PEDESTRIAN DEAD RECKONING AS A COMPLEMENTARY METHOD FOR WIRELESS SENSOR NETWORK AD-HOC PERSON LOCALIZATION

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Abstract: The problem of localization and navigation in areas without any or with only limited access to global navigation satellite systems (GNSS) is still not solved. This is especially the case for person localization applications as persons tend to spend a good part of their time in buildings or in cities (urban canyons). One possibility to approach this issue is to use wireless sensor network (WSN) technology. Especially scenarios that require ad-hoc person localization like firefighters that enter a burning building or similar setups, WSN seem to be a promising solution. However, if the node density is low or if the scenario also requires localization in uncovered areas, an additional localization method is required. Pedestrian dead reckoning (PDR) is an ideal complementary method to achieve short term accurate localization under these assumptions.

In this paper, an approach to PDR with low processing power for the use in WSN with a hip mounted inertial measurement unit (IMU) is presented. The purpose of the system is to provide a localization and tracking solution if temporarily none or only few anchor nodes are within communication range. This is achieved by detecting steps, estimating the length of each step and determining the step direction in WSN coordinates.

We experimentally evaluate the system under varying environmental conditions and show that the concept is a promising solution for the intended applications.

1 INTRODUCTION

To solve the challenge of node localization, a lot of research has been undergone in the field of localization in wireless sensor networks (WSN) during the last few years. The problem of correlating a measured value with its time and its location is a fundamental requirement in most applications. Figure 1 shows one example of an application of such WSN for localizing and tracking persons in scenarios where global navigation satellite systems (GNSS) are not available. Other possible application areas of a system that can provide localization under such conditions are for example firefighters or other rescue forces that want to logistically coordinate a mission. In these scenarios an easily installable and robust solution to the localization problem is required. To achieve this, one way could be to use a dedicated WSN for localization with the additional feature of providing communication within the network. Additionally, this allows the integration of other sensor readings, e.g., motion or movement sensors, or smoke detectors, which leads to a modular extensible localization and surveillance system (Gädeke et al., 2011b). Other application examples with similar requirements are security forces or localization of builders, tools and measurement equipment on construction sites. Another use case can be found in hospitals where patients and doctors

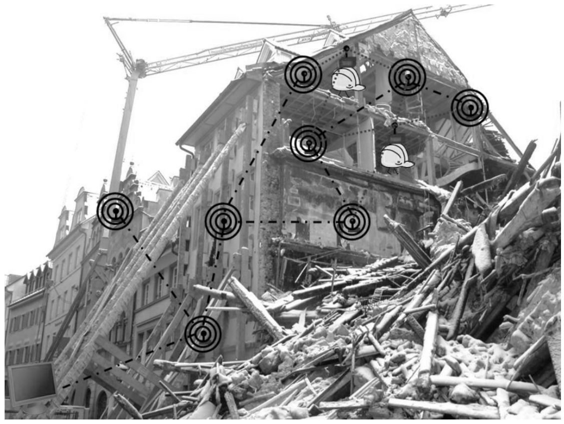

Figure 1: Application scenario: Localization of rescue forces in and around destroyed buildings (Gädeke et al., 2011b).

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need to be localized for navigation purposes and optimized scheduling.

In these intended applications, required accuracies are in the range of a few meters, i.e. on room level. The simplest method to achieve this in WSN is by evaluating the received signal strength (RSS) of radio packets from anchor nodes with known positions (Schmid et al., 2011a).

Especially in indoor scenarios however, location estimates from RSS range-based approaches are often subject to fluctuations due to the badly predictable behavior of RSS values. To cope with this, stochastic filtering can be used and a system model of the moving person can be incorporated. Also, inertial sensors can be used to improve the localization accuracy to a certain degree (Schmid et al., 2011b). However, in cases where the area of interest cannot be fully covered by the WSN or the anchor node density is too low, a complementary localization system is needed to provide short-time accurate localization during the periods without WSN coverage.

