Improving Sparse Organic WiFi Localization with Inertial Sensors

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***Abstract*—Personal location discovery and navigation within buildings has become an important research topic in the last years. One method to determine one's current position based on mobile-devices is to compare the set of available WiFi access points (APs), i.e. the fingerprint of a given space, to a previously collected database.**

In this context, this paper addresses the inherent problem of such systems that this fingerprint database needs to be established beforehand. Thus, situations can occur where a building is only partially represented in the database and localization can only be provided in a subset of the spaces of the building. This problem occurs especially in crowd-sourcing (organic) approaches where users consecutively contribute location-binds. In these situations an additional system is needed to provide localization.

We present a first study on the fusion of pedestrian dead reckoning (PDR) from inertial sensors with position estimates from a WiFi localization system. We outline a possible design of particle filter and analyze its behavior on experimental data. We conclude that the outlined method can help to improve WiFi localization and is especially useful within crowd-sourcing environments.

I. Introduction

Personal navigation in cities, airports or large shopping malls as well as, e.g., the position determination of rescue personnel at a disaster site require systems capable of discovering a pedestrian's location. For outdoor scenarios, the availability of Global Navigation Satellite Systems (GNSS) like GPS and their integration in most modern smart-phones has resulted in a simple and practicable solution to this problem. However, scenarios in or in between buildings (”urban canyons”) or seamlessly integrated in- and outdoor application areas where satellite signals are usually unavailable, still pose a challenge.

One approach to this problem is to make use of the more or less ubiquitous WiFi networks. Various ways to use WiFi for this purpose have been proposed [1], [2]. In this context, systems that rely on user input to collect a fingerprint database are often referred to as ”organic” localization systems [3], [4].

Another approach to this problem is grounded in the recent technological developments and price decline for micro-electro-mechanical (MEMS) inertial sensors. The broad availability of inertial (acceleration and gyro) and magnetic sensors in low-cost inertial measurement units (IMU) and modern smart-phones has led to an increase of research interest in personal inertial navigation and pedestrian dead reckoning (PDR) techniques [5], [6]. One common problem of these approaches is, however, that sensor drift and local magnetic disturbances make long-term accurate localization difficult.

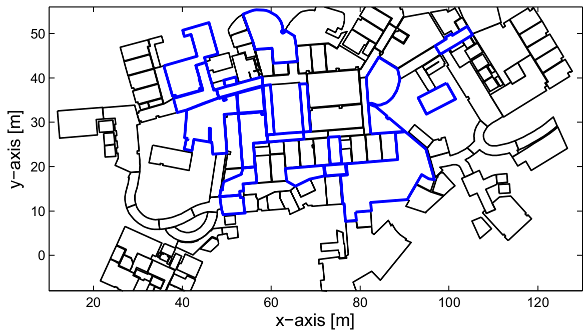

Fig. 1. During the growth phase of an organic positioning system, not all rooms have been surveyed by users, confounding localization in unsurveyed rooms. Spaces outlined in blue are represented in our fingerprint database.

In this paper we present an approach to fuse location estimates from an organic WiFi localization system with heading estimates and step recognition from an IMU. Especially during the initial growth phase of an organic WiFi localization system, such an approach could be useful. Personal location estimates could then be provided even if the area of interest is yet only partially represented in the fingerprint database. Also, in scenarios with a limited number of WiFi access points (AP), the accuracy could be increased. Our key contribution is to provide a practical evaluation of this fusion under realistic conditions. We collect IMU and WiFi localization data in different runs with different test persons and analyze how a position estimate can be obtained from a combination of these two data sources. Figure 1 depicts the floor plan of the building where we conducted our experiments and the spaces that were represented in the WiFi database. The considered data inputs are heading estimates from an attitude and heading reference system (AHRS) along with acceleration data and occasional input from a WiFi localization system. The objective of this paper is to practically evaluate particle filter information fusion under realistic conditions. In contrast to most previous work we try to experimentally study the problem in its whole complexity and not limit the evaluation to a well-defined subproblem. The use of heading information as a ”black-box” can be motivated under the assumption that future smart-phones are likely to provide this capability and we don't go into further details on this. A study of how to obtain heading estimates from the fusion of acceleration, gyro and magnetic sensor data could, e.g., be found in [7]. In this work we outline a framework and present experimental results of the system on one floor of a very large building. A subset of the spaces on this floor is represented in the database of Molé WiFi Positioning Engine [4].

