Indoor Smartphone Localization with Auto-Adaptive Dead Reckoning

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***Abstract*—A common localization method for mobile devices is the fusion of absolute position measurements with relative motion information from sensor units. For each location measurement technique, specific context conditions determine the accuracy of the obtained location estimates. This paper presents a hybrid smartphone localization system fusing an absolute localization method, e.g., Wi-Fi-based signal strength fingerprinting, in an adaptive way with inertial pedestrian navigation, taking into account that each of the involved methods might deliver good results at one location but might also fail at another. Based on an accuracy factor reflecting the current context conditions of a location measurement the influence of each of the involved positioning estimates is weighted accordingly. In a case study using Wi-Fi fingerprinting, accuracy has been improved by 43% in an indoor environment.**

Keywords–Smartphone Positioning; Indoor Positioning; Dead Reckoning; Wi-Fi Fingerprinting; Step Detection;

I. INTRODUCTION

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, or a university campus. Such sites are often heterogeneous in the sense that a single localization method delivers good results in one sub-area but fails in another. Solutions typically require hybrid methods comprising a suitable combination of an absolute positioning method with sensor-based relative 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. As far as outdoor environments are concerned absolute positioning is commonly based on global navigation satellite systems (GNSS) [1], like the well-known Global Positioning System (GPS) [2], 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 [3], satellite systems are not expected to provide sufficient accuracy inside of buildings without being supported by expensive complementary ground component (aka "pseudolite") technology [4].

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 [5–9]. 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 [10], e.g., iBeacons [11], might foster their use for the same purpose within the next few years.

Regardless of the beacon types and localization algorithms, absolute indoor localization methods 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.

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, gravity sensors, or barometers, are used to track relative position changes. For example, distance estimation in pedestrian dead reckoning (PDR) systems [12] is typically based on step detection with motion sensors and step length estimation. This is combined with direction information from an electronic compass. Moreover, a barometer could help in determining the current floor in a building. 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.

A hybrid method integrates 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

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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. However, 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.

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 which is considered accurate has a stronger impact on the result. The term ”adaptive” is used for a fusion algorithm which 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 [13].

This paper focuses on indoor localization by combining Wi-Fi-based fingerprinting (see II-A) with PDR. Nevertheless, the concept is also applicable to other absolute indoor and outdoor localization techniques, e.g., iBeacons or GPS. Actually, the SmartLocator implementation also comprises localization based on GPS and Near Field Communication (NFC) [14].

After presenting related work in the section II, the concepts of auto-adaptive dead reckoning are described in section III. Section IV discusses experimental results showing the achieved accuracy improvements over non-hybrid as well as hybrid methods with non-dynamic method fusion. Section V 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, 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 [5–9].

Fingerprinting is based on a probability distribution of signal strengths at a given location. A map of these distributions is used to predict a location from RSSI samples. From each visible access point the mobile device receives beacon signals. The set of all pairs consisting of access point ID and RSSI value can be seen as a fingerprint for the device’s current location. In order to determine the device position, a database is searched for similar fingerprints. The database itself is created in an offline learning phase, which links fingerprints to a number of known locations called calibration points.

A major advantage of Wi-Fi fingerprinting is that it does not require specialized hardware [6][15][16]. 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 estimated positions highly depends on the density of the radio map [6], 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 [17][18]. 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 [19], 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 [20]. 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 [21]. A modified Pan-Tompkins algorithm is used for signal preparation. Pan-Tompkins, in the context of step detection, has been used by Ying [22] before.

C. Method Fusion

An interesting approach combining Wi-Fi-based fingerprinting with PDR was proposed in [23]. Their fusing algorithm uses a limited history of location measurements for both

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methods to achieve accurate position estimations. Another promising solution is described in [24] . 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 [25].

Particle filtering, however, comes with some drawbacks, particularly the algorithmic complexity which results in a high processor load and impacts power consumption. Moreover, suitable floor maps have to be supplied and maintained.

III. Proposed Positioning System

This section describes auto-adaptive dead reckoning and its implementation in the SmartLocator positioning system. SmartLocator actually implements a multi-method approach comprising indoor as well as outdoor positioning with seamless transitions. In order to exploit the capabilities of a modern smartphone, the system supports various absolute positioning techniques such as GPS, NFC, and Wi-Fi. Additional support for Bluetooth Low Energy beacons is in preparation. The absolute methods are used opportunistically, depending on their availability.

