Fine-grained Evaluation of Local Positioning Systems for Specific Target Applications

Erwin Aitenbichler[1], Fernando Lyardet[2], Aristotelis Hadjakos[1], and Max Mühlhäuser[1]

[1] Technische Universität Darmstadt, Hochschulstrasse 10, 64289 Darmstadt, Germany
[2] SAP Research CEC Darmstadt, 64283 Darmstadt, Germany

Abstract. Location-aware software has become widespread outdoors. Indoor applications are now on the rise. However, careful selection of the appropriate local positioning system (LPS) and application fine-tuning are required in order to guarantee acceptable user experience. We present a simulation-based approach that includes application characteristics, LPS characteristics, and building characteristics to this complex task and illustrate how the appropriate LPS can be chosen and how applications can be fine-tuned. A sophisticated indoor navigation system is used as sample application. The paper also provides insights into subtle details and caveats of different LPS technologies from an application and building viewpoint.

1 Introduction

While the Global Positioning System (GPS) is the de-facto standard for outdoor positioning, there is currently no single standard for indoor positioning. Here, developers can choose from several different Local Positioning System (LPS) technologies which all have their specific advantages and disadvantages [1, 2]. The most important question for a developer when choosing an LPS is if it suits the needs of a specific application.

A first hurdle for the comparison is that depending on the underlying technology, the accuracy of an LPS is specified in different ways. For RF-based systems it is common to specify the radius of a circle containing 95% of all measurements for a given location or the RMS error as accuracy. In contrast, for an Infrared Badge system the maximum range could be specified as a property.

Beside *accuracy*, the *resolution* of an LPS is an important property. These two properties are often only loosely connected. For example, the system with the highest resolution may often not be the best choice. Consider an application that needs to determine in which room a user currently is. WLAN-based systems provide 3D coordinates with centimeter resolution and are known to have an accuracy of about 2-3 meters, but if the user is standing close to a wall, a system accuracy of 2-3 meters does not allow to distinguish between rooms reliably. An Infrared Badge system has only room resolution, but because light does not pass through walls, it also has room accuracy. Thus, the latter system is a better match for the given application.

A more fundamental problem is that these diverse LPS properties cannot be directly matched with the diverse requirements of an application. For example, the following application requirement could be specified: “Explain object X to the user as soon as she can see it, but never if she cannot see it." To match application requirements with the characteristics of currently available LPSes, a general approach is needed. In this paper, we present a simulation framework allowing a detailed analysis of the impact of LPS properties on an application.

This paper is structured as follows. After a discussion of related work in Section 1.1, we present the architecture of our simulation framework in Section 2. The general properties of LPS are evaluated in Section 3. As an example for a reasonably complex application we present the Context-aware Indoor Navigation System (CoINS) in Section 4. Then we present the results of a simulation-based evaluation of CoINS with four different LPSes currently useable with modern mobile phones in Section 5. We then derive the *application success rate* from the experimental data. This measure denotes the probability that the user can be guided correctly, i.e., the system will provide the user with the correct directions at the correct time. Finally, the paper is concluded in Section 6.

1.1 Related Work

General descriptions of LPS properties and system comparisons are subject of book chapters in [2] and [1]. Over the past few years, a notable progress in the field of LPS research was the fusion of data from multiple LPS systems with very different characteristics. Hightower et al. describe the use of particle filters to combine the data from WLAN and Infrared, which is a symbolic location source [3]. Woodman et al. describe the combination of WLAN with a Pedometer, which is a relative location source [4].

However, to the knowledge of the authors, there are currently no existing approaches for the generic matching of LPS properties with application requirements.

2 Simulation Framework

Figure 1 shows the architecture of the simulation framework. The **Application Description** is an XML file specifying the requirements of an application in an LPS-independent way. The most important elements for pedestrian applications are *location tests* and *walk tests*:

- **Point(P):** Expresses that the application needs to determine that a user is at a location P. The permitted tolerance can be specified as a simulation parameter.
- **Rect(P,Q):** Expresses that the application needs to determine that a user is in the spatial area defined by a cuboid ranging from P to Q.
- **Walk(P,Q):** Expresses that a user is expected to walk from P to Q and the application needs to determine that the user has reached Q.

Such elementary tests can be combined to describe more complex requirements:

- **Test** is a structuring element that surrounds the tags described above. The simulator determines the probabilities of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) for each test. Tests can be nested and previously executed tests can be referenced and included as subtests.