II. Related Work

A. Inertial assisted WiFi Localization

Most fingerprinting WiFi localization systems base their location estimation on availability of APs and their respective received signal strength (RSS) values [1]. Various approaches exist to match a measurement (a scan) of the available APs with a location in the database [3], [4]. One possibility to include knowledge about the considered system, i.e., pedestrians, is to make use of accelerometers to detect whether a person is moving or not (step recognition). This information can be used to assign the same spatial position to several scans. By this, a smoothing over time and a higher accuracy can be achieved [4], [8].

B. Inertial Pedestrian Dead Reckoning

Another approach to indoor localization is to make use of IMU data. Classic inertial navigation, i.e., the integration of acceleration and gyro signals is a difficult task due to the inherent drift of state of the art low-cost MEMS sensors. The inclusion of additional system knowledge, e.g., by placing the IMU on the foot of a pedestrian leads to very good results with errors on the order of a few percent of the traveled distance [9]. However, in the majority of applications, placing an IMU on the foot of a pedestrian can be considered unpractical. Approaches with a hip-mounted IMU usually rely on pedestrian dead-reckoning (PDR) techniques. Detecting steps and estimating the step direction with different methods has been shown to lead to accuracies on the order of about 5 to 8% of traveled distance [6], [10]. One of the reasons to prefer this IMU position is to assume an IMU contained in a future smart-phone and carried in the pocket or in a belt-bag [5]. However, the fundamental problem remains, that such systems are unable to provide long-term stability without additional external input.

C. Information Fusion for Person Localization

An approach to combine and improve methods from both areas is the fusion of information of multiple data sources or additional system knowledge. One important technique in this context is the inclusion of map knowledge if available. By limiting the estimated path to accessible spaces (e.g. by preventing the crossing of walls), the localization accuracy can be increased. One way to do this is by means of a particle filter, i.e., a sample based probabilistic representation of the current position [11]. Different approaches to evaluate the potential of these methods for the fusion of WiFi locations with inertial data and map knowledge have been proposed [8], [12], [13]. However, most previous work in this area is limited to fairly easy and possibly unrealistic instances of the problem, i.e., single or small numbers of straight corridors, very small office spaces or only simulations.

III. Particle Filter-based Location Discovery

In Bayesian state estimation, a state estimate $\hat{x}_k$ and the associated uncertainty at time k are derived from the posterior probability density function (pdf). This pdf $P(x_k|z_{1:k})$ includes all available data from all measurements $z_{1:k}$ up to time k. Under the assumption that measurements and state transitions are independent of preceding events (Markov assumption), its computation can be done recursively based on a prior state estimate $\vec{x}_{k-1}$ and the measurements $z_k = h_k(x_k)$ occurring during the last time step. The Kalman filter provides an optimal solution if the system state can be represented with a Gaussian probability distribution and both the system and the measurement model are linear with zero-mean Gaussian noise terms. However if either is nonlinear or if the system or measurement noise cannot be sufficiently approximated with a Gaussian, it becomes more difficult to calculate the posterior.

If different information sources like maps, inertial data and WiFi fingerprints are to be fused, one opportunity is to make use of a sample based representation of the state such as the particle filter.

The particle filter approximates the state pdf with a number N of discrete samples (particles) with states x_k^i and associated weights w_k^i for $1 \leq i \leq N$.

$$P(x_k|z_{1:k}) \approx \sum_{i=1}^{N} w_k^i \delta(x_k - x_k^i). \tag{1}$$

Herein, the particle weights are normalized such that $\sum {w_k}^i = 1$. One possible state estimate is then $\hat{x}_k = \sum w_k^i x_k^i$. In the considered real-time location discovery application in this paper, the state of a particle simply consists of its 2D-position $x_k^i = [x_k^{i,1}, x_k^{i,2}]$. Note that in order to achieve a meaningful representation of the pdf, N has to be high enough.