Although a general discussion of the fusion of several absolute methods is out of scope of this paper, it is worth noting that positions determined with GPS, Wi-Fi, or BLE are considered inaccurate, whereas NFC-based positioning is treated as accurate. The smartphone nearly has to get in touch with an NFC tag in order to read it. Hence, reading a tag with a precisely known position also reveals the exact position of the reading device. Whenever a precise location 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 paper is to present the way of fusing PDR with an absolute positioning method. The term "auto-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. Although this section concentrates on the fusion of PDR and Wi-Fi fingerprinting, the approach is not confined to a specific absolute localization method. It is rather a particular strength of the approach to be method-independent.

Figure 1 illustrates how absolute location sources are combined with relative positioning information.

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

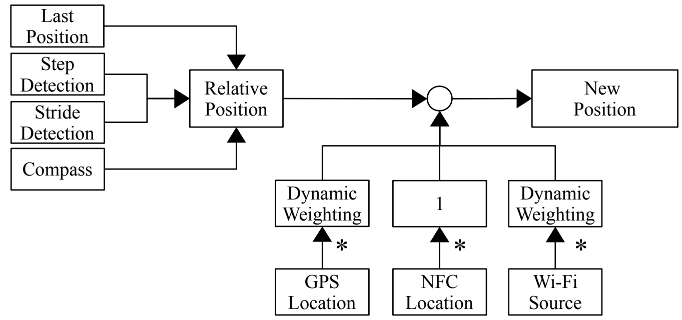


Figure 1. SmartLocator Positioning Concept

A. Fingerprinting

The fingerprint-based position is computed with help of the naïve Bayes classifier [6][15][16], which is more accurate than algorithms comparing distances between RSSIs [26–29]. This advantage has been confirmed during the evaluation of this positioning system.

The naïve Bayes classifier is based on the Bayes theorem, which defines the probability P of the class C under the assumption that x is given as follows:

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

In case of fingerprinting, $P(C|x)$ describes the probability that fingerprint x belongs to the class C, which represents a position. x is a vector of RSSI values.

It is assumed that all values of the input vector x are independent of each other. For this reason, the conditional probability $P(x|C)$ is the product of the probability of each element in x given class C, $P(x_i|C)$.

$$P(x|C) = \prod_i P(x_i|C) \tag{2}$$

A common approach to compute the likelihood $P(x|C)$, which depends on the training data, is the following [26][15, p. 36]:

$$P(x_i|C) = \frac{1}{n}\sum_{j=1}^{n} K_{Gauss}(x_i, y_j) \tag{3}$$

$$K_{Gauss} = \frac{1}{\sqrt{2\pi}\sigma} exp\left(-\frac{(x-y)^2}{2\sigma^2}\right) \tag{4}$$

K denotes the kernel function. x is the observed fingerprint and y are all fingerprints, recorded for location C. n is the number of recorded fingerprints for location C.

The actual position is interpolated from the three best fitting fingerprints.

$$C_{NN} = \frac{\prod_{i=1}^{3} C_i * P(C_i|x)}{\sum_{i=1}^{3} P(C_i|x)} \tag{5}$$

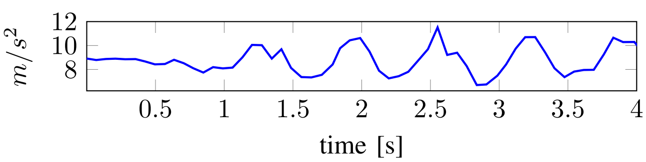
B. Step Detection

The step detection algorithm recognizes pedestrian movements based on a simple peak detection algorithm described by Link et al. [21]. 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.

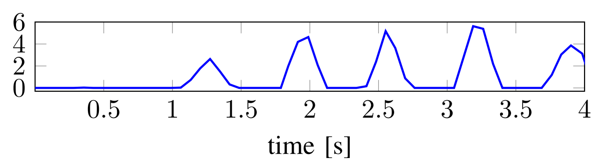
$$y(n) = \begin{cases} \frac{1}{4}[2x(n) + x(n-1) - x(n-3) - 2x(n-4)] & \text{if } y(n) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

$$y(n) = (1 + y(n))^2 - 1 \quad (7)$$

A derivative operator uses low-pass filtered accelerometer 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 2 shows the incoming acceleration signal before (a) and after (b) this preparation.



(a) Raw Acceleration at Z-Axis



(b) Squared Derivative Signal

Figure 2. 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 3. 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.