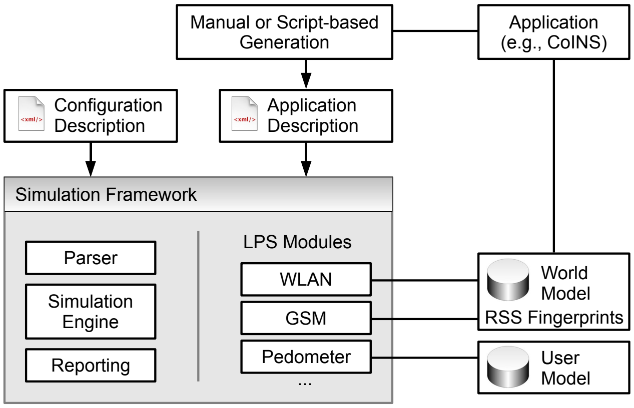


Fig. 1. Simulation Framework Architecture

- **Testunit** serves as a structuring element to group tests of the same kind. The difference to nested tests is that nesting expresses a is-subtest-of relationship, while test units express an is-kind-of relationship.

The **Application Description** can either be written manually or generated automatically using a script. For complex applications like CoINS the latter approach is beneficial. Here, the script directly interacts with the route planning component of CoINS to generate test cases.

The **LPS Modules** simulate the behavior of specific LPS systems. These modules may need additional information from the World Model, such as Received Signal Strength (RSS) fingerprints or user body dimension data to simulate a pedometer-based LPS. The LPS modules and their associated data are application-independent.

The **Configuration Description** controls the whole simulation. It defines which tests of the application description should be executed using which LPS systems and what kind of reports should be generated.

2.1 LPS Modules

This section gives a brief overview of the indoor positioning systems that are supported by the LPS Modules of the simulator.

Wireless LAN: Devices with WLAN interfaces can be tracked within a WLAN infrastructure. The simplest form of WLAN tracking determines in which cell the user currently is. This way, it is possible to locate users with an accuracy of about 25-50m. By using location fingerprinting, the accuracy of WLAN systems can be improved to about 3m [5, 6]. However, fingerprinting requires the creation and maintenance of radio signal propagation maps, which is considerable effort if not done by robots [3]. WLAN tracking can be completely done in the infrastructure without requiring any special software on the client or it can be done on the client. There are several software products for WLAN positioning available, e.g., PlaceLab [7] or Ekahau [8]. The big advantage of this approach is that it does not require any specialized hardware and thus can be used in conjunction with off-the-shelf smartphones and portable computing devices.

GSM: The location of a mobile phone can be either determined network-based or client-based. Unfortunately, there is only little standardization of APIs beside the E911 requirement and cellphone locations can often only be obtained by purchasing operator-specific APIs. These are often limited to single operators and countries, and each location fix costs a fee. However, similar to WLAN, it is also possible to perform client-based positioning with GSM [9]. Furthermore, it is also possible to apply fingerprinting techniques.

Ultra-WideBand: UWB systems utilize a much larger RF spectrum for their measurement signals. This allows them to handle multipath effects adequately, resulting in an order of magnitude better accuracy compared to systems based on a single frequency. One of the most advanced UWB location systems is available from Ubisense [10]. The Ubisense system comprises UbiTags carried by people or objects and several stationary UbiSensors. UWB systems employ the so-called inverse-GPS (IGPS) principle, which is similar to GPS, but with reversed roles: UbiTags emit short UWB pulses, which are received by at least three UbiSensors. The sensors measure the time differences of arrival of the UWB pulse and use trilateration to calculate the tag's position. In addition, Ubisense measures the angles of arrival to improve the reliability of the position information. UWB systems provide an accuracy down to about 15cm. However, they require specialized hardware at the user and in the infrastructure.

Pedometer: Pedometers are usually based on an acceleration sensor and count steps by analyzing its signal data. This principle works most reliable when wearing the sensor on the foot or in the shoe [11]. The accuracy decreases when the sensor is worn on a helmet [12], in the pocket [13], or in the hand [14], but users can still be located with a reasonable accuracy. Such a positioning system is typically constructed out of a pedometer and an electronic compass to get orientation information. However, because the positioning error continuously increases in such a system, sensor fusion with an absolute positioning system, e.g., WLAN, can considerably improve its accuracy [4].

QR Codes: Quick Response (QR)-Codes [15] are two-dimensional barcodes that were standardized by ISO in the year 2000 (ISO/IEC 18004). To date, QR reading software is available for almost any smartphone. QR codes can be used to create "physical world hyperlinks". A user having a camera phone can scan the image of a QR Code causing the phone's browser to launch and redirect to the programmed URL. QR codes can be used to determine physical location by encoding locations into URLs.

Infrared Badge Systems detect if a badge worn by a user is within line-of-sight distance of a stationary receiver. Elpas [16] is a badge-based system that combines Infrared, low frequency RF proximity sensing, and high frequency RF. It can cover entire buildings and depending on the amount of infrastructure deployed, its accuracy varies between 25m and 2m. Elpas provides only symbolic location. The number of supported distinct positions is equal to the number of sensors deployed.

It is also interesting to investigate the use of GPS indoors. GPS [17] is basically not suitable for indoor positioning, because the system requires a direct line of sight from the receiver to multiple satellites. GPS Repeaters can be installed into the infrastructure of buildings to make GPS available indoors. A repeater consists of a receiving antenna mounted with a clear view to the sky and a sending antenna mounted indoors. The sender has a range of about 3-10 meters and forwards the combined signals of all visible satellites observed at the location of the outdoor antenna. Consequently, the number of supported distinct positions is equal to the number of repeaters.

