Multi-Scheme Smartphone Localization with Auto-Adaptive Dead Reckoning

Michael Jäger, Sebastian Süß, Nils Becker
Institute of Software Architecture
Technische Hochschule Mittelhessen - University of Applied Sciences
Gießen, Germany
Email: {michael.jaeger, sebastian.suess, nils.becker}@mni.thm.de

***Abstract*—Most indoor localization approaches for mobile devices depend on some building infrastructure to provide sufficient accuracy. A commonly used method is the fusion of absolute position measurements with relative motion information from sensor units. This paper examines the requirements for smartphone localization in areas consisting of several buildings and open space, where a single positioning method might deliver good results at one location but might also fail at another. It is shown that, for several disparate reasons, a localization system combining alternative positioning techniques and going beyond the scope of a single hybrid method, is desirable. The paper proposes such a multi-scheme system with a three-layer architecture consisting of base methods, hybrid methods, and scheme selection. Automatic selection of an appropriate scheme is described for heterogeneous infrastructure within multi-story buildings and for indoor-outdoor transitions. Support of several distinct hybrid methods can be based on the same generic fusion algorithm. The paper proposes a novel lightweight fusion algorithm, called "auto-adaptive dead reckoning". It can be used in indoor and outdoor environments to combine an absolute localization method, e.g., Wi-Fi-based signal strength fingerprinting, in an adaptive way with inertial pedestrian navigation. Based on an accuracy factor reflecting the current context conditions of a location measurement the influence of each of the involved estimates is weighted accordingly. In a case study using Wi-Fi fingerprinting, accuracy has been improved by 43% in an indoor environment. Hence, more genericity can be obtained without loss of accuracy.**

Keywords–Indoor Positioning; Pedestrian Activity Classification; Dead Reckoning; Wi-Fi Fingerprinting.

I. Introduction

This article is based on [1], where the concept of indoor smartphone localization with auto-adaptive dead reckoning has been introduced. This work is extended by a multi-scheme concept combining alternative positioning techniques and providing multi-floor and multi-building support even in the case of heterogeneous infrastructure, as well as seamless indoor-outdoor transitions.

Location awareness has become a key feature of many mobile applications. A common problem in the context of navigation and tracking applications is the accurate localization of a mobile device within a well-known area comprising several buildings and also open space, e.g., a company premises, an airport, an exhibition center, or a university campus. Such sites are typically heterogeneous in the sense that a single localization method delivers good results in one sub-area but fails in another. Popular indoor solutions use hybrid methods comprising a suitable combination of an absolute positioning method with sensor-based relative positioning.

A. Absolute Positioning

With respect to mobile devices like smartphones an absolute positioning method estimates the device location in terms of latitude and longitude. Relative positioning determines the distance and heading of the movement, when a device is moved to a new position. Elevation might also be of interest, especially in order to determine the floor-level in a multi-story building. As far as outdoor environments are concerned absolute positioning is commonly based on global navigation satellite systems (GNSS) [2], like the well-known Global Positioning System (GPS) [3], the Russian GLObal NAvigation Satellite System (GLONASS), the Chinese BeiDou, or the european Galileo system. While deviation of second generation GNNS will be in a magnitude of some centimeters in outdoor use [4], satellite systems are not expected to provide sufficient accuracy inside of buildings without being supported by expensive complementary ground component (aka "pseudolite") technology [5].

Thus, the quest for accurate and inexpensive indoor localization techniques has fostered intensive research over the last decade and resulted in a number of different promising approaches. While solutions based on cellular signals have not successfully solved the problem of insufficient accuracy, the use of IEEE 802.11 wireless networks, e.g., Wi-Fi, has been widely adopted for real-time indoor localization purposes [6–10]. The rapidly growing usage of Wi-Fi access points as navigation beacons is, among other reasons, due to the ubiquitous availability of Wi-Fi networks and to the fact that a smartphone can easily measure Wi-Fi signal strength values. "Received Signal Strength Indication" (RSSI) values of several Wi-Fi access points are used to determine the current position of a Wi-Fi receiver. The advent of cheap bluetooth low energy (BLE) beacons [11], e.g., iBeacons [12], might foster their use for the same purpose within the next few years.

Ultra-wideband (UWB) radio has the potential to become the most successful base technology for indoor smartphone positioning. It can be used similar to Bluetooth for inter-device communication. But, most important, UWB has been designed specifically to enable precise distance measurements even through walls. Localization of an UWB-equipped smartphone is based on distance measurements between the device and UWB tags. As of summer 2015, the first UWB-enabled smartphones became available on the market [13].

Regardless of the beacon types and localization algorithms, absolute indoor localization methods currently rely on a dense beacon mesh to allow for accurate localization. In a heterogeneous area, thus, a practically important issue is the device localization at spots that lack a sufficiently good beacon signal coverage.

B. Pedestrian Dead Reckoning

A substantially different approach to localization is dead reckoning, a well-established relative positioning method. Starting from a known position, inertial and other sensors, e.g., accelerometers, gyroscopes, magnetic field sensors, or barometers, are used to track relative position changes. For example, distance estimation in pedestrian dead reckoning (PDR) systems [14] is typically based on step detection with motion sensors and step length estimation. This is combined with direction information from an electronic compass. Modern smartphones are crammed with all kinds of sensors and, thus, are well-suited for inertial navigation. Sensor-based localization is, however, subject to unbound accumulating errors, and therefore needs frequent recalibration.

An additional challenge for indoor PDR systems is the floor level determination within multi-story buildings. Measuring vertical displacement is straightforward for barometer-equipped smartphones. Vertical movements are usually associated with floor changes using elevators, stairs, or escalators. From the athmospheric pressure measurements the vertical displacement can be inferred sufficiently accurate to determine the final floor level unambiguously [15]. The exact height of this level, taken from the building model, can in turn be used to recalibrate the pressure altimeter. In the absence of a barometer, sensor-based pedestrian activity classification can be used to detect floor changes and to determine the final level.

C. Fusion of Absolute Positioning with PDR

Accuracy requirements for localization systems depend on their intended use. A pedestrian indoor navigation system frequently needs to distinguish if a user is in a corridor or in an adjacent room, or has to lead the user unambiguously to one of two doors placed side by side. Whereas errors of more than one meter are undesirable in such a setting, an accuracy of a few centimeters is barely ever needed. GPS or Wi-Fi-based fingerprinting typically have average errors of several meters. According to [16], the average errors of inertial positioning systems range between 60 centimeters and "corridor width". The aim of combining inertial and less accurate absolute methods is to provide an average accuracy significantly below one meter while limiting the accumulation of inertial measurement errors.

A hybrid method is a fusion of an absolute positioning method with sensor-based navigation. For example, in a GPS-based automotive navigation system sensor-based speed and direction measurements are used to track the current position whenever GPS signals are degraded or unavailable, e.g., in a tunnel. Similarly, a PDR system can be combined with GPS into a hybrid solution for outdoor areas or, together with any absolute indoor position method, e.g., Wi-Fi-based, for use within a building.

An interesting aspect of hybrid systems is the distribution of roles. The absolute positioning could be seen as a minor subsystem of the sensor-based system supplying the start position and, occasionally, intermediate positions for recalibration. However, existing systems typically use the absolute positioning method as a primary method, whereas sensor-based location measurements are only used in case of degraded beacon signals. The absolute base-method is used to compute position estimates ("fixes") at regular intervals. Each fix is considered a new known start position for inertial navigation. Whenever a fix is not available due to poor signal coverage, the relative movement from the last fix location is used to determine the current device location. A car navigation system, e.g., will use inertial navigation in a tunnel. After leaving the tunnel, it will return to the primary method GPS. This commonly used combination pattern does not take into account that, depending on the current beacon reception conditions and despite the accumulating sensor measurement errors, the dead-reckoned position will often be more accurate than the base method fix.

D. Auto-Adaptive Dead Reckoning

This paper proposes a hybrid localization solution, called "auto-adaptive dead reckoning", incorporating a more sophisticated way of combining absolute and relative positioning. Considering that the accuracy of each of the involved methods might fluctuate extremely between measurement locations, the fusing algorithm evaluates context conditions, that are critical for the accuracy, with every measurement. A measurement value that is considered accurate has a stronger impact on the result. The term "adaptive" is used for a fusion algorithm that associates a weighting factor with each fused method in order to adapt the algorithm to site-specific measurement conditions, e.g., Wi-Fi signal coverage within a building. Static adaptation refers to a configuration time weighting, whereas auto-adaptive (or dynamic) fusion refers to a dynamic weighting for each individual measurement. This advanced fusing technique has been implemented as a component of a mobile application for the Android platform, called SmartLocator [17]. It is explained in more detail in Section IV.