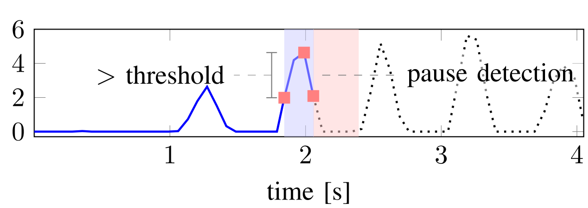


Figure 3. Step Detection Example. Red Squares Represent Analyzed Values

C. Auto-Adaptive Dead Reckoning

The major innovation of SmartLocator's 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 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 $Loc(i, t)$ be a measurement obtained by localization method $M(i)$ at time t, e.g., an absolute Wi-Fi or GPS position. The contribution of $Loc(i, t)$ to the resulting location information depends on the method-specific accuracy factor. The accuracy factor $Q(Loc(i, t))$ is obtained by context evaluation and reflects the measurement's context-dependent reliability.

In addition, a time-dependent factor α_t is added to the accuracy factor. In this way, positions have a stronger influence if the last position determination was long ago. The linear α_t used in SmartLocator is represented by figure 4.

$$\alpha = max(Q(Loc(i, t)) + \alpha_t, 1) \quad (8)$$

$$Loc(t) = Loc(i, t) * \alpha + Loc(t-1) * (1 - \alpha) \quad (9)$$

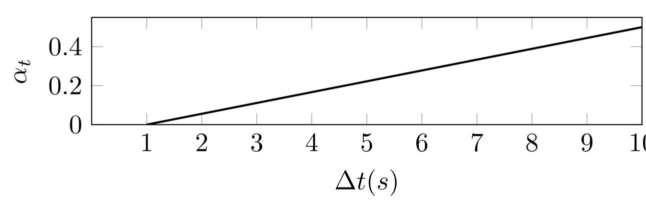


Figure 4. Time-Dependent Factor

1) Accuracy Factors: The accuracy factor $Q(Loc(i, t))$ depends on the method i used for positioning. This section describes various methods to compute the accuracy factor for Wi-Fi fingerprinting, GPS and NFC.

Wi-Fi: Evaluations revealed an average error of 2.94 meters for pure Wi-Fi positioning. However, the error varied from 0.07 to 7.99 meters. Figure 5 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. The accuracy factor $Q(Loc(\text{wifi}, t))$, illustrated in figure 6, takes this relation into account to reduce the influence of unreliable position measurements.

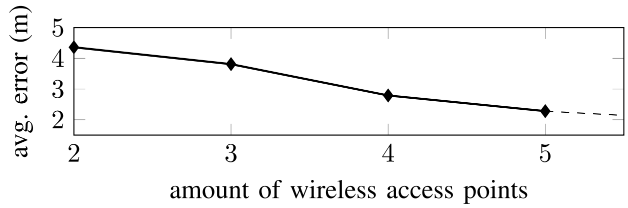


Figure 5. Accuracy Factor for Wi-Fi positioning

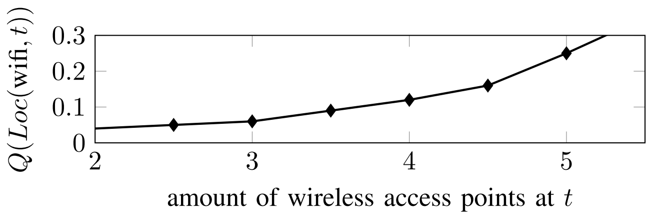


Figure 6. Wi-Fi Accuracy Factor Depending on Amount of Access Points

GPS: The GPS position is determined via the smart phone's operating systems' API. Each GPS position includes an accuracy property, which represents an estimated average error in meters. The accuracy-factor, shown in figure 7, is based on this accuracy property.

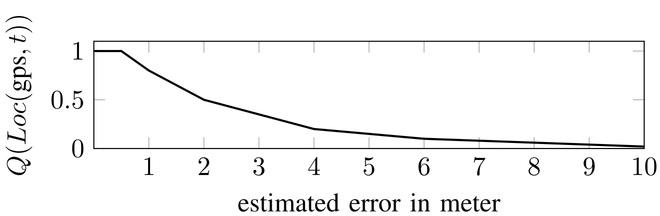


Figure 7. Accuracy Factor for GPS positioning

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 $Q(Loc(\text{nfc}, t))$ always returns the maximum value of 1, which means that an NFC position overwrites prior location determinations completely.

IV. EVALUATION

SmartLocator has been tested under realistic circumstances in a university campus. Using eight Wi-Fi access points for positioning, fingerprints at 67 different locations have been recorded. The fingerprint locations are distributed equally 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.