3 Evaluation of Positioning Systems

Because WLAN, GSM, acceleration sensors, and cameras are available in modern cellphones, we selected positioning based on WLAN, GSM, pedometer, and QR codes for a detailed evaluation. As a first prerequisite for a simulation, the LPS properties are determined at the application site. WLAN and GSM positioning require the creation of RSS fingerprint maps. To simulate pedometer input, the movement characteristics of several people using body-worn sensors are collected.

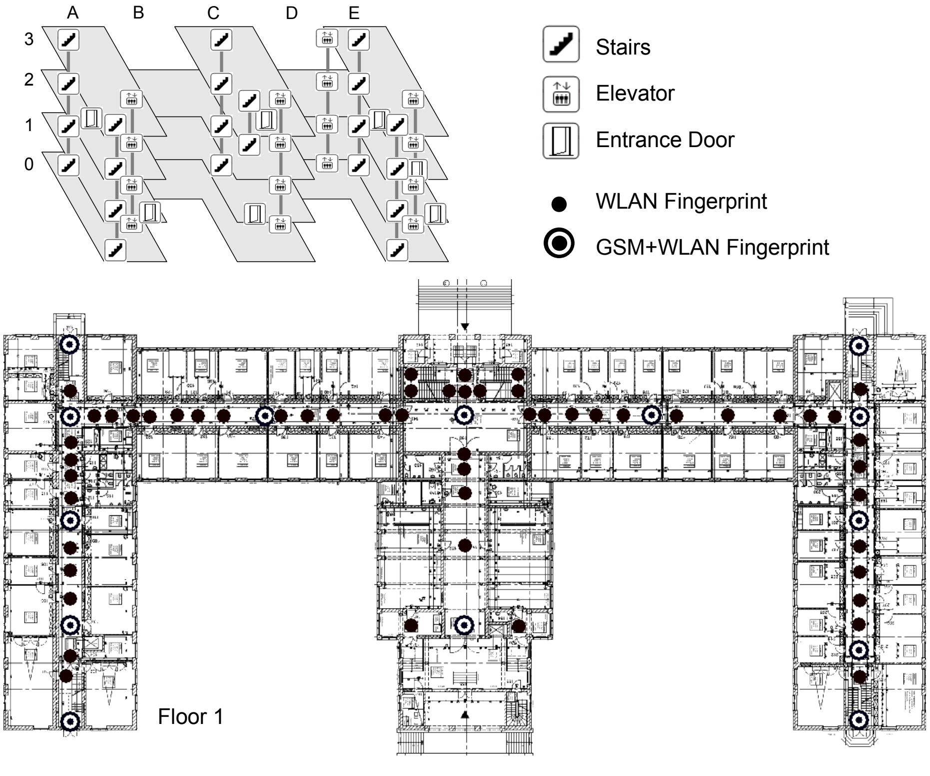


Fig. 2. Layout of the Piloty Building and Fingerprint Locations for One Floor

Figure 2 shows the Piloty Building at the University of Darmstadt. It is a four-story building that accommodates most of the computer science groups. The floors are connected through six different stairs and four elevators. The footprint of the building is approximately 110m x 55m.

The small dots show the locations where the WLAN fingerprints were measured. A fingerprint was typically taken in front of each office door. The big dots show the locations where WLAN and GSM fingerprints where measured. In total we took WLAN fingerprints at 225 different locations and GSM fingerprints at 43 different locations.

3.1 WLAN Fingerprinting

A single RSS measurement of the access point i is denoted as s_i. When all visible access points are measured at a certain location, then the result is a vector $S = (s_1, ..., s_m)$. To reduce the effect of noise, S is measured multiple times, resulting in a data set $T = (S_1, ..., S_n)$. A fingerprint for a defined position $p = (x, y, z)$ is a tuple of location and average RSS vector: $f = (p, \frac{1}{n}\sum_{i=1}^{n} S_i)$. Fingerprints are measured at all locations important to an application. The result is the set $F = \{f_1, ..., f_n\}$ containing all fingerprints.

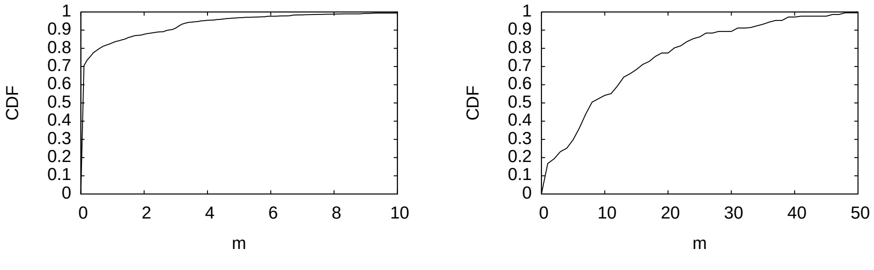
A mobile terminal that wants to determine its position first measures an RSS vector S_x. Because of the structure of this environment, the position is estimated by calculating the weighted average of the two closest fingerprints in signal space. These are

$(p_1, S_1) = \arg\min_{(p,S)\in F} |S - S_x|$ and
$(p_2, S_2) = \arg\min_{(p,S)\in F \wedge p\neq p_1} |S - S_x|$.