E. Supporting Different Localization Schemes

Going beyond the auto-adaptive dead reckoning approach, this paper introduces a novel concept for the integration of distinct localization methods in the same system. A "Localization Scheme" is a realization of a localization approach, comprising a selection of base technologies, a system model, and appropriate algorithms. A multi-scheme localization system supports several alternative schemes with automatic scheme selection. In fact, there are several distinct motivations for envisioning a multi-scheme approach:

Localization Infrastructure Dependencies: Regarding a user entering and leaving several buildings while roaming through a complex area, it is quite obvious that a single localization technique is not sufficient. In the outdoor environment GPS can be used, either stand-alone or fused with PDR into a hybrid scheme. Regarding the indoor case, though infrastructure-less positioning is possible, most solutions build on specific infrastructure, e.g., Wi-Fi radio maps, to obtain more accurate measurements. Ideally, all the buildings in the area of interest are equipped with a homogeneous localization infrastructure. Even in this case, a localization system has to switch between indoor and outdoor localization schemes. However, most areas with several buildings will not be homogeneous in this sense, but will rather require different techniques for indoor positioning. For example, some buildings might have an infrastructure for Wi-Fi absolute positioning, some might be equipped with iBeacons, and others will have no appropriate infrastructure at all. Even within a single building, different localization approaches could be required, e.g., because a specific infrastructure is not available in all floors.

Different Pedestrian Activities: Another aspect influencing the localization approach is the way of pedestrian movement. A positioning system using PDR must in some manner deal with different movement patterns, e.g., vertical movements due to stairs or elevator usage.

Device Hardware Capabilities: Novel smartphone hardware features often offer new opportunities for positioning, e.g., NFC- or BLE-support, barometers, hardware step detectors, or UWB. Whenever new hardware facilitates an advance in localization, it will be exploited for that purpose. However, not all devices are equipped with all kinds of available sensors and radios. For example, only a few smartphone models have built-in barometers. However, a barometer could be used to determine the current floor after an elevator trip in a relatively simple and reliable way, whereas other methods, e.g., based on radio beacons or inertial sensors, have several disadvantages. Another example are hardware step detectors, which might be preferable to software solutions due to lower power consumption. A localization system might keep up with the ever-increasing device diversity in several ways:

1) The system uses only commonly available hardware components, e.g., Wi-Fi and common inertial sensors, thereby forgoing the new opportunities.
2) The system requires a high-end smartphone with several non-standard hardware features in order to exploit these for positioning.
3) A system uses different positioning techniques for devices with distinct positioning capabilities.

Hence, a multi-scheme approach does not only address the diversity of contextual conditions, or rather the availability of some positioning infrastructure. It is also a suitable concept for considering different pedestrian moving patterns and different positioning-related hardware capabilities.

F. Requirements for Localization in large and complex Areas

Subsuming and extending the discussion above, the following requirements should be met by a complex area positioning system:

Requirement 1. *A positioning scheme should provide sufficient accuracy.*

Though accuracy requirements for pedestrian localization depend to some degree on the intended application domain, most of currently available absolute methods, e.g., GPS, Wi-Fi-based, BLE-based, are considered too inaccurate to be used stand-alone. Thus, the important consequence of this requirement is that fusion with PDR or some other enhancement is necessary.

Requirement 2. *Several positioning schemes have to be supported.*

In addition to a GPS-based outdoor scheme, the system has to support at least one, but typically more than one indoor scheme. Several PDR-schemes in order to address different pedestrian moving patterns and detect floor-level changes, as well as scheme selection depending on device capabilities are not considered as requirements, but rather as desirable features.

Requirement 3. *The system should automatically select the most appropriate scheme.*

While roaming in the area, repeated manual selection of a new positioning technique is not acceptable for a user. There must be a mechanism for detecting transitions between subareas requiring different localization approaches and for selecting an appropriate scheme.

Requirement 4. *Unnecessary power consuming measurements have to be avoided.*

With respect to localization, power consumption issues arise with high processor load due to probabilistic fusion algorithms and with the use of sensor and radio equipment. As a consequence, it is not acceptable to use several techniques simultaneously, when a single one is sufficient. For example, continuously searching for a GPS fix, while the user stays in a building for hours, will drain the battery unnecessarily. The same holds for dispensable Wi-Fi scans etc.

Several camera-based localization schemes have been proposed. Since these are inherently power-consuming they have been out of consideration in the multi-scheme approach presented in this paper.

G. Overview

This paper presents a smartphone localization system satisfying the requirements listed above. It is based on a three layer architecture. At the bottom layer, the system comprises a PDR subsystem and several basic absolute positioning methods, namely, Wi-Fi-based fingerprinting, BLE-based fingerprinting, Near Field Communication (NFC) [18], and GPS. The intermediate layer consists of hybrid positioning schemes. Each scheme fuses PDR with an absolute positioning method using a generic and efficient auto-adaptive dead reckoning algorithm. At the top layer, a multi-scheme mechanism is used to detect necessary scheme switches and select the most appropriate scheme automatically.

After presenting related work in Section II, the proposed positioning system is described in the succeeding two sections.

The focus of Section III is on the overall architecture and the automatic selection of an appropriate localization scheme, while Section IV explains the fusion of PDR and absolute positioning using the auto-adaptive dead reckoning approach.

Section V discusses experimental results showing the achieved accuracy improvements over non-hybrid as well as hybrid methods with non-dynamic method fusion. Section VI reviews some benefits and shortcomings of the presented approach and future research plans.

II. Related Work

A large number of solutions to the problem of real-time indoor localization have been proposed, and several efficient algorithms for absolute and relative positioning have been published. Auto-adaptive dead reckoning, as presented in this paper, is based upon Wi-Fi fingerprinting, BLE-fingerprinting, GPS, NFC, and PDR.

A. Wi-Fi-based Fingerprinting

Using an existing Wi-Fi infrastructure for indoor localization is an obvious and well-investigated approach. While RSSI-based distance calculations have proven to be too inaccurate to be used for trilateration-based indoor localization, RSSI-fingerprinting methods are particularly useful in the context of real-time smartphone positioning [6–10].

Fingerprinting is based on probability distributions of signal strengths for a set of access points at a given location. A map of these distributions is used to predict a location from RSSI samples. This radio map is created in an offline learning phase for a number of known locations called calibration points. In order to determine the device position, RSSI values are collected from all visible access points and the radio map is searched for locations with similar signal strengths.

A major advantage of Wi-Fi fingerprinting is that it does not require specialized hardware [7][19][20]. Nevertheless, a non-dynamical Wi-Fi infrastructure with good coverage is needed to achieve reasonable positioning results.

However, the most important disadvantage is the elaborate fingerprint database creation and maintenance. Since the accuracy of position estimates highly depends on the density of the radio map [7], the construction of a high-density map is inevitable for Wi-Fi-only positioning solutions. The auto-adaptive algorithm, in contrast, allows for a significant reduction of the number of calibration points without loosing too much overall accuracy.

In order to avoid the map creation overhead completely, zero-effort solutions based on crowdsourcing have been proposed [21][22]. Although efficient map creation is outside the scope of this paper, it should be noted that map creation and map usage algorithms are typically loosely coupled. Thus, any successful approach to automate map creation could possibly be generalized for usage with existing fingerprinting systems.

B. Sensor-based Positioning

According to [16], PDR systems can be classified as Inertial Navigation Systems (INSs) or Step-and-Heading Systems (SHSs). While the INSs typically require specialized hardware, the SHSs are well-suited for PDR with smartphones.

The SmartLocator solution presented in this paper implements an SHS, which builds upon efficient algorithms for step detection and heading estimation. The heading is determined by a sensor fusion method described in [23]. Step detection exploits the smartphone's accelerometer signals. Whenever a peak with a certain amplitude at the z-axis is noticed, a step can be assumed [24]. A modified Pan-Tompkins algorithm is used for signal preparation. Pan-Tompkins, in the context of step detection, has been used by Ying [25] before.

For larger areas different pedestrian moving patterns have to be considered, as elevators, stairs, or escalators will be used temporarily. Promising approaches to sensor-based pedestrian activity classification have been presented in [26] and [27].

