Compass and WLAN Integration for Indoor Tracking on Mobile Phones

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***Abstract*—Indoor positioning with smartphones in ubiquituos computing scenarios still poses some problems with respect to accuracy and precision as well the need for a calibrated infrastructure and map data. This paper presents a method for indoor positioning based on the combination of 802.11 WLAN fingerprinting using weighted kNN and a simple indoor movement model based on digital compass information. We introduce a novel computation scheme for the distance in WLAN signal space, additionally considering the Euclidean real world distance between each fingerprint and the position predicted by the movement model. A detailed evaluation in a test environment at our site demonstrates a performance gain of more than 10% as compared to a classical Kalman filter. Moreover, we also show that the Kalman filter offers a slightly better capability to correct the accumulation of errors over time when accurate movement information in form of step detection is available.**

***Keywords*-Indoor Location Systems; 802.11 Fingerprinting; Mobile Phone Tracking; Location-Based Services.**

I. Introduction

Location-based Services (LBS) [1], such as navigation and information services, are among today's most popular mobile services in ubiquitous computing scenarios. Furthermore, the position of objects or persons is essential in many ubiquitous computing applications since information about the surroundings is often more important than information on places far away. Fortunately, the increasing market penetration of modern smartphones, small devices with high processing power and localization capabilities, boosts the availability of location-dependent information. An example is the Global Positioning System (GPS) [2] offering accurate positioning free of charge in outdoor environments. However, GPS is (for the moment) not able to provide accurate indoor position information for ubiquitous services. Especially in the case of indoor navigation the position error should not exceed a few meters to be able to distinguish between several rooms and floors to provide step-by-step guidance and generate navigation instructions.

In the past few years, multiple indoor positioning techniques have been developed. Systems based on ultra wideband or ultrasonic systems utilize an expensive dedicated infrastructure, but offer high accuracy position estimates. Those are often only available in a small area, where higher accuracy compensates the high cost. An advantage of these precise systems is that tracking functionality can easily be integrated by sampling position estimates over time. Since the error of each estimate is small, a realistic track can be observed over a period of time.

Other systems make use of existing infrastructure with little or no additional expenses and therefore are limited in their accuracy. These kinds of positioning systems are often based on WLAN, Bluetooth or inertial measurement units (IMU). In contrast to expensive systems, they are often used to offer localization services in large indoor areas, especially in complex buildings such as museums, shopping malls, airports, hospitals, or university buildings. Adding high quality tracking functionality to these systems is considerably more complex, due to the possibility of unrealistic jumps of consecutive position estimates over a large distance (WLAN) and the accumulation of errors over time (IMU). But exactly the high quality tracking information is of great importance to a large number of services such as navigation, tracking of users and goods, or automated quality control in factory settings. Zheng and Xiaofang offer a good overview on use-cases and techniques for computing and working with spatial trajectories in [3].

In this paper, we expand SMARTPOS [4], an indoor positioning system for smartphones based on WLAN fingerprinting and a digital compass, to support continuous positioning and tracking. While the unmodified system achieves a high accuracy within few meters for positioning it is prone to jump between consecutive estimates and therefore offers low quality tracks. We show that the user's orientation measured by the digital compass of the smartphone can be used for a more stable position estimation. The key contribution is the inclusion of the predicted position based on the previous position and a movement model into the fingerprint nearest neighbor calculation. Basically, this favors fingerprints near the last position estimate resulting in smoother paths, which are more realistic and more accurate as we demonstrate in this paper. The applied movement model is either simply defined by constant velocity or step detection with constant step-length, both enhanced with a direction measured by a digital compass.

The remainder of this paper is structured as follows: In the next section, a short overview of existing indoor positioning and tracking systems is given and differences to our system mentioned. In Section III, the original SMARTPOS system [4] is presented, while in Section IV the enhancements of the system for continuous positioning are explained in detail. In Section V, their impact on the tracking performance is analyzed and discussed. Section VI concludes the paper and gives hints on future work.

II. Related Work

The topic of indoor positioning and tracking is deeply investigated in academic and industrial research and one of the most active research topics concerning LBS. A vast variety of technologies and algorithms have been proposed and still no satisfactory solution exists that offers satisfactory position information for every use case.