The estimated position p_x is

$$p_x = \frac{|S_1 - S_x|}{|S_1 - S_x| + |S_2 - S_x|} p_2 + \frac{|S_2 - S_x|}{|S_1 - S_x| + |S_2 - S_x|} p_1$$

The WLAN fingerprints were recorded with an UMPC at 225 different locations in the building, typically in front of each office door and at other spots that could be important for navigation. Each fingerprint was calculated by averaging at least 20 samples. In a separate measurement, a total of 8692 test samples were recorded at the same locations and the positioning algorithm was applied to that data. The result indicates an RMS error of 1.81m. Figure 3(a) shows the Cumulative Distribution Function (CDF).



(a) WLAN (b) GSM

Fig. 3. General Accuracy of Fingerprinting

3.2 GSM Fingerprinting

GSM positioning uses the same algorithm as described before for WLAN. The GSM fingerprints were recorded with an iPhone at 43 different locations in the building. In a separate measurement, a total of 430 test samples were recorded at the same locations. The result indicates an RMS error of 16.82m and the CDF is shown in Figure 3(b). The results of WLAN and GSM fingerprinting are summarized in Table 1.

Property	**WLAN**	**GSM**
Number of fingerprint locations	225	43
Number of test point samples	8692	430
Minimum number base stations per location	2	3
Maximum number base stations per location	13	9
Average number of base stations per location	6.16	6.72
RMS error	1.81m	16.82m

Table 1. Collected Fingerprints

3.3 Pedometer

To collect the necessary sample data for the Pedometer LPS simulation module we used our MotionNet [18] sensor system and recorded data from six different users. One sensor was worn on the foot, one on the head (on a headset) and one attached to an UMPC in the hand. Figure 4 shows the sensor signals and the derived step signals acquired during a 28m walk.

Steps can be detected very reliably from the foot signal using the following signal processing steps. First, a highpass filter (IIR, Butterworth, 10 Hz, 10^{th} order) is applied to remove static and low-frequency components from the signal. Next, the signal is rectified. A moving average filter (window size 0.1s) is then used to smoothen the signal. Finally, a hysteresis threshold filter obtains the binary step signal.

User	**E**(l_{step})	$\sigma(l_{step})$	**Foot**	**Head**	**Hand**
1	75.3 cm	1.98 cm	100%	98%	94%
2	83.1 cm	3.66 cm	100%	94%	94%
3	83.2 cm	3.39 cm	100%	96%	97%
4	70.1 cm	4.33 cm	100%	95%	96%
5	85.3 cm	2.33 cm	100%	99%	99%
6	72.2 cm	1.82 cm	100%	99%	98%
Avg	78,2 cm	2.92 cm	100%	97%	96%

Table 2. Step Detection Recognition Rates

The signals from hand and head are significantly weaker and therefore more difficult to process. To detect steps, we first apply a bandpass filter (IIR, Butterworth, 1-3 Hz,

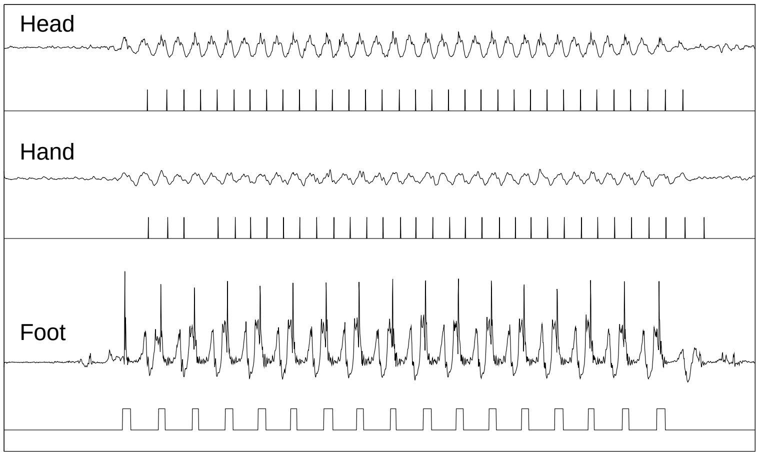


Fig. 4. Sensor Data and Derived Step Signals for Pedometer LPS

10^{th} order) to obtain a sine-like signal. Steps are counted if the maximum value between zero crossings exceeds a threshold value.

From the calculated step signals we can derive the average step length, its standard deviation, and the recognition rates at the foot, head, and hand of each user. Table 2 summarizes the results.