C. Method Fusion

An interesting approach combining Wi-Fi-based fingerprinting with PDR was proposed in [28]. Their fusing algorithm uses a limited history of location measurements for both methods to achieve accurate position estimations. Another promising solution is described in [29]. The algorithm builds on a statistical model for Wi-Fi-localization avoiding the effort of fingerprinting map creation, deliberately taking into account the resulting poor accuracy of the obtained position information. Both fusing methods comprise the use of floor plans and particle filters in order to obtain more accurate position information [30].

Particle filters are probabilistic approximation models based on Bayesian filters [31], which can be used for fusing PDR measurements with the results of absolute positioning methods. They also provide a means for incorporating movement constraints obtained from a floor map of a building or a footpath or road map. In the context of smartphone localization, a particle consists of an estimation for position and heading together with a weight value representing the probability that the estimation is correct. The current state of a smartphone is not represented by a single location and heading, but rather by many particles. State changes have to be handled according to the underlying motion model by a recursive algorithm whose computational cost depends to a considerable degree on the number of particles. Basically, when a step is detected, each particle is propagated to a new position by exploiting Bayes theorem, and new weight values are computed. Next, a resampling filter is applied to replicate particles with large weights and to remove those with negligible weights.

When used in a laboratory environment with a high-quality PDR system, i.e., a special purpose, firmly attached, foot-mounted sensor system, particle filters have shown to produce very accurate position estimates. With a stock smartphone sensor system, however, movements of the device are more loosely coupled with the movements of its user, which induces more uncertainty into the measurements. In a probabilistic model this additional uncertainty leads to a considerable increase in the measurement error variances, which in turn has to be accounted by an increased number of particles. As a consequence, particle filters induce high processor load and have considerable impact on power consumption [16]. Moreover, suitable floor maps have to be supplied and maintained.

III. Multi-Scheme Positioning

This section describes the proposed multi-scheme approach and the implementation of scheme selection in the SmartLocator positioning system. After introducing the system architecture in Section III-A, Section III-B presents the coarse localization subsystem used to determine the current building and floor-level. Section III-C describes the implementation of the high-level scheme switching.

A. System Models and Architecture

Since multi-scheme support is one of the outstanding features of the proposed system, the term ”localization scheme”, the motivation for a multi-scheme approach, and the relation between scheme selection and method fusion deserve some further explanation.

It is a common property of many advanced fusion-based localization approaches that they are based on a specific dynamic state-space system model with a hidden state. Partial information about this state can be obtained by observations or measurements. The model contains a set of assumptions about the measurement methods used and the context in which the measurements are taken. A common approach is to use a system model for pedestrian movements based on heading and stride size. The positions obtained from an absolute positioning method are the observations, which can be used to infer information about the system state. The fusion of PDR and absolute method is used to recalibrate the PDR state and can be implemented, e.g., by a particle filter.

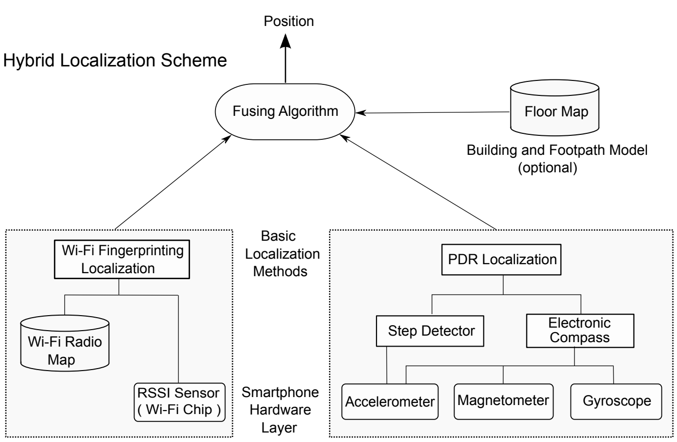


Figure 1. Layers of a typical Hybrid Localization Scheme.

The architectural layers of such hybrid localization systems are shown in Figure 1. The illustration abstracts from the fact that the PDR subsystem could also use internal fusing algorithms for sensor measurements, e.g., a Kalman filter as part of the electronic compass implementation [32]. To avoid confusion, the term ”localization method” is used for the lower level subsystems of the basic localization method layer, e.g., PDR, GPS, Wi-Fi- or Bluetooth-fingerprinting. Instead, the term ”localization scheme” denotes the uppermost architectural layer of a hybrid system, which is characterized by the high-level fusion algorithm.

A complex area with heterogeneous positioning infrastructure requires the combination of different localization techniques. The relation between the model-based view and the requirements for complex areas can be clarified by some examples:

- If the same PDR system is combined with GPS outdoors and with Wi-Fi indoors, a switch between these schemes corresponds to a replacement of the observation model.
- Changing the way of moving around, e.g., taking an elevator to change the floor, or using a shuttle bus between two buildings of the area, corresponds to the replacement of underlying pedestrian movement model.
- Supposing that a building map is used in a particle filter to detect and eliminate through-the-wall movements, this map usage should perhaps be switched off in order to avoid unnecessary processor load in a wall-free environment or in an unmapped subarea. This would correspond to a change in the fusion algorithm.

Figure 2 depicts the components of a hybrid localization scheme from a model-based view. Supporting different schemes, i.e., different localization approaches, in a single system makes sense for a variety of reasons already presented above. However, the figure illustrates that a scheme change can be related to

1) a change in the pedestrian activity,
2) a change of the PDR recalibration mechanism,
3) or a change in some location-depending algorithmic aspect of the fusion algorithm.

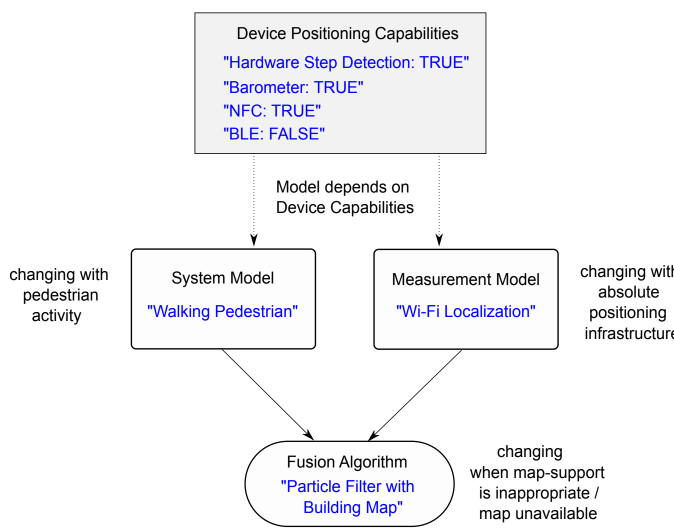


Figure 2. System-theoretic View of a Localization Scheme and its Components.

Whereas the scheme changes listed above are dynamic, i.e., imposed by location changes, the dependencies between schemes and hardware features are location-independent and static. Multi-scheme support corresponds to the alternative usage of several distinct models. Hence, scheme switching is not a replacement for method fusion, but rather a higher level concept for automatically selecting an appropriate (possibly hybrid) localization scheme. Support for several localization schemes with automatic scheme selection introduces a new top-level layer into the system architecture as shown in Figure 3.

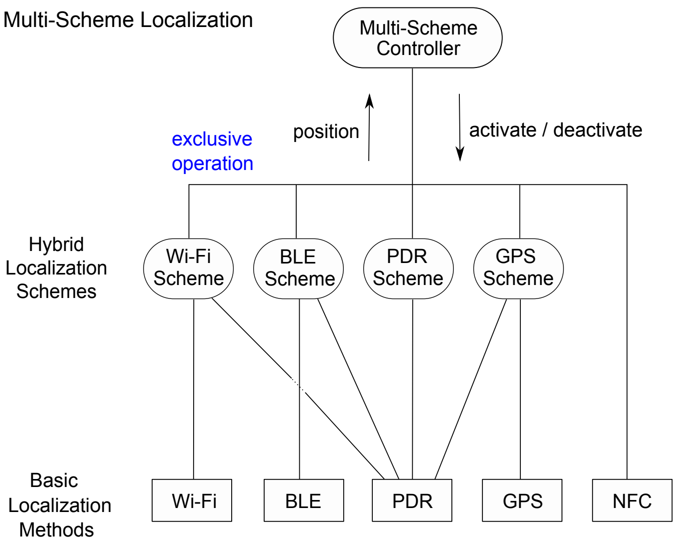


Figure 3. Layers of a Localization System with Multi-Scheme Support.