The system model is now incorporated in the prediction step in assigning each particle a new position according to:

$$x_{k+1}^i = f(u_k, x_k^i) \tag{2}$$

wherein u_k represents the system input and x_{k+1}^i is a realization of the proposal distribution $f(\cdot)$ for each particle.

In the measurement step, each particle's weight is updated according to all obtained measurements by using the likelihood function of each measurement:

$$w_{k+1}^i = w_k^i P(z_{k+1}|x_{k+1}) \tag{3}$$

In the resampling step, the problem of weight accumulation in only a few particles (sample degeneracy) is prevented by generating a new particle set. Essentially, strong particles are reproduced whereas particles with negligible weight are deleted. It is possible to include a resampling step in every iteration which might however result in a worse representation of the distribution (sample impoverishment). Alternatively, the resampling step can be dependent on a quality measure, e.g., the so-called effective sample size $N_{eff} = 1/\sum_{i=1}^{N}(w_k^i)^2$ [11].

After normalization of the weights a new state estimate can be obtained from these particles.

The main advantage of this Sequential Importance Resampling (SIR) particle filter is that both prediction and measurement allow the incorporation of nonlinear functions which makes it very suited for the considered application.

IV. Design and Implementation

For the given application scenario, we propose to use step recognition, step length and direction estimation from an IMU with an included AHRS as input into the system model (2). Position estimates from the WiFi localization system are used to update the weights in the measurement model (3). Additionally, a subset of these position estimates are also used in the system model (2). The building maps are incorporated in the measurement model (3). A resampling procedure is applied to prevent degeneracy of the filter. In the following, this design is outlined in greater detail by analyzing the available information sources in our scenario.

A. Step Recognition, Step Length and Direction Estimation

For step recognition and step length and direction estimation, we consider data from a hip-mounted Xsens MTi-G IMU, i.e., carried in a belt-bag or in a person's pocket. Our approach for this is based on the method outlined in [10] as summarized:

- **Step recognition**: detect peaks in total acceleration energy, apply additional thresholding and windowing
- **Step direction** φ: use heading information as provided by the IMU's AHRS, estimate IMU alignment versus test person's body and corresponding linear transformation matrix by applying a principal component analysis to accelerations in forwards/sidewards direction [6]
- **Step length** SL: assume proportionality of step length to occurring z-axis accelerations during one step, $SL \sim \sqrt{max(a_z) - min(a_z)}$ [14]

However, especially if a calibration-free solution for different persons is intended, these step recognition and length estimation methods will provide only limited accuracy. Also, albeit being able to provide a good enough long-term stable estimation (due to the inclusion of magnetic sensors), the heading provided by the IMU's AHRS is very sensitive to magnetic disturbances. Thus, to include these data in the system model, a rather high noise input has to be assumed.

As the particle filter allows the use of a nonlinear function for this, we use Gaussian error distributions (with corresponding dimensionality) for the direction $b \sim \mathcal{N}(0|\nu_b)$ and the length of a step $l \sim \mathcal{N}(0|\nu_l)$. Thus, upon detection of a step, the spatial propagation of a particle can be calculated by drawing samples $\hat{b}^i$ and $\hat{l}^i$ from these distributions:

$$f_1(u_{k,1}, x_k^i) = \varphi(1+\hat{b}) \cdot SL(1+\hat{l}) \tag{4}$$

and updating the system. An example of the resulting particle distribution is depicted in Figure 2.