4 The CoINS Application

After the general analysis of the positioning systems, the next step is to create the application description. In this work we use the Context-aware Indoor Navigation System (CoINS) [19] as reference application that should be simulated. First, the following section provides a brief overview of CoINS.

The aim of the Context-aware Indoor Navigation System (CoINS) is to provide efficient user navigation in buildings with a strong emphasis on the “human factor”. When considering the human as part of the system, the term *efficient* does not longer simply correspond to the shortest path calculated by some mathematical method. To efficiently navigate users to their destinations, it is also vital that they can quickly comprehend and execute the navigation instructions they receive from the navigation system. For example, a good route description would consist of a low number of turns, turns would be at ”landmarks” the user can easily identify, and would always clearly indicate the directions in which the user is supposed to walk.

4.1 World Model

The CoINS world model is a hybrid model that combines symbolic graph-based models with geometric models. A symbolic model is required for indoor navigation, because *room numbers*, *corridor names*, *floor numbers*, etc. have an intuitive semantics to users. Using geometric coordinates for end-user interaction would not be suitable. The geometric model is needed for determining the shortest paths and to obtain orientation information for guiding users into the correct directions. The world model serves two main purposes.

First, it supports transformations between geometric coordinates and symbolic locations and vice versa. When a 3D tracking system is used that provides geometric coordinates to locate users, the model must be able to transform this coordinate into a symbolic location, such as a room number. The pathfinding algorithm of CoINS starts with the symbolic models to create a coarse plan of the route. After that, the geometric models are used for fine-planning.

Second, the model enables efficient pathfinding. The design of the CoINS world model has been refined over several iterations to ensure that the search sets are as small as possible and that the basic relations needed by the pathfinding algorithm can be checked efficiently. In most cases, users will mostly move in two dimensions. Movements in the height dimension usually only occur when changing floors, which is modeled by using separate maps for each floor.

4.2 User Centric Adaptation

The user model we have developed and applied in our indoor navigation technology combines three aspects besides user identification data: physical capabilities, user preferences, and location access rights. This model presents a Multiattribute Utility Theory-based architecture that enables decision making according to user interests.

To select the most suitable path for a specific user we use the Simple Multi-Attribute Rating Technique [20]. Under this technique, every path can be described by individual preference attributes and through the value functions of each single attribute, the preference strength can be measured.

4.3 CoINS Architecture

CoINS is based on the open-source communication middleware MundoCore [21]. For the implementation of CoINS, we adopted a service-oriented architecture, because it allows deploying application components according to different scenarios and improve their reuse by other applications. E.g., if a client only supports a web browser, all components of CoINS can run on a server in the Internet. A more powerful client such as an UMPC could already run the whole CoINS system locally.

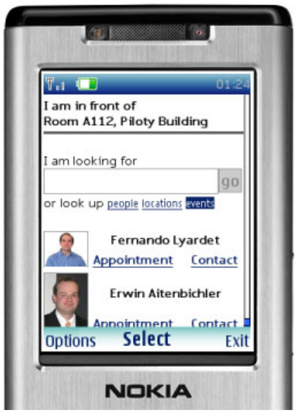
CoINS uses the Mundo Context Server [22] to track the locations of users. Because this software provides an abstraction layer above the physical sensors, CoINS can use standardized queries and does not have to be aware of the underlying sensor technology.

The Presentation Component of CoINS can be either accessed as web interface through a web server or from rich clients. The web-based solution has the advantage that no software deployment is necessary on clients, but location tracking is limited to QR codes or purely infrastructure-based solutions. In contrast, rich clients can provide more customized user interfaces and support additional local positioning systems.

5 Evaluation of CoINS

We performed our experiments in the Piloty building of TU Darmstadt. Despite room numbers being systematically constructed of building wing letter, floor number, and room number, e.g., A121 stands for wing A, floor 1, room 21, navigation in the building is not always straightforward. For example, one computer pool in level 0 is accessible to students 24 hours a day. The connecting doors around this area are locked for security reasons. Also, several connecting doors on other levels cannot be passed by students or visitors. Not all elevators can reach all levels and the three wings of level 3 are not directly interconnected on level 3. Consequently, the building structure is complex enough to pose some challenges to an indoor navigation system.

Directions = { IntermediateSegment Connector } EndSegment End;
IntermediateSegment = [Turn] ”walk” (”to end of corridor” | Straight);
EndSegment = [Turn] [Straight];
Connector = Door | Elevator | Stairs | ϵ;
End = ”destination is on your” (”left” | ”right”);
Straight = ”straight for” number ”meters”;
Door = ”go through door”;
Elevator = ”take elevator” [Side] Floor;
Stairs = ”take stairs” [Side] Floor;
Side = ”on your” (”left” | ”right”);
Floor = ”to floor” Number;



I am in front of
Room A112, Piloty Building

I am looking for

or look up people locations events

Fernando Lyardet

Erwin Aitenbichler

Fig. 5. CoINS: EBNF Grammar for Directions and Screenshot

To start the guiding process, a user opens the CoINS application on her mobile terminal and selects the desired destination. The application allows to search the database for people, room numbers, events, etc. Alternatively, a user could read a QR code from the business card of an employee to select the destination. CoINS then determines the user's current location and calculates the navigation route.