The multi-scheme controller has to determine dynamically which localization scheme is the most appropriate one at the current device location. There are some noteworthy relations between the components of the bottom and intermediate-level layers:

1) PDR is used in several schemes to improve accuracy: Fingerprinting-based methods using Wi-Fi or BLE-beacons can be fused with PDR the same way as GPS.
2) Methods that provide sufficient accuracy on their own are not fused with PDR. A currently supported accurate method is the reading of NFC tags with known position. Future methods based on the upcoming UWB and next generation GNNS technologies will also fall into this category.
3) The PDR scheme in the model is not necessarily identical to the basic PDR method. It is rather a sensor-based algorithm to be used in the absence of radio beacons, which might make use of a floor map or path model to recalibrate the measurements.

B. Coarse Localization Subsystem (CLS)

In order to recognize the current floor-level after a vertical movement, as well as for the detection of indoor/outdoor transitions, a coarse localization subsystem consisting of a set of special localization methods is used. The CLS architecture is illustrated in Figure 4.

The CLS can be considered as a simple, special-purpose, secondary localization system. It does not use radio maps or method fusion. Instead, the CLS base algorithms, e.g., the Wi-Fi-based context determination, are lightweight algorithms which essentially check, whether a floor-specific beacon constellation is detected, or whether a GPS-fix is available. The outdoor environment is treated as a special floor-level in this context. An important difference to the primary multi-scheme localization is the possibility of simultaneously searching for usable Wi-Fi, BLE, and GPS-signals. The CLS supports two operating modes.

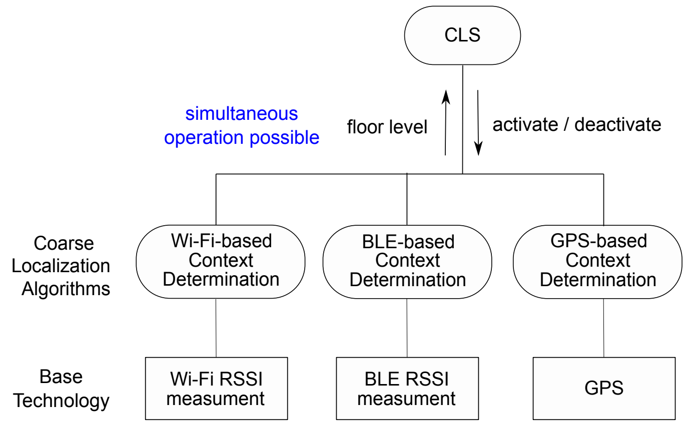


Figure 4. The Coarse Localization Subsystem.

- The *limited mode* is used to check the current floor-level against a small set of possible levels. A typical use is the floor-level determination after elevator usage. Since the former position is available, the set of reachable floors can be determined in advance as will be explained in Section III-C.
- The *unlimited mode* is used for an initial estimation of building and floor whenever there is no former location available, e.g., when the system is started. Compared to the limited mode, the set of possible floors to be checked is the set of all floors of all buildings.

The CLS reports successful context determinations immediately, but stays turned on until it is explicitly deactivated by the multi-scheme controller.

C. Transition Detection and Scheme Selection

When a roaming user moves to an area requiring a different positioning technique, the multi-scheme controller has to detect this situation, to determine the new positioning scheme, and to switch to the selected scheme.

Positioning Context: A positioning context is a spatial area with exactly one associated localization scheme. Although arbitrary contexts could be defined, only three types are considered here, i.e., the outdoor context, a specific building, or a floor of a building. Figure 5 gives an example of positioning contexts with their associated localization schemes.

Positioning Context Map: The association of a scheme with a context is done via a *positioning context map*. With each positioning context this map associates

- A localization scheme descriptor (LSD) identifying the algorithm to be used and containing links to radio map and building model.

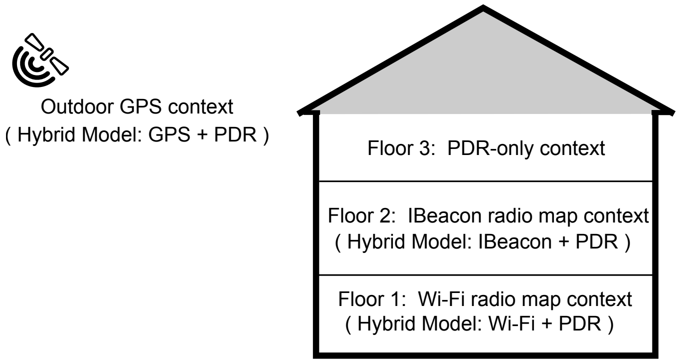


Figure 5. Positioning Contexts Example.

- A context determination descriptor (CDD) identifying the method to be used for recognizing the context, e.g., Wi-Fi or BLE, and a context-specific beacon constellation.

The construction and maintenance of this map is, in fact, very lightweight. SmartLocator is based on an Openstreetmap (OSM) ([33]) model with extensions for multi-story buildings. In the extended OSM model, any building and any floor is represented by a relation. Those relations can be tagged with additional information, e.g., a localization scheme descriptor. All relations are associated with the outdoor context per default. Thus, if a new localization infrastructure is established in a floor of a building, that is supported by a localization scheme S, in order to update the map one only needs to tag the floor relation with the descriptor for S.

Locations and Port Objects: In the building model, the location of an object consists of a latitude-longitude pair, a building ID, and a floor-level. Doors, stairs, or elevators are special port objects, which represent links between buildings, between two or more floors of the same building, or between the building and the outdoor environment. An elevator, e.g., is represented by several port objects, all sharing the same latitude and longitude, but with different floor-levels. A door leading from one building directly into another one is represented by a pair of port objects belonging to two distinct buildings but having the same geographic position attributes.

The neighbourhood of a port object consists of the object itself and all other port objects that are linked to it as "reachable" objects. Essentially, these are the possible endpoints of elevators, escalators or stairs, together with the objects of adjacent contexts (other building, outdoor environment) which share the same geographic position. Each port object is linked to its neighbours, such that the neighbourhood can be computed efficiently. A port object is member of its own neighbourhood to model situations like an elevator trip ending in the original floor.

Transitions between Floors and other Positioning Contexts: When a user is roaming through a building, the positioning system always knows the current building and floor-level and checks against the building model, whether the user is near one of the floor's port objects. If this is the case, the system enters a transition detection state providing continuous attempts to detect movements across the borders between two adjacent positioning contexts. Entering this state, those adjacent positioning contexts are computed as follows. First, the port object's neighbourhood is extracted from the building model. For each location in this neighbourhood, the corresponding positioning context is determined and the context-associated descriptors LSD and CDD are looked up in the positioning context map.

The list of CDDs for the adjacent contexts is subsequently used for an activation of the CLS in limited mode. The CLS will repeatedly check for BLE-, Wi-Fi-, or GPS signals according to the CDDs of the adjacent contexts and report the context identification results until transition detection is eventually deactivated by the multi-scheme controller. The deactivation criteria depend on the type of port object. In case of an elevator, the transition is assumed to be completed, when the user is walking again. At this time, a unique floor-level identification is required from the CLS. For staircases, the end of transition is assumed after counting as many steps as the staircase has according to the building model and a unique floor identification is available from the CLS. Only if the floor has changed, the position is recalibrated to the staircase endpoint location. Admittedly, this is to some extend error-prone with respect to the horizontal location, e.g., when a sportive person takes two steps at once, or if someone turns back after nearly having reached the end of the stairs. In the case of a door, transition detection ends when five steps have been counted from the begin of transition. Obviously, these five steps need not necessarily be steps away from the door. In those rare scenarios, where the transition detection is switched off but the user is still at or near the original port object location, the system will immediately return to transition detection state again.

Leaving transition detection state means deactivation of the CLS. If a transition was detected, the scheme is switched according to the LSD of the new context. In transition detection state, several ambiguous situations are possible, reflecting either the uncertainty about the current floor-level during a vertical movement, or about the exact progress of passing through a door. For example, a user could walk towards a building entrance door, stay there for a while, turn around and walk back. Though a context transition does not happen in this case, the system is in transition detection state as long as the users smartphone position is estimated to be near the door. Two adjacent contexts might be identified by the CLS at the same time, e.g., if at a building entrance a GPS position is available but also the floor-identifying Wi-Fi access point RSSI value ranges have been verified.

The context transition for border locations is depicted in Figure 6, the numbers denoting the order in information flow. The intermediate states have been omitted for clarity.

It should be noted that an appropriate infrastructure is mandatory in this context. In practice, existing Wi-Fi infrastructure will commonly be usable for this purpose without much additional effort.