Many pedestrian indoor positioning systems rely on WLAN fingerprinting algorithms [4], [5], [6], [7], which offer position estimates with sufficient accuracy (i.e., 1-3m) while utilizing the existing WLAN infrastructure and therefore avoiding high expenses. These algorithms belong to the area of pattern matching and work in two phases: The first phase is called the calibration phase, where a database is created by the collection of received signal strength indicator (RSSI) at certain reference positions from the surrounding access points (AP). The accumulated information of RSSI, AP and reference position at a specific time/interval is called a fingerprint. In the second phase, the positioning is carried out by comparing current RSSI measurements with the previously stored values from the database. Different algorithms calculate the position as the reference position of the nearest fingerprint in signal space [5], the average of the k-nearest neighbors (kNN) with or without the distance in signal space as additional weight [4]. Some algorithms also utilize Bayesian methods [6], [7] based on probability distributions derived by multiple measurements over a length of time. COMPASS [7] is one of the first fingerprinting systems that addresses the problem of attenuation effects caused by the human body by adding a digital compass to the system. In the calibration phase, fingerprints for several selected orientations (typically each $45°$ or $90°$) are collected at reference positions. In the positioning phase, the user's orientation is measured by a digital compass and only the fingerprints with a similar orientation estimate are used for the positioning algorithm. However, none of the above-mentioned approaches considers the user's movement. A good overview of other existing positioning systems using radio frequency (RF) technologies such as radio frequency identification (RFID), ultra wide band, WLAN and Bluetooth is given in [8].

Another class of pedestrian indoor positioning systems is based on IMUs such as accelerometer or magnetometer. These systems offer only relative positioning capacities as they measure position changes rather than an absolute position. This results in an accumulation of sensor errors over time, which is the reason why most systems consider additional information, e.g., WLAN fingerprinting or map information, for recalibration. Woodman and Harle show in [9] that a building model can compensate the drift of inertial sensors and add WLAN positioning for obtaining an initial position fix in their Dead Reckoning system. However, WLAN positioning is not considered for the correction of position data. Evennou and Marx compare a Kalman and a particle filter for fusing location estimates of a WLAN fingerprinting algorithm with high quality accelerometer data [10]. They report a high increase in accuracy compared to individual systems, but do not yet include the target's or its predicted position in the WLAN fingerprinting. Ruiz et al. utilize a tightly coupled Kalman filter to fuse foot-mounted IMU-based position estimates with additional RSSI information by RFID tags [11]. Their approach is similar to ours, since they include the estimated position by IMU in the position estimation by RFID, but they use pathloss instead of fingerprinting techniques and foot-mounted sensors instead of cell phones. Chan et al. describe a system [12], which utilizes orientation information to predict the region, in which the next matching fingerprint is to be expected. Fingerprints outside that predicted region are completely ignored for the nearest neighbor estimation, so that wrong orientation information can lead to wrong location assumptions. Our system is not as restrictive and weights several factors applying the distance calculation on fingerprints all around instead of a regional limited choice.

In the last few years, many indoor positioning systems have been adopted or developed for deployment on cell phones. These offer additional sensors, which can directly be integrated to enhance the position accuracy of existing systems by combining the information of different sources to a position estimate of higher accuracy than any single source could provide. Martin et al. present one of the first WLAN positioning systems, which integrates both calibration and positioning on a mobile phone [13]. They use various nearest neighbor algorithms, but do not use additional sensors nor a prediction model. Perttula et al. show in [14] that modern smartphones have enough processing power to support Bayesian location estimation methods for WLAN fingerprinting, but no further sensors are added to the system to improve the localization capabilities. In [15], Liu et al. propose a particle filter based on a hidden Markov model to combine the inertial sensors of a smartphone with WLAN fingerprinting and report a significant increase in accuracy. Nevertheless, they do not include the predicted position in the choice of position candidates by the measurement model.

In our approach, we integrate WLAN fingerprinting with IMU data by the means of a prediction model based on the IMU data and a measurement model based on the predicted position and WLAN fingerprinting. The novelty of our approach is given by the direct inclusion of the predicted position in the WLAN fingerprinting approach by combining the Euclidean distance in map and signal space.

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III. The SMARTPOS System

In this section, we give a short overview of SMARTPOS (for more details see [4]), an indoor positioning system based on 802.11 fingerprinting and a digital compass. The focus is on the functionality and the previously gathered results, which are helpful to understand enhancements for tracking functionality described in the following section.