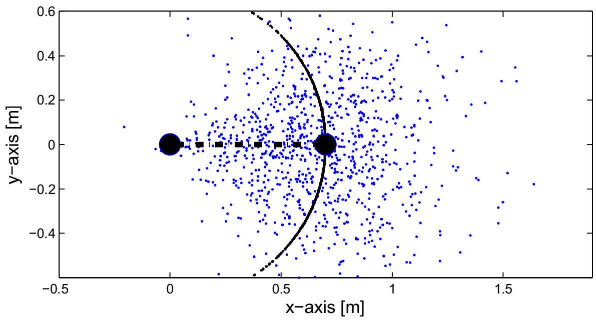

Fig. 2. Representation of particle distribution if one step with length $SL = .7\ m$ and direction $\varphi = [-0.5, 0.5]$ is detected starting at $[0, 0]$.

This PDR method is prone to error, e.g., caused by local magnetic disturbances. These disturbances result in very indeterministic behavior of the AHRS for short periods of time and strong direction estimation errors. To cope with these, the obvious method would be to chose larger ν_b and ν_l. However, increasing these parameters also results in a reduced estimation quality for the underlying probability distribution of the system state as the number of particles per area decreases. This could be avoided by either increasing the total number of particles or by taking into account that certain errors cannot be caught. This can result in a loss of track. We propose using a smaller number of particles to improve computability at the cost of losing track from time to time and having to recapture the position estimation from a WiFi position update.

B. Molé WiFi Positioning Engine

In the growth phase of an organic WiFi fingerprinting localization system, the user receives position updates even when only a subset of a building's spaces are part of the system's database. Under these circumstances, the user will always receive an incorrect estimate when in a yet-to-be bound (user-surveyed) area.

Depending on the underlying positioning system, each estimate is typically accompanied by a confidence value or score, such as a probability from a naïve Bayesian approach as, e.g., in the OIL system [3]. Molé's score is the output of its maximum overlap (MAO) algorithm, which computes a similarity between the user's fingerprint and a subset of bound areas. In Molé, every fingerprint in the database is represented by a set of mappings from each observed access point to a data triple $AP_j \Rightarrow \langle \omega_j, \mu_j, \sigma_j \rangle$. Here ω_j is the weight of the j-th AP for $\sum \omega_j = 1$ and μ_j and σ_j are parameters for an (assumed) Gaussian distribution $\mathcal{N}(\mu_j|\sigma_i)$ of the RSS values obtained for this AP during calibration. The MAO similarity is computed by intersecting the observed RSS distributions with the respective database entries and multiplying the result by the weight of the AP. Additionally, a punishment for falsely detected APs is introduced resulting in a similarity value s_m with $-1 \leq s_m \leq 1$ for each space S_m in the database of M spaces ($1 \leq m \leq M$). In the most simple form, the space with the highest similarity value S_{mx} is selected as the current location estimate. Molé also makes use of the smart phone's acceleration sensor to combine multiple WiFi scans to a single RSS distribution which results in a higher accuracy. Further details on Molé can be found in [4].

We propose to fuse these WiFi position estimates in two different ways. In the measurement step, every particle's weight w_k^i is updated depending on its current position x_k^i and its distance d_k^i to the centroid $c(S_{mx})$ of the MAO space estimate S_{mx}

$$w_{k,m}^i = \begin{cases} w_k^i \cdot s_{mx}, & \textbf{\textit{if}}\ x_{k+1}^i \textit{ is in } S_{mx} \\ w_k^i \cdot (1 - s_{mx}) \cdot \dfrac{1}{(d_k^i)^t}, & \textit{otherwise} \end{cases} \tag{5}$$

with $s_{mx} = s_{mx}/2 + .5$ to avoid negative values and a distance weighting factor t that is chosen according to the number of available WiFi fingerprints in the database. While this approach is a rather simple approximation of conditional probability of a measurement, a more elaborate weight update would require a detailed knowledge of which spaces are represented in the database and a corresponding calibration procedure. For the purpose of this proof of concept we choose to use this simple approximation. Additionally, MAO estimates are used as system input if $s_{mx} > th$ (very good estimate):

$$f_2(u_{k,2}, x_k^i) = \begin{cases} c(S_{mx}) & \textbf{for } mN \text{ particles} \\ x_k^i & \textbf{for } (1\text{-}m)N \text{ particles} \end{cases} \tag{6}$$

On receiving a strong MAO estimate, we inject a randomly selected fraction m of the particles into the centroid of the MAO space. The remaining particles are not moved. This is justified within our model because the particles are an approximation of the underlying probability density.