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

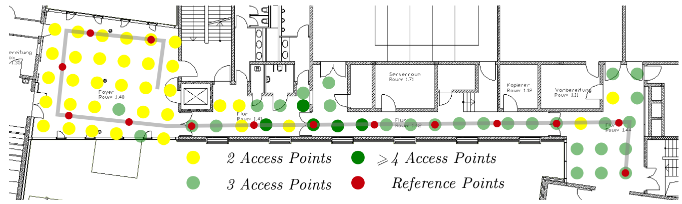
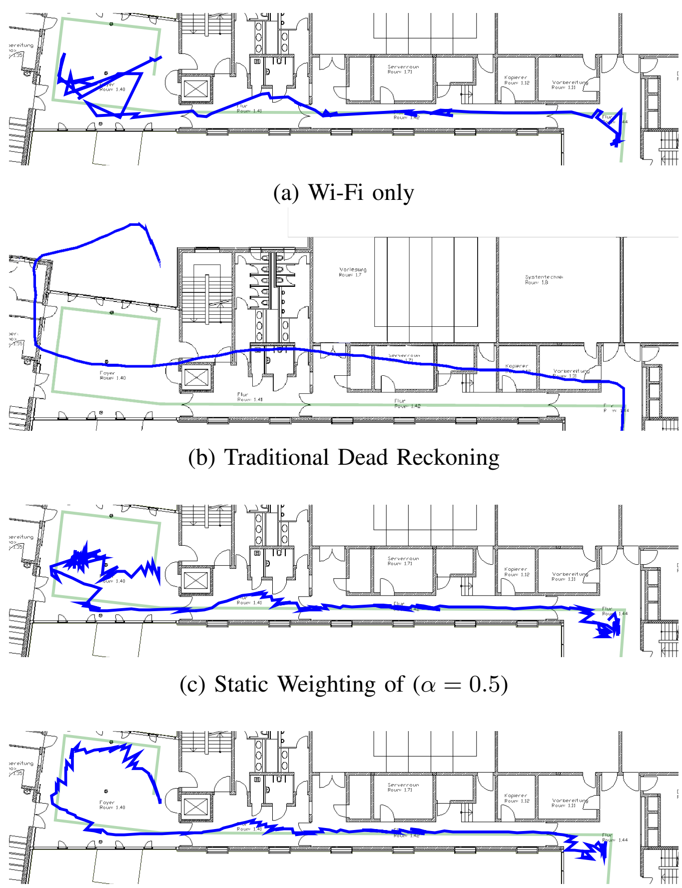


Figure 8. Wi-Fi Positioning Test Area with Fingerprints

at the track. Those known reference positions are compared to the estimated positions, to determine the accuracy of the different approaches. Figure 8 shows the test environment, including the test track, which is illustrated by a grey line.

Figure 9 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 9b shows the results gathered with traditional dead reckoning, which means that absolute positioning results overwrite prior positioning estimations. Figure 9c presents a static weighting of 0.5, i.e., new absolute positions are just reckoned up by half. Figure 9d visualizes the positioning results achieved with a dynamic, auto-adaptive combination.



(a) Wi-Fi only

(b) Traditional Dead Reckoning

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

(d) Auto-Adaptive Weighting

Figure 9. Comparison of Different Weightings

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 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.

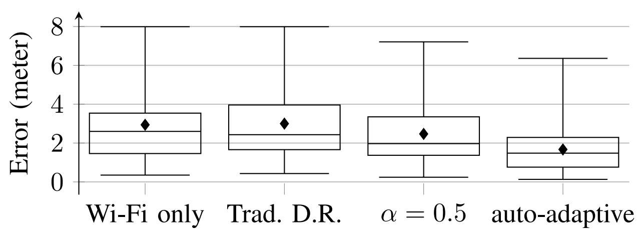


Figure 10. Comparison of Wi-Fi-only Positioning, Classic Dead Reckoning, Static and Dynamic Weighting

V. Conclusion

The positioning system described in this paper reveals a significant increase of localization accuracy through auto-adaptive combination of absolute and relative positions. Even though the accuracy estimations for Wi-Fi positioning are rather rudimentary, the average error has been reduced by 1.27 meters to 1.67 meters. Comparing the average absolute deviation with the results of other solutions, e.g. [23], 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 [30] and the additional use of floor map information [24] 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.

It is an important characteristic of the auto-adaptive fusion method that it is independent from the evaluated positioning methods. It could be applied to any other technique as long as a weighting factor can be determined. It can be assumed that GPS-based outdoor positioning and BLE-based indoor techniques benefit similarly. However, the quantitative evaluation is still in progress.

We consider some performance aspects at last. The low-complexity fusion method and the avoidance of elaborate probabilistic algorithms for particle filtering result in a good real-time behavior. 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.

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