A common scenario is that a user leaves a building after adaptive dead-reckoning" refers to this fusing approach. From the perspective of PDR, absolute localization is needed to obtain an initial position and for recalibration. In contrast to a full recalibration, we propose a partial recalibration determined by a dynamic weight, which reflects the accuracy of the absolute location estimation.

It is a particular strength of the approach to be generically usable with any absolute positioning method. Figure 7 illustrates how absolute location sources are combined with relative positioning information. A deep discussion of all of the supported absolute methods is out of the scope of this paper. Therefore, only the Wi-Fi fingerprinting scheme is considered as a typical example.

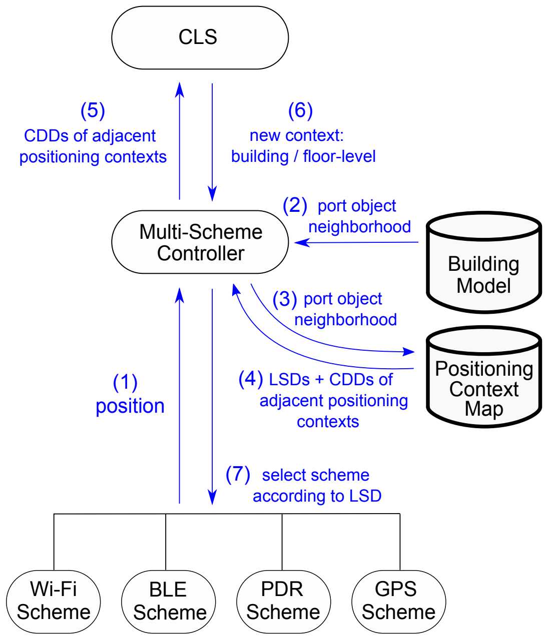


Figure 6. Context Detection near a Context Border Location.

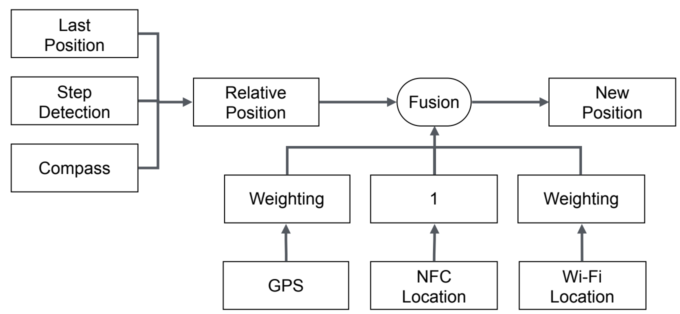


Figure 7. SmartLocator Positioning Concept.

working there for hours. As long as the current location is not directly adjacent to a door or elevator leading to the outside of the building, GPS is turned off and the device tracks itself using the context's indoor scheme. Only when the user moves to a door leading to the outside, i.e., a port object with an outside context neighbour, GPS will be turned on again.

IV. Intermediate-Level and Basic Positioning

This section describes auto-adaptive dead reckoning and its implementation in the SmartLocator positioning system. As already described above, positions determined with GPS, Wi-Fi, or BLE are considered inaccurate, whereas NFC-based positioning is treated as accurate. Using small low-cost NFC paper tags the maximal reading distance for a smartphone will be below 20mm. Thus, the accuracy of an NFC-based device location estimation is essentially determined by the accuracy of the position information associated with the NFC tag, while the distance between tag and device is typically insignificant. The problem of determining accurate positions of fixed objects is out of the scope of this paper. However, the position of an NFC tag can often be determined by attaching it to an object appearing in a floor plan, e.g., a door or a stair railing, and measure the tags location relative to this object.

Whenever an accurate location measurement can be obtained, it overrides all other measurements.

In addition to the absolute positioning capabilities, SmartLocator incorporates a PDR subsystem with step detection and heading estimation. The stride size is simply set to a user-specific fixed value. However, using the absolute localization methods, it could straightforwardly be augmented with automatic stride size recalibration.

The emphasis of this section is to present the way of fusing PDR with an absolute positioning method. The term "auto-

The following subsections describe the Wi-Fi fingerprinting approach (Section IV-A), the step detection algorithm (Section IV-B) and the auto-adaptive fusion (Section IV-C).

A. Fingerprinting

During the training phase a radio map is created, containing Wi-Fi samples for a set of calibration locations. Each entry consists of a location and a set of signal strength values $\{s_1, \ldots, s_n\}$ obtained at this location. If k is the number of accesspoints, each sample s_i is a vector of k integral measurements (in dBm).

A position estimation is a result of the process chain shown in Figure 8. After scanning the RSSIs from all visible access points a Wi-Fi fingerprint is created. To select only well-known beacons, a SSID and a BSSID filter are applied. Subsequently, the MinRSSI filter eliminates access points which are unusable for localization due to their low RSSI level. Before the cleared fingerprint is matched against the radio map a BSSID filter is applied to reduce the number of calibration points and thus the expense of distance determination.

The distance between the current fingerprint and the calibration point fingerprints in the radio map is computed using the naïve Bayes classifier [7][19][20], which is more accurate than algorithms comparing distances between RSSIs [34–37]. This advantage has been confirmed during the evaluation of this positioning system.

If $s = (s_1, \ldots, s_k)$ is the vector of RSSI values obtained at the current location and $P(x|s)$ denotes the probability that s is obtained at an arbitrary location x, the problem is to

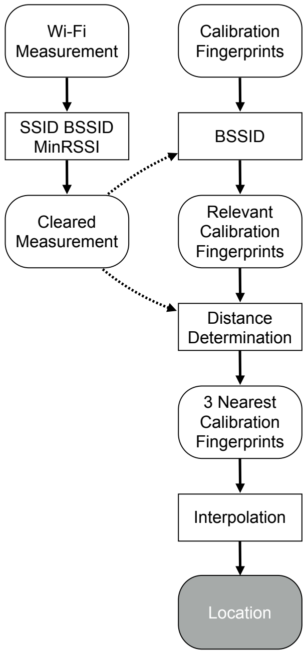


Figure 8. Fingerprinting Process Chain.

determine the location that maximises this probability. Using Bayes theorem,

$$P(x|s) = \frac{P(s|x)P(x)}{P(s)}, \tag{1}$$

assuming that $P(x)$ is identical for all locations, and considering that $P(s)$ is location-independent, the remaining problem is the determination of $P(s|x)$, since

$$\underset{x}{\operatorname{argmax}}\, P(x|s) = \underset{x}{\operatorname{argmax}}\, P(s|x). \tag{2}$$

Assuming that RSSI values of all access points are independent of each other,

$$P(s|x) = \prod_{i=1}^{k} P(s_i|x). \tag{3}$$

A common approach to determine $P(s_i|x)$ from the radio map for a single access point AP_i is to assume a Gaussian distribution of the RSSI values obtained at a location x [34][19, p. 36]. The probability density function of this distribution is

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}, \tag{4}$$

where μ and σ denote the mean and the standard deviation, respectively, which are estimated from the samples in the radio map using the maximum likelihood method.

Since the radio map contains only fingerprints of calibration locations, an interpolation scheme is used to determine the actual position. Using the k-nearest neighbors algorithm for $k = 3$, the position estimation $\hat{x}$ is obtained by interpolating the locations l_1, l_2, l_3 of the three best fitting fingerprints using $P(l_i|s)$ as a weighting factor:

$$\hat{x} = \frac{\sum_{i=1}^{3} l_i P(l_i|s)}{\sum_{i=1}^{3} P(l_i|s)}. \tag{5}$$

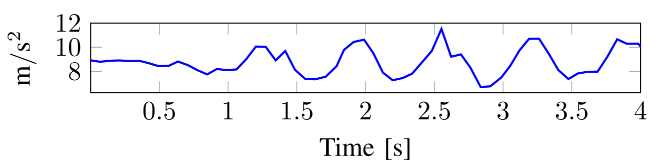
B. Step Detection

The step detection algorithm recognizes pedestrian movements based on a simple peak detection algorithm described by Link et al. [24]. To improve the amount of detected steps and decrease the appearance of false positive detections, the signal is prepared by applying a slightly modified version of the *Pan-Tompkins* method.