If both a step is detected and a strong measurement is available during one time step, $f(\cdot)$ becomes:

$$f_3(u_{k,all}, x_k^i) = f_1 \circ f_2 \tag{7}$$

and the particles are propagated based on the detected step after the injection. This results in an ability to recapture the track of a person after a possible loss of track.

C. Inclusion of Map Knowledge

The map of the building is used in the measurement step (3) to update the weight of each particle according to:

$$w_{k+1}^i = \begin{cases} R \cdot w_{k,(m)}^i, & \textbf{if } \textit{particle crossed a wall} \\ w_{k,(m)}^i, & \textit{otherwise} \end{cases} \tag{8}$$

The obvious choice would be to select $R = 0$ and to assign zero weight to particles that have crossed the wall as proposed in most previous work [8], [12]. However we found that assigning very small weights $R = 0.005..0.02$ to particles although they have crossed a wall can help to reduce the number of necessary particles. In our organic localization scenario this inclusion of map knowledge might be the most crucial step. Low-frequency IMU alignment errors or inconclusively estimated directions for a few steps (Section IV-A) can be filtered out.

D. Systematic Resampling

Particularly if using only comparatively small numbers of particles for better computability, the weights accumulate rapidly to only few particles. In order to prevent this, we use systematic resampling. In this procedure, a new particle set is generated based on the current set. Particles can either be deleted or reproduced, the higher the particle's weight, the higher the probability to be reproduced [11].

E. Algorithm Overview

The proposed particle filter update can thus be summarized:

1) Initialization: distribute N particles with positions x_i for $1 \leq i \leq N$ over whole floor, assign equal weights $w_{i,initial} = 1/N$
2) System update $\forall i \in N$ update according to $f(\cdot)$:
   - **if** *step detected* **then** *draw from (4)*
   - **if** *strong MAO input* **then** *draw from (6)*
   - **if** *step and strong MAO input* **then** *draw from (7)*
3) Measurement update $\forall i \in N$:
   - **if** *MAO input* **then** *assign new weight (5)*
   - **if** *particle moved due to detected step* **then** *assign new weight (8)*
4) Normalize particle weights: $w_k^i = w_k^i / \sum_{i=1}^{N} w_k^i$
5) Apply systematic resampling algorithm **if** $N_{eff} < .5N$

In our implementation, the update (steps 2 to 5) is carried out periodically on a time-triggered basis. Another possibility would be to update on an event-triggered basis.

V. Experimental Evaluation

A. Experimental Setup

In order to evaluate the proposed approach, 6 experimental runs were conducted with 3 experimental subjects of different heights and gender. The subject were told to walk around randomly and to cover the whole floor. Occasionally they were to stop, e.g., to open a door or to account for a waiting time to pick up papers at a printer. A total distance of almost 5 *km* was covered in about 1.5 *hours*. Table I gives an overview of the conducted runs.

Experiment number	1	2	3	4	5	6
Test person	1	1	2	2	3	3
Distance (m)	666	656	618	571	898	939
Duration (s)	1030	1086	1169	832	1044	1289

TABLE I
Duration and covered distance in the 6 experimental runs

Heading and acceleration data from an Xsens MTi-G IMU carried in a belt bag were collected at a data rate of 100 *Hz*. Synchronously with these, Molé WiFi location estimates were collected on a Nokia N900 smart-phone carried in the pocket of the test-person. To allow for an off-line analysis and evaluation of the proposed method, corresponding ground truth was established. Walking paths and approximate timestamps were manually noted down during the experiments. Afterwards all timestamps (e.g. stops at doors) were fine tuned based on the raw acceleration sensor readings. Then, a linear interpolation between those points was performed such that a more or less accurate ground truth was available for every time step.

