking.

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