CoINS gives the user textual directions how to proceed to finally get to the desired destination location. Figure 5 shows the grammar describing the directions CoINS could possibly generate. It is somewhat simplified but in principle covers all possible directions CoINS would generate for the Piloty building

The locations that must be recognized by an LPS can be derived from this grammar. The whole navigation route can be decomposed into multiple segments. An LPS is expected to provide the information if the user has reached the end of a segment, i.e., *Connector* or *End*. This way, CoINS is able to verify whether the user has successfully followed the instructions and it can proceed with explaining the next segment to user.

A route consists of a *start location*, an arbitrary number of *intermediary segments*, and one *end segment*. In case of the Piloty building, an intermediary segment always ends with the end of a corridor, a connecting or exit door, stairs, an elevator, or in open space. When the end of such a segment is reached, the user receives the next direction. Finally, the end segment ends with the desired destination, e.g., an office room. Hence, a location system suitable for CoINS must fulfill the following requirements:

- When starting the navigation, the system must be able to determine the absolute position of the user with a high accuracy. At least floor and section of the building must be correct.
- The ends of intermediary segments must be detected with a very high accuracy, because a navigation route will typically consist of multiple segments. Especially it is vital that the system does not report any false positives, because the user must be able to see the stairs or an elevator when the system tells her to use it.
- The accuracy when detecting the end of the end segment should be reasonably high, but it does not have to be as high as for the ends of intermediary segments, because the user is already close to the destination. It is not so important that the system is able to recognize the exact door when navigating to a specific office.

5.1 Start Locations

The start locations for navigation are often identical with the ends of intermediary segments, because the user would often start at an entrance door or elevator. However, in general it is necessary to detect the correct floor and wing anywhere in the building. Table 3 shows the results for WLAN and GSM fingerprinting. The user can also take a picture of a QR code to determine her location. QR codes are printed on the doorplates in the Piloty building. The column TP contains the percentage of true positives and the column FP contains the percentage of false positives.

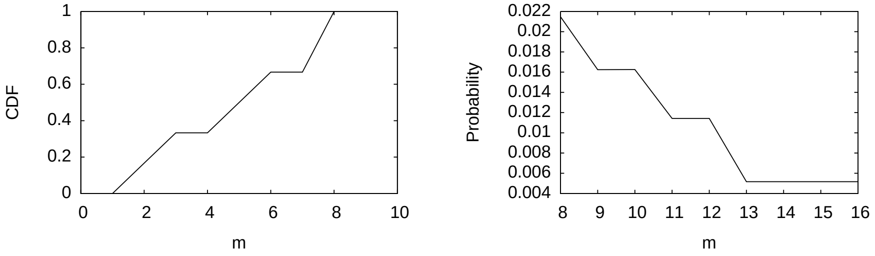
Test	**GSM TP**	**GSM FP**	**WLAN TP**	**WLAN FP**	**QR TP**	**QR FP**
Correct floor	26%	8.75%	99.8%	0%	100%	0%
Correct floor and wing	13.1%	2.21%	99.1%	0%	100%	0%
Correct entrance	100%	1.14%	100%	0%	100%	0%

Table 3. Start Locations

The results show that GSM is not accurate enough to distinguish between the floors of the building. For that reason, we introduce a new test that tries to distinguish between the six entrance doors of the building in one level. The results are shown in Figure 6 and indicate that this is possible. We choose the radius r_s=8m for the small circle and the radius r_l=12m for the large circle. r_l must not exceed 13m, because the minimum distance between any two test points in this set is 26m. The meaning of these two circles is explained below.

5.2 Intermediary Segments

There are 33 areas in the building which are ends of intermediary segments. To verify that we can reliably detect these areas, the following experiment was performed. From



(a) True Positives (b) False Positives

Fig. 6. Accuracy of Locating Entrance Doors with GSM

the center of each area we draw two concentric circles and then distinguish the following cases.

- If a user stands in the small circle, i.e., very close to the location of a *Connector*, we absolutely expect the system to react. We chose *3 meters* as diameter for this circle. It is mandatory that an LPS detects this occurance with a probability close to 100%. The test is counted as a *true positive* if 50% of the test point samples fulfill this criteria.
- If a user stands in the large circle, i.e., close enough to the location of a *Connector* to physically see it, then it is acceptable when the system reports that the user has reached the segment end. From empirical tests we have determined that about *4 meters* are the upper bound for this feature.
- If the user stands anywhere outside these two circles, the system must never report that the user has reached the end of the segment. This would result in the user receiving an instruction that would be useless to her. Hence, such *false positives* must be avoided and the probability of this occurance must be close to 0%.