The experiment was limited to one floor of a fairly large office building. WiFi fingerprints for 23 of the total of 158 spaces had been collected for the Molé database as shown in Figure 1. The MAO position estimates were available at a rate of $1/5$ Hz. This low update rate was chosen deliberately, as WiFi scanning is energy consuming and very high update rates are unrealistic for real application scenarios. Also, higher update rates tend to cause higher fluctuation in the output estimates due to less smoothing of RSS values over time. It is worth mentioning, that the considered building has a very high density of APs making it a very practical surrounding for any WiFi localization system. As both of these effects are difficult to quantify we used one possible configuration for the purpose of this paper.

The goal of this our study was to evaluate the considered approach for varying persons under realistic conditions.

B. Calibration and Parameter Determination

All presented results were obtained with one parameter setting for all runs and all test persons. Initially, the particles were equally distributed on the whole floor. Parameters for step detection and step length estimation were determined in advance in a separate experiment (training data set) to prevent over-fitting. To account for the different heights and walking pattern of the three test persons rather high noise parameters were chosen. For the fusion of the Molé MAO estimates, $t = 1$ was chosen and 10% of the particles were injected upon occurence of a strong MAO estimate ($s_{mx} > .15$). These values strongly dependent on the number and distribution of the spaces currently represented in the fingerprint database. Likely, these cannot be transferred to other situations without preliminary calibration. Further development work would be needed in order to find an adequate procedure for other environments. The scope of this paper is to describe initial results on the presented method.

C. Results and Discussion

The considered PDR approach alone results in errors of 5 to 8 percent of the traveled distance [10]. However, due to magnetic disturbances or incorrectly detected step directions, the actual short term errors are difficult to handle. Figure 3 shows one example of a reconstructed PDR trajectory with and without the use of map matching and inclusion of MAO position estimates (center of mass of particles depicted). Most of the time, the estimated trajectory from PDR is more or less accurate (left) which would result in high accuracies if map matching is applied. But, from time to time, unpredictable errors and inaccurate direction estimates occur and the track becomes ambiguous (right). Reasons for this could be falsely detected steps or direction errors caused by magnetic disturbances.

On the other hand, tracking by means of WiFi signals alone is also not sufficient in the considered scenario. The only

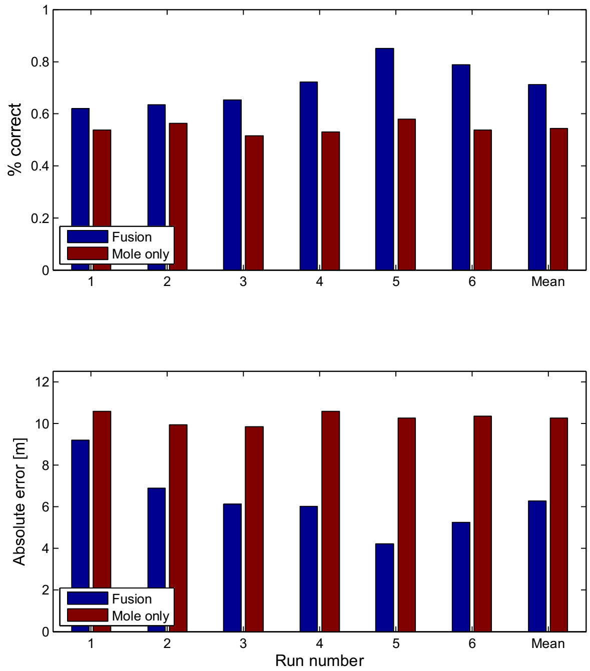

Fig. 4. Comparison of mean error and percentage of correct estimates for data fusion and Molé only localization.

possible position estimates are the spaces represented in the fingerprint database (Figure 1). Thus, the output is likely to be wrong if this area is left. Fusing the two systems helps in this situation. Short term accuracy is obtained from the inertial inputs. An occasional loss of track is accepted and the WiFi system is relied on to recapture the position when the user returns to the covered area. This results in a smaller position error compared to using either one of the approaches alone.