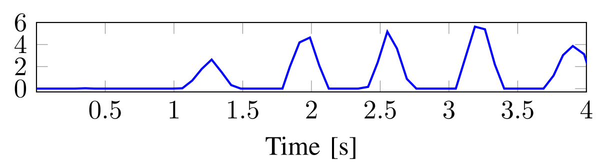
$$y(n) = \begin{cases} \frac{1}{4}[2x(n) + x(n-1) - x(n-3) - 2x(n-4)] & \text{if } y(n) > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

$$y(n) = (1 + y(n))^2 - 1 \tag{7}$$

A derivative operator uses low-pass filtered acceleration values in order to suppress low-frequency components and enlarge the high frequency components from the high slopes (6). Negative values are discarded, as they are not needed for the peak detection. Figure 9 shows the incoming acceleration signal before (a) and after (b) this preparation.



(a) Raw Acceleration at Z-Axis.



(b) Squared Derivative Signal.

Figure 9. Acceleration Measurements Before and After Preparation.

The step detection algorithm examines the signal for peaks by comparing the last three values, represented by the red squares in Figure 10. A step is assumed whenever the signal changes by a certain threshold. After a step has been detected, the algorithm pauses for 300ms to prevent a step from being detected twice.

C. Auto-Adaptive Dead Reckoning

The major innovation of SmartLocator's intermediate-level hybrid localization is the accuracy-dependent fusion of absolute and relative positions. Traditional dead reckoning systems overwrite past position determinations whenever a new absolute position is available. This is not reasonable whenever absolute positions' accuracy is bad or varying. Therefore, every

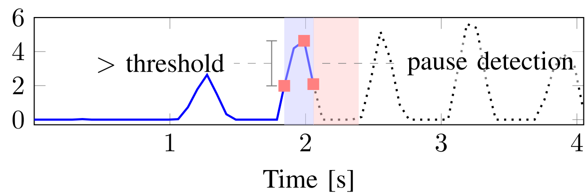


Figure 10. Step Detection Example. Red Squares Represent Analyzed Values.

absolute position is reckoned with past position estimations. The weighting of the new absolute position depends on an estimation of its accuracy. As a consequence, accurate absolute positions have a greater influence on the final position than less reliable position estimates.

E.g., Wi-Fi positions determined in an area with poor Wi-Fi coverage just have little influence on the final position estimation and the position determined by detecting the pedestrian's steps and heading is weighted strongly. On the other hand, Wi-Fi positions which are determined in an area with lots of access points and good signal quality are used to correct the drift which may occur due to inaccuracies in step detection and heading estimation.

Let $AbsPos$ be a location coordinate estimate obtained by an absolute positioning method at time t_{AbsPos}, e.g., a Wi-Fi or GPS position. The contribution of $AbsPos$ to the resulting location information $FusedPos$ depends on the method-specific accuracy factor $accuracy(AbsPos)$. This factor, which is obtained by context evaluation, reflects the measurement's context-dependent accuracy.

In addition, a time-dependent factor $drift(t_{AbsPos})$ is added to the accuracy factor. In this way, sensor drifts in the relative position will be taken into account and absolute positions have a stronger influence if the last position determination was long ago. The linear $drift(t_{AbsPos})$ used in SmartLocator is represented by Figure 11.

New calculations of $AbsPos$, $PDRPos$ or $FusedPos$ are triggered by time, NFC read, signal loss or user movement events.

$$FusedPos = AbsPos * \alpha + PDRPos * (1 - \alpha) \quad (8)$$

$$\alpha = max(accuracy(AbsPos) + drift(t_{AbsPos}), 1) \quad (9)$$

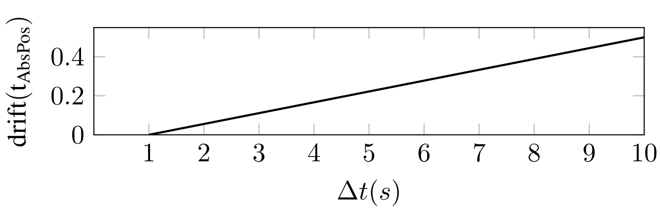


Figure 11. Time-Dependent Factor.

Accuracy Factors: The accuracy factor $accuracy(AbsPos)$ depends on the currently used positioning method. The following methods are used for Wi-Fi fingerprinting, GPS and NFC.

Wi-Fi: Several evaluations with an existing Wi-Fi infrastructure yielded an average error of 2.94 meters for pure Wi-Fi positioning. However, the error varied from 0.07 to 7.99 meters. Figure 12 shows the analysis of the gathered test data, revealing a relation between the average error and the amount of access points, which have been available for position determination. Even in case of good Wi-Fi coverage, error varies from 0.3 to 7.3 meters.

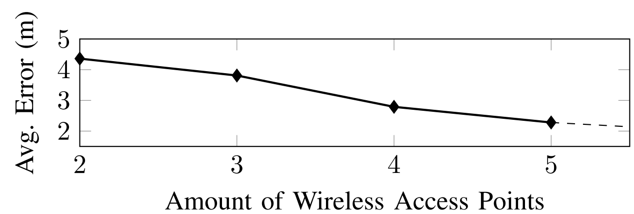


Figure 12. Accuracy Factor for Wi-Fi Positioning.

The accuracy factor of the Wi-Fi positioning method, illustrated in Figure 13, takes this relation into account to reduce the influence of unreliable position measurements.

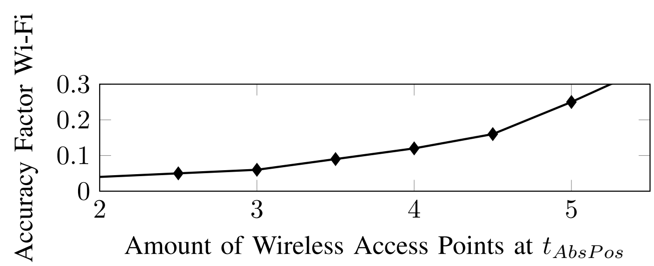


Figure 13. Wi-Fi Accuracy Factor Depending on Amount of Access Points.

GPS: The GPS position is determined by the smartphone through the operating system API. This API associates with each GPS position an accuracy property, which represents an estimated average error in meters. The accuracy factor, shown in Figure 14, is based on this accuracy property.

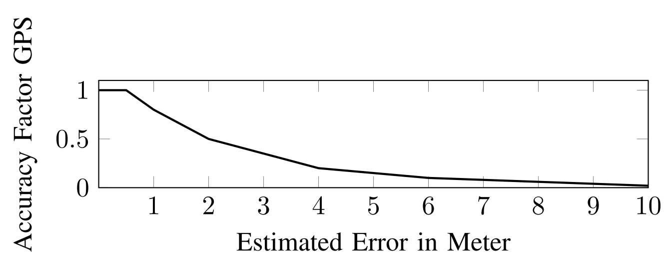


Figure 14. Accuracy Factor for GPS Positioning.

NFC: Near Field Communication (NFC) is used for positioning by placing passive NFC tags at points of interest. In order to scan an NFC tag, the smart phone needs to get in touch with it. Therefore, the location of the smart phone can be expected to be the location of the NFC tag. As a consequence, the accuracy factor of NFC always returns the maximum value of 1, which means that an NFC position overwrites prior location determinations completely.

V. Evaluation

SmartLocator has been tested under realistic circumstances in a university campus. However, it is a system undergoing continuous further development. The heuristic rules for scheme switching, as described in Section III, are still under evaluation. Also, experiments addressing the use of short-range, low signal level BLE-beacons for accurate positioning at port locations are not finalized.

Therefore, the focus of this evaluation is a detailed discussion of the Wi-Fi fingerprinting approach. Using eight Wi-Fi access points for positioning, fingerprints at 67 different locations have been recorded. The fingerprint locations are distributed uniformly with a distance of two meters. Hence, an area of about 280 m^2 is covered. Four orientations have been measured for any location. Three fingerprints for each orientation, resulting in an overall amount of 804 fingerprints.

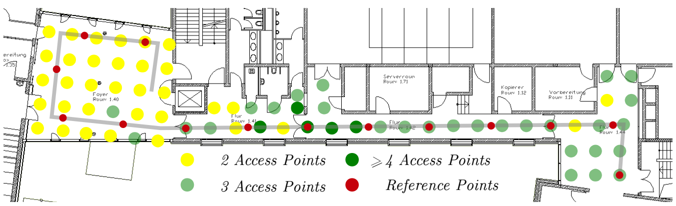


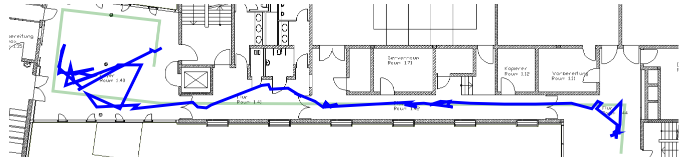
Figure 15. Wi-Fi Positioning Test Area with Fingerprints.