A. Description

SMARTPOS runs stand-alone on a mobile phone and consists of a management module for the creation and maintenance of a fingerprint database and a module for location determination. In the database creation step, RSSI is stored for several reference positions (RP) in the building. At each reference position four fingerprints are recorded, each time aligning the phone along one of the four main axes of the building. A single fingerprint consists of

- a list of the average RSSI values of five consecutive measurements for each visible access point (AP) along with the MAC-address of the specific AP
- the pixel coordinates of the reference position on a bitmap of the floor
- and the average of the measurements of the phone's compass during the sampling time, which is an indicator for the user's orientation

B. Previous Results

We evaluated the impact of several variations of deterministic fingerprinting, using a k-nearest-neighbor (kNN) algorithm with varying parameter k. In a testbed consisting of a wing of a university building (approximately 200m^2) and with a database consisting of 79 RPs and thus 316 individual fingerprints, we evaluated the impact of weighted kNN, the treatment of missing values, and the performance gain by including the user's orientation in the position estimation step. The evaluation was carried out with respect to the accuracy and the precision of SMARTPOS with the following results:

- Weighted kNN results in a slightly higher accuracy than non-weighted kNN
- Ignoring missing RSSI causes higher accuracy and precision for larger k as compared to assigning a fixed minimal RSSI value (which was -100dBm) below the phone's sensibility for all missing AP information
- Considering orientation information greatly increases accuracy and precision for a smaller k

IV. Continuous Positioning

To increase the accuracy of SMARTPOS in continuous positioning scenarios, we enhance the position estimation with a prediction step. This step is computed by the means of a movement model supported by the smartphone's compass. There are several ways to combine WLAN position updates with a movement model and measurements from inertial sensors. Most commonly either a Kalman or a particle filter is used to fuse the data from different sources (compare [10]). While a particle filter is a discrete approximation of a probability density function, a Kalman filter is an approximation of a linear dynamic system from noisy measurements. For indoor positioning, a Kalman filter is usually a linear combination of the position estimated by a measurement model $p_{mes,i}$ and the estimate of a prediction model $p_{pre,i-1}$ based on the previous state vector and the direction and velocity of movement (see equation (1)).

$$p_{i|i-1} = p_{mes,i} \cdot (1-\gamma) + p_{pre,i-1} \cdot \gamma \qquad (1)$$

This algorithm works well, but we see the possibility of optimization using kNN. Since a new estimated position (or one of the k nearest neighbors) can be at an unrealistically large distance from the last estimate, we want to modify the choice of nearest neighbors. Therefore, we propose a novel approach similar to a Kalman filter, applying a measurement and a prediction model, but instead of interpolating the predicted position estimate and the measured estimate, we include the interpolation into the nearest neighbor algorithm. We influence the choice of nearest neighbors in signal space by the deviation (Euclidean distance) of the position predicted by the movement model and the position of each neighbor candidate in the real world. Hence, we include a probability of presence into the distance to neighbors in signal space.

A. Measurement Model

The measurement model consists of a basic weighted kNN algorithm with a refined distance definition (between a current measurement and a fingerprint) allowing to include the map distance directly into the computation of the nearest neighbors: Let s_i be the Euclidean distance of the current RSSI measurement (at time t) to the recordings of the i'th fingerprint in the database. Let m_i be the Euclidean distance on a map between the predicted position p_t at time t and the position of the i'th fingerprint. We define the distance $d_i = (1-\alpha) \cdot s_i + \alpha \cdot m_i$ between the current measurement and the i'th fingerprint as a linear interpolation of s_i and m_i, assigning a fixed constant weighting factor α. This definition of a distance between a measurement at a given predicted position and a previously recorded fingerprint leads to smoother paths favoring fingerprints near to a predicted position over fingerprints further away. Obviously, the value of α needs to be configured in order to balance the prediction model and the measurement model.

B. Prediction Model

Having obtained a position estimate at least once, we can apply a prediction model to continuously estimate the current position of a moving target until another measurement can be utilized to recalibrate the predicted position. We apply either a constant movement model or a step

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counter mechanism (similar to the one from Link et al. [16] without map correction) based on accelerometer data, both enhanced with the readings of the smartphone's compass. In the first case, the position is updated according to the constant speed, the elapsed time and the current orientation of the phone between two consecutive compass readings. In the case of the step counter, a step is detected whenever the vertical acceleration drops by more than 2m/s^2 within five consecutive accelerometer readings (i.e., approx. 1s). Those readings are not considered for step detection twice, so when a step is detected, the previous readings are discarded. This mechanism ensures that a single large drop in vertical acceleration measured by consecutive accelerometer readings is not interpreted as multiple steps. A constant step-length is assigned and every detected step is mapped in the direction derived by the compass at the same time. Note that the smartphone needs to be held in approximate horizontal fashion for either the step detection algorithm and the compass. For the moment, we do not apply any map matching techniques to clarify the impact of the prediction model on the measurement model.