5.3 End Segments

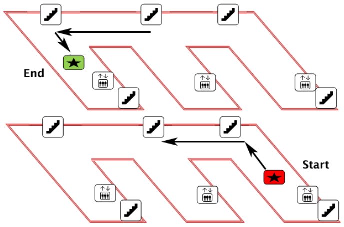
The end segment extends from the last intermediary segment to the destination location of the navigation. This is typically the location of an office. Hence, the simulator simulates a user walking from the location of the last connector to the destination location. The error calculation is the same as for intermediary segments.

5.4 Routes

A route consists of a start point, zero or more intermediary segments, and an end segment. The application description comprises 2282 different combinations of intermediary segments. Figure 7 shows an example route and how the individual errors are accumulated to give the TP and FP values for the whole route. The test method is very strict: If some segment of the route fails with a probability P, then the whole route also fails at least with probability P.

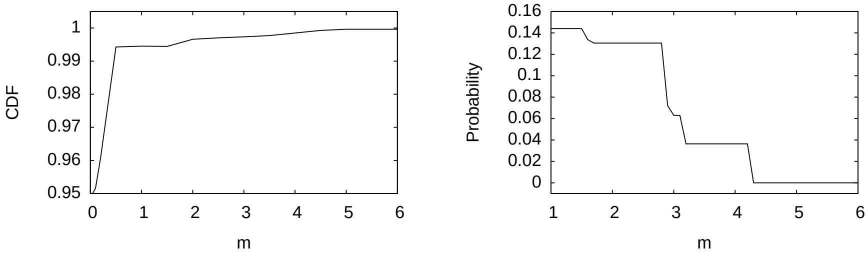
Segment Type	Segment Name	TP	FP
start	E120	0.98	0.05
intermediate	EC1	1.00	0.00
intermediate	CA2	1.00	0.40
end	A210	1.00	0.00
route	E120-A210	0.98	0.43

(a) Error Calculation

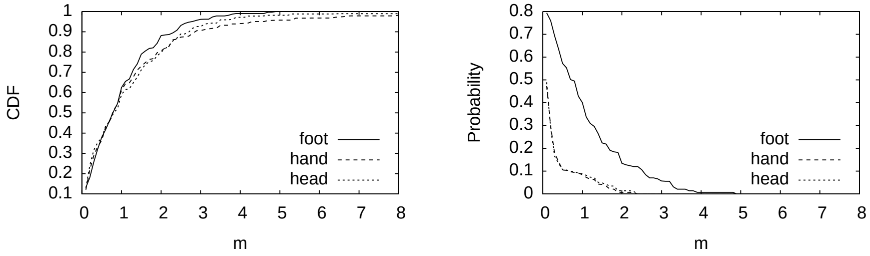


(b) Route Example

Fig. 7. Accumulation of Errors when Testing Routes



(a) True Positives for WLAN LPS (b) False Positives for WLAN LPS



(c) True Positives for Pedometer LPS (d) False Positives for Pedometer LPS

Fig. 8. Success and Failure Rates for Entire Routes

Figure 8 shows the results of the WLAN test. Based on the TP curve, we can select r_s=1m, which meets the defined requirement. However, the false positives are still considerable at r_l=4m. We can either stay with this requirement and accept a FP probability of 3.6% or change r_l to 4.3m.

Figure 8 shows the results from the Pedometer test. The sensor worn on the foot provides the best results. Steps can be detected reliably from this sensor, while not all steps can be detected based on the data from the head and hand sensors.

5.5 Application Success Rates

Finally, from the simulation output, the overall application success rates can be calculated. The results are summarized in Table 4. The results indicate that WLAN positioning with the initial requirements r_s=150cm, r_l=400cm cannot be satisfied well, because the application success rate would only be 95.5%. If we allow r_l=430cm then the application success rate becomes 99.1% and is only limited by the accuracy of the start position fix. An application success rate of 99.1% means that about 110 of 111 users will not encounter a single glitch when interacting with the CoINS system.

The test case GSM+Pedometer is constrained, because GSM is only able to distinguish between the six building entrances. Hence, guidance can only start at the entrances in this case.

Reading a QR code is a reliable way to determine one's start position. However, this method requires manual user interaction. Once the position is known, CoINS can perform quite accurately using compass and pedometer. If the step sensor is mounted on the foot or in the shoe, the results are significantly better compared to sensor on head or in the hand. The case *sensor in the hand* is quite interesting, because a mobile phone with an acceleration sensor could be directly used to implement a pedometer.