A track of 70 meters has been walked in various speeds, with different devices and in different directions to get a representative evaluation. 14 reference positions have been marked at the track. Those known reference positions are compared to the estimated positions, to determine the accuracy of the different approaches. Figure 15 shows the test environment, including the test track, which is illustrated by a grey line.

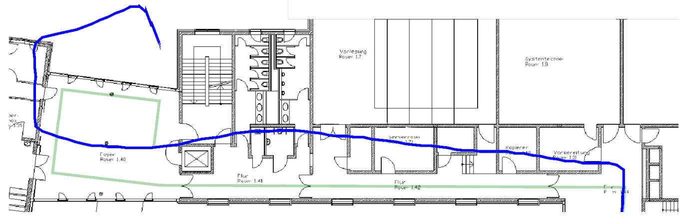
Figure 16 shows a visualization of one test run. The test started in the bottom right corner and followed the light green path. The blue line represents the actual positioning result. Figure 16b shows the results gathered with traditional dead reckoning, which means that absolute positioning results overwrite prior positioning estimations. Figure 16c presents a static weighting of 0.5, i.e., new absolute positions are just reckoned up by half. Figure 16d visualizes the positioning results achieved with a dynamic, auto-adaptive combination.

Remarkably, all figures reveal a clearly visible deviation from the real path at the same location (in front of the restrooms, left of the middle). This results from a coincidence of two local environment conditions. The first factor is the poor Wi-Fi-coverage in this area. Furthermore, a heavy metal fire door impacts the magnetometer of the electronic compass. Obviously, if neither of the involved measurement methods obtains an accurate location, the method fusion cannot compensate the resulting drift completely.

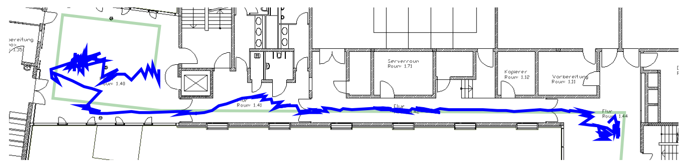
The evaluation revealed that the traditional dead reckoning (Trad. D.R.) approach performed even a little bit worse than the pure Wi-Fi positioning. A static combination of relative and absolute positions was able to slightly improve the positioning accuracy, especially in the foyer at the left side of the



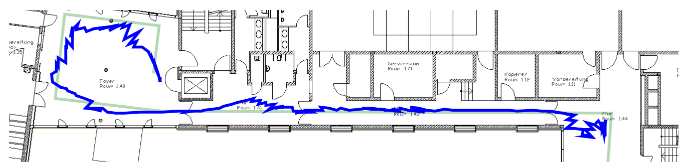
(a) Wi-Fi only.



(b) Traditional Dead Reckoning.



(c) Static Weighting of ($\alpha = 0.5$).



(d) Auto-Adaptive Weighting.

Figure 16. Comparison of Different Weightings.

floor plan. Auto-adaptive combination of Wi-Fi and relative positioning is able to reduce the average positioning error significantly. The average error has been improved from 2.94m (Wi-Fi only) to 1.67 meters, the upper quartile from 3.54m to 2.29m. Figure 17 shows the error ranges for the evaluated approaches.

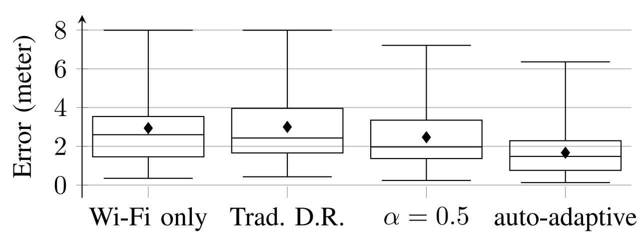


Figure 17. Error Ranges for Different Weightings.

VI. Conclusion

The presented approach has two important aspects. First, it introduces a general concept for integrating different localization methods into a single layered system. This is exploited for dynamically selecting a positioning scheme that is most appropriate for the current location with respect to supporting infrastructure. However, the multi-scheme approach is just as well suitable for pedestrian activity classification and selective support of algorithms that build on non-standard device hardware features. The main benefit of the multi-scheme approach is that a user can rely on seamless localization in larger areas, typically exhibiting heterogeneous positioning conditions. A disadvantage is the need for a building map containing information about building entrance locations, stairs, elevators, and positioning context information as described in Section III-C. However, compared to a detailed building model containing all rooms, corridors, and doors, or even a fingerprinting database, this map is leightweight, and its construction and maintainance does not require much additional effort.

The second remarkable characteristic is the auto-adaptive dead reckoning algorithm for fusing PDR and an absolute positioning method into a hybrid scheme. Due to the genericity with respect to the absolute positioning method, this fusion approach is well-suited as a central building block within a multi-scheme architecture. Nevertheless, auto-adaptive dead reckoning provides accurate measurements even in areas with low radio beacon coverage. A comparison of Wi-Fi-based auto-adaptive dead reckoning with other advanced indoor localization systems shows that errors are in the same order of magnitude. For example, the Zee localization system [22] combines crowdsourcing of Wi-Fi fingerprints with a sophisticated map-based particle filter algorithm, which records a user's path through a building and uses map-matching to obtain additional information about PDR parameters and absolute locations. Zee can be combined with Horus [19] or EZ [38] and performs very well in a building with narrow corridors and obstacles that restrict the set of possible paths. The 50%ile and 80%ile errors are reported as 1.2m and 2.3m, respectively, which is slightly better than the results of the auto-adaptive dead reckoning evaluation. Furthermore, if largely unrestricted roaming is possible, e.g., in spacious halls, a map-based approach like Zee cannot exploit its strengths. The auto-adaptive dead reckoning approach seems to be quite promising, although additional evaluations with different environment conditions are necessary to gain more confidence in the statistical evaluation. More sophisticated accuracy estimation methods [39] and the additional use of floor map information [29] could probably improve this result further.

The evaluation shows that areas with bad Wi-Fi coverage and large rooms benefit the most. As a result, this positioning system can be used in areas which do not meet the requirements for Wi-Fi-only positioning approaches.

An unsolved problem is the determination of an initial position at starting locations with poor Wi-Fi coverage. Considering the enormous effort needed to construct a fingerprinting database, it obviously makes sense to also consider the selective deployment of NFC tags in such areas. These tags are cheap, permit exact localization, and will be supported by the vast majority of future smartphones. Moreover, the implementation of NFC-based localization has shown to be rather uncomplicated.

Compared to the more elaborate particle filters, auto-adaptive dead reckoning is a lightweight algorithm imposing only modest CPU load. The low-complexity fusion method and the avoidance of elaborate probabilistic algorithms result in a good real-time behaviour. Several test runs with different smartphones have shown that even on low-end hardware the SmartLocator runs without any visible performance problems. However, a more detailed analysis of algorithmic performance factors would be interesting, since time-consuming computations have negative effects on response times and power consumption.

Moreover, the approach carefully avoids unnecessary sensor usage. Investigations of the influence of sensor scanning on power consumption with different smartphones [40, 41] reveal that the GPS antenna is a major power consumer reducing battery life up to 50%, whereas the impact of inertial sensors, magnetometers, or barometers is negligible unless high sampling rates inhibit the monitoring processor from staying in a low-power idle mode. The proposed multi-scheme algorithm generally activates only one localization scheme at a given location, using only the scheme-related device components. Simultaneous activation of several absolute localization methods is restricted to a few special scenarios, i.e., system initialisation and detection of border-crossing movements, like indoor-outdoor transitions, near port locations. Furthermore, if no motion is detected, the localization system changes into a power-saving mode, reducing its activities to motion sensor scanning every two seconds. The properties of the multi-scheme algorithm imply several power consumption scenarios as shown in Table I.

TABLE I. OPERATION MODES AND POWER CONSUMPTION.