V. Evaluation

For the evaluation, a test database of fingerprints in a wing of our site was created. All information was gathered with a HTC Desire smartphone. The 57 reference positions are arranged in an approximate grid with fingerprints measured in the direction of all four main axes of the building, which results in 228 fingerprints in total (the gray dots in Figure 1).

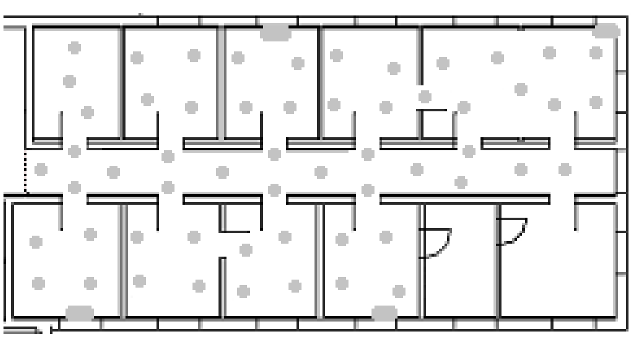

Figure 1: Reference positions (gray dots) and access points (gray rounded rectangles).

We then recorded two tracks (see Figure 2) storing the RSSI values of consecutive active scans (approx. sample rate of 1 Hz) together with the MAC-address of the APs and the readings of the compass as well as the accelerometer (both with an approx. sample rate of 5 Hz). All data is enriched with a timestamp of the specific measurement time and saved in a file. This ensures that our results originate from an identical setting for all the different positioning methods. The quality of the positioning method is evaluated in respect to two criteria: the accuracy indicated by the mean position error and the precision indicated by the standard deviation. In the following the results from a detailed evaluation in the described setting are presented and discussed.

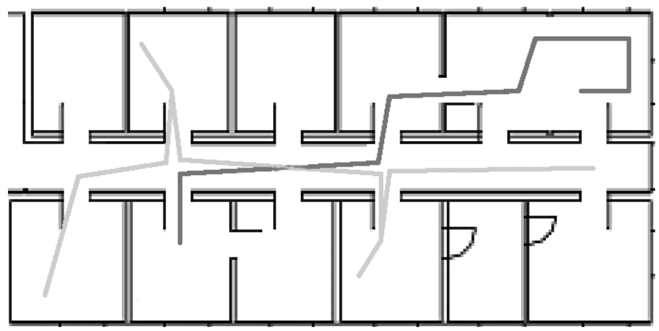

Figure 2: Two test tracks (T1 in light gray with a length of 42m, T2 in darker gray with a length of 27m) starting from right to left.

SMARTPOS is evaluated as follows: First the tracking performance of the deterministic kNN approach and the impact of using orientation information is analyzed. Afterwards, a movement model is added and the Euclidean distance between the reference position and the user's currently estimated position is introduced into the distance calculation of the current RSSI readings and each fingerprint as described. We show that the right choice of the movement model is crucial to the accuracy of the system. Furthermore, we demonstrate the accuracy of the compass by combining an experimentally calculated movement model to the compass readings without considering RSSI. Finally, our proposed algorithm is then compared to a classical Kalman filter.

A. *Tracking Accuracy of the original SMARTPOS*

While standard kNN with $k = 3$ (3NN) is based on RSSI measurements only, we include the user's orientation into our algorithm in the oriented kNN with $k = 3$ (O3NN). In the latter case, only those fingerprints that have a maximal deviation of 50° of the user's orientation are considered for the nearest neighbor algorithm. Table II shows the results for both tracks. As assumed, the consideration of the user's orientation leads to a significant reduction in error (above 10%) and a even larger precision gain (approx. 33%).

Table I: Tracking Accuracy of the original SMARTPOS:

	3NN T1	3NN T2	O3NN T1	O3NN T2
Average error	2.01 m	1.74 m	1.72 m	1.52 m
Standard dev.	1.52 m	1.00 m	1.02 m	0.67 m

B. Combining Euclidean Distance in Signal and Map Space

In this section, the effect of the combination of the Euclidean distance in map and signal space (see Section IV) on the tracking accuracy is further investigated. We experimented with different movement models, alternating the fixed velocity value, and different measurement models for the empirical determination of the parameter α in our test environment.