System(s)	**Start Location**	**Route**	**Total**
WLAN (4.3m)	99.1%	100.0%	99.1%
WLAN (3.2m)	99.1%	96.4%	95.5%
GSM+Pedometer (foot, 5m)	98.8%	100.0%	98.8%
QR+Pedometer (foot, 5m)	100.0%	100.0%	100.0%
QR+Pedometer (foot, 4m)	100.0%	98.3%	98.3%
QR+Pedometer (head, 4m)	100.0%	97.2%	97.2%
QR+Pedometer (hand, 4m)	100.0%	94.0%	94.0%

Table 4. CoINS Application Success Rates

6 Conclusion

We have described an application-oriented method for evaluating LPS systems in an application and building context. The system uses a clear separation between the descriptions of application requirements and LPS properties to make both parts interchangeable. Building characteristics are considered where appropriate. The system provides the following three key benefits:

- Most importantly, with the calculation of the application success rate it is possible to directly get an estimate for the end user experience from the LPS characteristics. This result can be used as a basis for LPS selection.
- The simulator helps to determine the optimal values for application parameters, such as tolerance values.
- The reporting function can be used to identify the subtests responsible for the highest errors. A user could then selectively improve the LPS system in those areas, e.g., by measuring additional fingerprints or deploying additional sensors.

The presented evaluation method was applied to our CoINS system together with LPS technologies that are available in modern mobile phones. With the help of the simulator, we could confirm that CoINS can perform well with the given LPS systems if the application parameters are configured properly.

Acknowledgements This work was supported by the SmartProducts project, funded as part of the Seventh Framework Programme of the EU under grant number 231204.

References

1. Aitenbichler, E.: A Focus on Location Context. In Max Mühlhäuser, I.G., ed.: Ubiquitous Computing Technology for Real Time Enterprises, ISR (2008) 257–281
2. Kolodziej, K.: Local Positioning Systems: LBS applications and services. CRC Press (2006)
3. Hightower, J., Borriello, G.: Particle Filters for Location Estimation in Ubiquitous Computing: A Case Study. In: UbiComp 2004: Ubiquitous Computing. Volume 3205 of LNCS., Nottingham, UK, Springer (2004) 88–106
4. Woodman, O., Harle, R.: Pedestrian Localisation for Indoor Environments. In: UbiComp 2008: Ubiquitous Computing. (2008)
5. Song, Y.: In-House Location Tracking. Master's thesis, Darmstadt University of Technology (2002)
6. Bahl, P., Padmanabhan, V.N.: A Software System for Locating Mobile Users: Design, Evaluation, and Lessons. Technical report, Microsoft Research (2001)
7. LaMarca, A., et al.: Place Lab: Device Positioning Using Radio Beacons in the Wild. In: Proceedings of Pervasive 2005. (2005)
8. Ekahau: WiFi-based Real-time Tracking and Site Survey Solutions. http://www.ekahau.com/ (2009) last visited: 16.01.2009.
9. Hartl, A.: A Provider-Independent, Proactive Service for Location Sensing in Cellular Networks. In: GTGKVS Fachgespräch (Online Proceedings). (2005)
10. Ubisense: Homepage. The Smart Space Company. http://www.ubisense.net/ (2009) last visited: 16.01.2009.
11. Nike: Nike Plus. http://nikeplus.nike.com/ (2009) last visited: 19.01.2009.
12. Beauregard, S.: A Helmet-Mounted Pedestrian Dead Reckoning System. In: 3rd International Forum on Applied Wearable Computing (IFAWC). (2006)
13. Blanke, U., Schiele, B.: Sensing Location in the Pocket. In: UbiComp 2008 Adjunct Proceedings. (2008)
14. Randell, C., Djiallis, C., Muller, H.: Personal Position Measurement Using Dead Reckoning. In: Proceedings of the Seventh IEEE International Symposium on Wearable Computers. (2003)
15. Denso Wave Inc.: QR Code Homepage. http://www.denso-wave.com/qrcode/ (2009) last visited: 19.01.2009.
16. Visonic Technologies: Elpas. http://www.visonictech.com (2009) last visited: 16.01.2009.
17. Kaplan, E.: Understanding GPS Principles and Applications. Artech House Publishers (1996)
18. Hadjakos, A., Aitenbichler, E., Mühlhäuser, M.: SYSSOMO: A Pedagogical Tool for Analyzing Movement Variants Between Different Pianists. In Ruffaldi, E., Fontana, M., eds.: Enactive08 Proceedings, Pisa, Edizioni ETS (2008) 75–80
19. Lyardet, F., Szeto, D.W., Aitenbichler, E.: Context Aware Indoor Navigation. In: Proceedings of the European Conference on Ambient Intelligence (AmI'2008). Volume 5355 of LNCS., Springer (2008) 290–307
20. von Winterfeldt, D., Edwards, W.: Decision Analysis and Behavorial Research. Cambridge University Press (1986)
21. Aitenbichler, E., Kangasharju, J., Mühlhäuser, M.: MundoCore: A Light-weight Infrastructure for Pervasive Computing. Pervasive and Mobile Computing **3**(4) (August 2007) 332–361 doi:10.1016/j.pmcj.2007.04.002.
22. Aitenbichler, E., Lyardet, F., Mühlhäuser, M.: Designing and Implementing Smart Spaces. Cepis Upgrade (August 2007) 31–37