Operation mode	**Active Components**	**Power Consumption**
No motion	Motion sensors	Very low
Indoor Wi-Fi	PDR and Wi-Fi	Low
Indoor BLE	PDR and BLE	Low
Outdoor GPS	PDR and GPS	High
Indoor/indoor border	PDR/Wi-Fi/BLE	Moderate
Indoor/outdoor border	PDR/GPS/Wi-Fi or PDR/GPS/BLE	High High
Initialisation	PDR/GPS/Wi-Fi/BLE	High

REFERENCES

[1] N. Becker, M. Jäger, and S. Süß, "Indoor smartphone localization with auto-adaptive dead reckoning," in Proceedings of the 2015 Tenth International Conference on Systems, Barcelona, Spain, 5 2015, pp. 125–131.
[2] C. J. Hegarty and E. Chatre, "Evolution of the global navigation satellitesystem (gnss)," Proceedings of the IEEE, vol. 96, no. 12, 2008, pp. 1902–1917.
[3] US Government, "Official U.S. government information about the global positioning system (GPS) and related topics," http://www.gps.gov, 2015, accessed: March, 3rd 2015.
[4] P. Misra and P. Enge, Global Positioning System: Signals, Measurements and Performance Second Edition. Lincoln, MA: Ganga-Jamuna Press, 2006.

[5] J. Wang et al., “Pseudolite applications in positioning and navigation: Progress and problems,” Positioning, vol. 1, no. 03, 2002.
[6] M. Youssef and A. Agrawala, “The Horus WLAN location determination system,” in Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services, ser. MobiSys ’05, 2005, pp. 205–218.
[7] P. Bahl and V. N. Padmanabhan, “RADAR: An in-building RF-based user location and tracking system,” in INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE, vol. 2. IEEE, 2000, pp. 775–784.
[8] M. Weber, U. Birkel, R. Collmann, and J. Engelbrecht, “Wireless indoor positioning: Localization improvements with a leaky coaxial cable prototype,” in 2011 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Guimaraes, Portugal, pp. 21–23.
[9] T.-N. Lin, S.-H. Fang, W.-H. Tseng, C.-W. Lee, and J.-W. Hsieh, “A group-discrimination-based access point selection for WLAN fingerprinting localization,” Vehicular Technology, IEEE Transactions on, vol. 63, no. 8, 2014, pp. 3967–3976.
[10] M. Brunato and R. Battiti, “Statistical learning theory for location fingerprinting in wireless LANs,” Computer Networks, vol. 47, no. 6, 2005, pp. 825–845.
[11] C. Gomez, J. Oller, and J. Paradells, “Overview and evaluation of bluetooth low energy: An emerging low-power wireless technology,” Sensors, vol. 12, no. 9, 2012, pp. 11 734–11 753.
[12] N. Newman, “Apple iBeacon technology briefing,” Journal of Direct, Data and Digital Marketing Practice, vol. 15, no. 3, 2014, pp. 222–225.
[13] Spoonphone.com. Bespoon. [Online]. Available: http://spoonphone.com/en/ [retrieved: Jul., 2015]
[14] S. Beauregard and H. Haas, “Pedestrian dead reckoning: A basis for personal positioning,” in Proceedings of the 3rd Workshop on Positioning, Navigation and Communication, 2006, pp. 27–35.
[15] K. Muralidharan, A. J. Khan, A. Misra, R. K. Balan, and S. Agarwal, “Barometric phone sensors: more hype than hope!” in Proceedings of the 15th Workshop on Mobile Computing Systems and Applications. ACM, 2014, p. 12.
[16] R. Harle, “A survey of indoor inertial positioning systems for pedestrians,” IEEE Communications Surveys & Tutorials, no. 15, 2013, pp. 1281–1293.
[17] N. Becker, “Development of a location-based information and navigation system for indoor and outdoor areas,” Master’s thesis, Technische Hochschule Mittelhessen, Giessen, Germany, 2014.
[18] R. Want, “Near field communication,” IEEE Pervasive Computing, vol. 10, no. 3, 2011, pp. 4–7.
[19] M. A. Rehim, “Horus: A WLAN-based indoor location determination system,” Ph.D. dissertation, University of Maryland, 2004.
[20] Y. Chen and H. Kobayashi, “Signal strength based indoor geolocation,” Princeton University, Tech. Rep., 2002.
[21] P. Bolliger, “Redpin-adaptive, zero-configuration indoor localization through user collaboration,” in Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments. ACM, 2008, pp. 55–60.
[22] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, “Zee: zero-effort crowdsourcing for indoor localization,” in Proceedings of the 18th annual international conference on Mobile computing and networking. ACM, 2012, pp. 293–304.
[23] S. Ayub, A. Bahraminisaab, and B. Honary, “A sensor fusion method for smart phone orientation estimation,” in 13th Annual Post Graduate Symposium on the Convergence of Telecommunications, Networking and Broadcasting, 2012.
[24] J. B. Link, P. Smith, N. Viol, and K. Wehrle, “Footpath: Accurate map-based indoor navigation using smartphones,” in Indoor Positioning and Indoor Navigation (IPIN), 2011 International Conference on. IEEE, 2011, pp. 1–8.
[25] H. Ying, C. Silex, A. Schnitzer, S. Leonhardt, and M. Schiek, “Automatic step detection in the accelerometer signal,” in 4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007). Springer, 2007, pp. 80–85.
[26] X. Chen, S. Hu, Z. Shao, and J. Tan, “Pedestrian positioning with physical activity classification for indoors,” in Robotics and Automation (ICRA), 2011 IEEE International Conference on. IEEE, 2011, pp. 1311–1316.
[27] S. Khalifa, M. Hassan, and A. Seneviratne, “Adaptive pedestrian activity classification for indoor dead reckoning systems,” in Indoor Positioning and Indoor Navigation (IPIN), 2013 International Conference on. IEEE, 2013, pp. 1–7.
[28] L.-H. Chen, E.-K. Wu, M.-H. Jin, and G.-H. Chen, “Intelligent fusion of wi-fi and inertial sensor-based positioning systems for indoor pedestrian navigation,” 2014.
[29] F. Ebner, F. Deinzer, L. Köping, and M. Grzegorzek, “Robust self-localization using Wi-Fi, step/turn-detection and recursive density estimation,” in International Conference on Indoor Positioning and Indoor Navigation, vol. 27, 2014, p. 30th.
[30] S. Thrun, W. Burgard, and D. Fox, Probabilistic robotics. MIT press, 2005.
[31] J. Hightower and G. Borriello, “Particle filters for location estimation in ubiquitous computing: A case study,” in UbiComp 2004: Ubiquitous Computing. Springer, 2004, pp. 88–106.
[32] D. Roetenberg, H. J. Luinge, C. T. M. Baten, and P. H. Veltink, “Compensation of magnetic disturbances improves inertial and magnetic sensing of human body segment orientation,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 13, 2005, pp. 395–405.
[33] M. Haklay and P. Weber, “Openstreetmap: User-generated street maps,” Pervasive Computing, IEEE, vol. 7, no. 4, 2008, pp. 12–18.
[34] V. Honkavirta, T. Perala, S. Ali-Loytty, and R. Piché, “A comparative survey of WLAN location fingerprinting methods,” in Positioning, Navigation and Communication, 2009. WPNC 2009. 6th Workshop on. IEEE, 2009, pp. 243–251.
[35] T. King, S. Kopf, T. Haenselmann, C. Lubberger, and W. Effelsberg, “Compass: A probabilistic indoor positioning system based on 802.11 and digital compasses,” in Proceedings of the 1st international workshop on Wireless network testbeds, experimental evaluation & characterization. ACM, 2006, pp. 34–40.
[36] J. Letchner, D. Fox, and A. LaMarca, “Large-scale localization from wireless signal strength,” in Proceedings of the national conference on artificial intelligence, vol. 20, no. 1. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999, 2005, p. 15.
[37] A. Bekkelien, M. Deriaz, and S. Marchand-Maillet, “Bluetooth indoor positioning,” Master’s thesis, University of Geneva, 2012.
[38] K. Chintalapudi, A. Padmanabha Iyer, and V. N. Padmanabhan, “Indoor localization without the pain,” in Proceedings of the sixteenth annual international conference on Mobile computing and networking. ACM, 2010, pp. 173–184.
[39] H. Lemelson, M. B. Kjærgaard, R. Hansen, and T. King, “Error estimation for indoor 802.11 location fingerprinting,” in Location and Context Awareness. Springer, 2009, pp. 138–155.
[40] B. Priyantha, D. Lymberopoulos, and J. Liu, “Littlerock: Enabling energy-efficient continuous sensing on mobile phones,” Pervasive Computing, IEEE, vol. 10, no. 2, 2011, pp. 12–15.
[41] P. Zhou, Y. Zheng, Z. Li, M. Li, and G. Shen, “Iodetector: A generic service for indoor outdoor detection,” in Proceedings of the 10th ACM conference on embedded network sensor systems. ACM, 2012, pp. 113–126.