Small values of alpha result in a smaller influence of the prediction model on the measurement model while larger values add weight to the prediction model. In our test environment $\alpha = 0.7$ (with a speed of 1m/s (A07V10)) lead to the best results in both tracks, resulting in a mean tracking error of 1.33m (T1) and 1.00m (T2) with a standard deviation of 0.85m (T1) and 0.62m (T2). It has to be noted that the lower accuracy of the first track has its origin in the varying walking speed (zero velocity at turn-points), which the movement model is unable to take into account.

With the empirically solved assignment of a fixed value $\alpha = 0.7$, different velocities for the movement model were evaluated. In our model, velocities between 0.8m/s and 1.0m/s are suitable for tracking indoor movement of pedestrians, even in the case of non-constant walking speed. Even so, the mean error can vary to a maximal amount of approximately 10% within this speed interval. The minimal measured mean error was 1.22m (T1) and 0.90m (T2) with a standard deviation of 0.81m (T1) and 0.65m (T2) for a velocity of 0.8m/s.

Finally, the accuracy of the combination of the proposed measurement model with a prediction model based on step detection is evaluated. Each time a step is detected, the predicted position is moved 1.0m in the direction of the current compass heading. The results with our testdata show that the influence of the measurement model should be reduced and $\alpha = 0.85$ leads to a minimal mean error in both tracks, which was 1.33m (T1) and 0.88m (T2) with a standard deviation of 0.78m (T1) and 0.46m (T2). In this case, one can use the measurement model to overcome the accumulation of errors of the step detection algorithm such as wrong step-length, heading, or unreliable step detection.

C. Accuracy of Orientation Information

It is crucial for the prediction model to obtain realistic data readings. While accelerometer readings of todays smartphones are assumed to be too noisy for double integration or even simple integration for the assignment of a velocity to a movement model (a claim which is supported by our data), they can be used for step detection. Furthermore, we observe a high reliability in the compass information. There is an information lag in cases of abrupt turning, but the overall accuracy of the compass values in indoor environments is astonishing. Figure 3 shows an estimated track, which was computed by entering the real starting position and using solely the movement model with an empirically solved constant movement speed applied on the second track (i.e., a track which was recorded while moving with a constant speed). The average error to the real track is 0.82m with a standard deviation of 0.55m and therefore even better than the advanced SMARTPOS system. This is clearly due to the over-fitting of the model to the data, however, it remarkably supports the claim that compass readings contain valuable information for indoor positioning even for low cost smartphone sensors. The accumulated error over time in this experiment was 2.96m.

When using the step detection algorithm instead of a movement model, the average error was 1.20m (T1) and 1.10m (T2) with a standard deviation of 0.77m (T1) and 0.61m (T2) for a step-length of 1.0m. Moreover, the error accumulated over time at the end of each track (i.e. 1.90m in T1 and 0.85m in T2) was less than 5% of the track-length. These results indicate that hand-held step detection with smartphone accelerometer and measuring the direction of the step with a smartphone compass is possible and even without any additional correction schemes quite accurate. However, even a small percentage of error can result in large errors after some time, which makes correction methods indispensable.

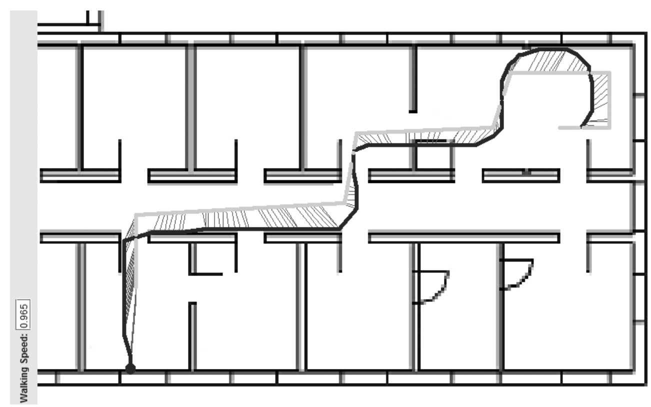

Figure 3: The real track in light gray, the estimated track in dark gray, error vectors are the thin lines in between.