As output, we consider two different ways to obtain a location from the probability density represented by the particles:

1) 2D coordinates of the center of mass of the particles
2) The space with the highest probability, i.e., containing the highest particle mass

For the first, we define the mean centroid error as the mean euclidean distance between the particle centroid and the reference position. For the second, we evaluate the percentage of the time during which the obtained space estimate from the particles is equivalent to the current reference space $p_{correct}$ or within its immediate adjacency $p_{adjacency}$. Although the establishment of the ground truth data was done with great care, it has to be noted that the obtained reference positions might be temporarily inaccurate due to the assumption of a constant velocity between the noted reference points. Thus, the presented results have to be interpreted as a mostly qualitative assessment of the obtainable improvements. Figure 4 shows both quality metrics for the six runs. To obtain comparable values for the Molé's MAO estimates alone, the average distance of the reference position to the centroid current MAO estimate is depicted.

It can be seen, that for all 6 runs a mean accuracy on the order of 4 to 6 *m* is achieved. Only in run 1, the achieved

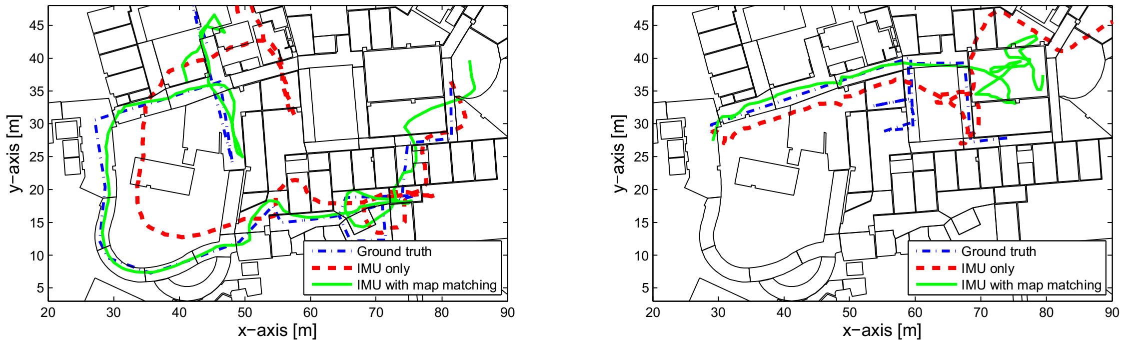

Fig. 3. IMU direction and step length estimates and improvement with map matching (center of mass of particles). Left: accurate direction and length estimates most of the time result in good match. Right: occasional irregularities occur and result in dead lock situations.

accuracy is a little worse due to an unlucky sequence of MAO measurements and IMU disturbances. Over all experiments the output is correct to within one space in about 75% of the time compared to 50% for WiFi localization alone.

VI. Open Questions and Future Work

In spite of the promising first results presented in this paper some open questions remain. For the near future, we plan to further experiment on the behavior of state of the art AHRS in buildings and analyze occurring disturbances. On the implementation side, portability to state of the art smartphones and their integrated sensors is targeted. Also, long-term experiments, i.e. whole days with a larger user variance would be needed for a more thorough parameter assessment and determination. Other important research topics include auto-parametrization for different users for the considered PDR and meaningful calibration procedures to obtain parameters for other environments.

VII. Conclusion

The presented results show that reasonable accuracies can be achieved with the outlined fusion approach under the given conditions. In the context of organic localization the position estimation accuracy can be improved especially if the area of interest is not completely represented in the database. This could increase user motivation to use the system and contribute additional location binds from the beginning and thus possibly allow the system to faster grow to a reasonable coverage.

Fusing inertial data could benefit in scenarios where a WiFi location system is to be used in areas with a lower AP density. Also localization in areas with an inherent more difficult behavior of RSS values, e.g. strong fluctuations caused by the presence of high number of persons might be improved. In the context of Molé's hierarchical name space, situations could be handled in which the location engine delivers only a partial estimate, e.g., a correct building and floor but no room due to a lack of user binds. This work presents first results on a realistic evaluation of a possible system concept. It can be concluded that the outlined approach seems promising for the intended applications.

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