D. Comparison with a Kalman Filter

We compare our results with a classical Kalman filter computing the position estimate as a linear combination of the position estimate computed by either the prediction and the measurement model. In this case, the measurement model does not use the novel measurement scheme, but a standard kNN approach for WLAN position estimation. A weighting factor $\gamma \in [0, 1]$ is applied to equation (1), with $p_{mes,i}$ being the position estimate of the measurement model at time i and $p_{pre,i-1}$ being the position estimate of the prediction model, based on the last estimated position p_{i-1}. The minimal mean error achieved by the Kalman filter (with a speed of 1.0m/s) is 1.51m (T1, $\gamma = 0.7$) and 1.14m (T2,

$\gamma = 0.8$) with a standard deviation of 0.89m (T1) and 0.53m (T2), which means the best case error is still $14-18$cm (i.e., more than 10%) larger than that of our proposed algorithm using the same movement model.

When using the step detection algorithm, however, the contrary is the case. Since step detection also models non constant speed and is therefore in many cases more accurate as a constant speed movement model, the prediction model becomes also more accurate than the measurement model. The system needs only minor corrections to compensate for the accumulation of errors, which is better achieved by a classical Kalman filter. The minimal mean error with $\gamma = 0.85$ in either track is 1.24m (T1) and 0.83m (T2) with a standard deviation of 0.69m (T1) and 0.42m (T2), meaning that the classical Kalman filter is about 7% better than our proposed algorithm.

Furthermore, both algorithms can easily be combined, by utilizing our algorithm for determining the nearest neighbors in the measurement model and the Kalman filter for the interpolation with the predicted position. Since this procedure obviously favors the prediction model, the interpolation parameters need to be applied to compensate for this effect. With $\alpha = 0.75$ and $\gamma = 0.5$ the minimal mean error was 1.14m (T1) and 0.87m (T2) with a standard deviation of 0.81m (T1) and 0.50m (T2), which is a error reduction in the first track, but an increase in the second track. Table II shows an overview on the evaluated parameters. The table also includes accuracies of related research systems for reasons of comparability with respect to the order of magnitude of the expected position error. A direct comparison is not possible due to different set ups and test environments.

Table II: Overview of evaluated tracking accuracies:

T1	avg. err.	std. dev.	end err.
Alpha0.7Velocity1.0	1.33 m	0.85 m	-
Alpha0.7Velocity0.8	1.22 m	0.81 m	-
Alpha0.85Steplength1.0	1.33 m	0.78 m	-
PredictionSteplength1.0	1.20 m	0.77 m	1.90 m
Gamma0.7Velocity1.0	1.51 m	0.89 m	-
Gamma0.85Steplength1.0	1.24 m	0.69 m	-
Alpha0.75Gamma0.5Steplength1.0	1.14 m	0.81 m	-
T2			
Alpha0.7Velocity1.0	1.00 m	0.62 m	-
Alpha0.7Velocity0.8	0.90 m	0.65 m	-
Alpha0.85Steplength1.0	0.88 m	0.46 m	-
PredictionVelocity0.975	0.82 m	0.55 m	2.96 m
PredictionSteplength1.0	1.10 m	0.61 m	0.85 m
Gamma0.8Velocity1.0	1.14 m	0.53 m	-
Gamma0.85Steplength1.0	0.83 m	0.42 m	-
Alpha0.75Gamma0.5Steplength1.0	0.87 m	0.50 m	-
Other Systems			
Woodman and Harle [9]	<0.5 m	-	-
Evennou and Marx [10]	1.53 m	-	-
Ruiz et al. [11]	1.35 m	-	<1.5 m
Chan et al. [12]	1.82 m	-	-

VI. Conclusion and Future Work

This paper presents enhancements for SMARTPOS, a positioning system running stand-alone on smartphones based on deterministic WLAN fingerprinting and a digital compass. The key concept is the addition of a prediction model to the system. We tested both a simple indoor pedestrian movement model with constant speed and a model based on step detection. For orientation information the digital compass of the smartphone is used. The position estimate p of the prediction model is utilized to include the map distance from p and a fingerprint's reference position into the nearest neighbor search in signal space.

We evaluated different weighting factors for the combination of map and signal distance and researched the effect of the walking speed on our model. All experiments were carried out in a testbed of approximately 200m^2 and evaluated on two different tracks. One track was recorded while walking with a constant speed, while the other tracks included turn points with zero velocity. In the track with constant speed the mean error was reduced to 0.90m with a standard deviation of 0.65m, while with the more complicated track we were able to reduce the mean error to 1.22m with a standard deviation of 0.81m. The results show that our approach outperforms a classical Kalman filter, using a linear combination of the prediction and the measurement model, when no accurate information about the movement of the target is available. If high quality position prediction is possible (e.g., with a sophisticated step detection algorithm using the smartphone accelerometer), the Kalman filter with a heavy weight on the prediction model is a better option.

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