In this paper short-time accuracy is achieved by integrating a pedestrian dead reckoning (PDR) unit into a WSN. Because of the low processing capabilities of the sensor node's microcontroller unit (MCU) the application requires an approach which does not include complex algorithms. A hip mounted inertial measurement unit (IMU) is considered for step detection, step length estimation and attitude calculation. We present results of a comprehensive experimental evaluation of this concept under different environmental conditions which supplement first results presented in (Gädeke et al., 2011a).

The remainder of this paper is structured as follows: In Section 2 a short survey of the state of the art and the related work in the field is given. In Section 3 the developed concept and information processing is introduced. Some details on the implementation and the undergone experimental study are given in Section 4 and the results are presented and discussed in 5. The paper is concluded in Section 6 and an overview of the next steps is given in 7.

2 STATE OF THE ART

The last years led to a price decline in micro electro mechanical systems (MEMS) due to the technological improvements for these components. Along with this development also the interest in pedestrian navigation solutions increased and many research groups based their work on MEMS IMU inertial localization and navigation. There are two main approaches for placing the IMU on the human body. Often considered is the placement of the IMU on the foot of the user. Other placements on the body need a step counting approach for localization which will be explained at the end of this paragraph. With a foot mounted IMU strapdown algorithms which are well known from aerospace or marine navigation can be applied. Usually high precision inertial sensors are used and allow for a small error growth. The attitude is obtained by a mathematical integration of the turn rates and the position is calculated from a double integration of the acceleration signal (Titterton, 2004). Today's MEMS inertial sensors still suffer from a large drift. To compensate for these drifts different additional system inputs have been proposed. The zero-velocity update (ZUPT) is among the most famous and sets the velocity to zero during each stance phase of the gait cycle (Foxlin, 2005), (Jimenez et al., 2010). Angular rate updates might be fused by the zero-angular rate update (ZARU) analogously (Jimenez et al., 2010). More recently, a heuristic drift reduction (HDR) algorithm which makes the assumption that pedestrians are mostly walking along straight paths has been used in different peculiarities (Borenstein et al., 2009), (Jimnez et al., 2011). Typically, slightly bended paths are the major challenge to these algorithms but it works very well for long corridors or streets. The results obtained by all approaches with foot-mounted IMUs are very competitive. The error for these systems are typically on the order of only a few percent of the distance traveled (Wan and Foxlin, 2010). But, achievable accuracies depend strongly on the inertial sensors performance and the applied data processing. However, behind these systems a complex system model is used and hence in a state space model, a large state vector is needed. Also, the dynamics occurring on the foot are quit high. That makes it necessary to use a high update rate for the data processing. Both of these characteristics require fast processing capabilities which also imply shorter battery lifetimes or larger batteries. For integration in a WSN this is contradictory to the low power hardware used within such a system.

On the other hand, beside the IMU placement on the foot many other positions on the human body have been evaluated. (Beauregard, 2006) considers the head, rucksack structures are used in (Niedermeier et al., 2009) and another popular position is the hip (Kourogi and Kurata, 2003). For all of these approaches strapdown algorithms with ZUPT and ZARU cannot be used. There is no possibility to correct the system model and hence, the error evolves too fast with current MEMS inertial sensors. For these IMU positions step recognition together with step length estimation is usually considered. In terms of accuracy, the performance for these approaches cannot compete with the performance of the foot-mounted systems. Relative errors are typically in the range of 10 % of traveled distance (Randell et al., 2003). Further improvements can be achieved by adapting parameters and algorithms to the user's current posture (Sun et al., 2009). However, different properties of the sensor signal are often requires for such an activity classification. An example is the frequency domain representation (Fourier transformation, e.g. FFT calculation) but also all kind of digital filters. These algorithms are based on matrix computations which are typically done by a digital signal processor (DSP). Especially with high data rates and floating point operations these are considered too complex for a typical MCU used on a wireless node.

To achieve pedestrian localization with ultra-low power hardware used in WSN a hip mounted IMU is considered. Beside the lower power consumption this placement is also more practical and realistic for the applications considered in this paper. The lower dynamics in the acceleration signal also allows for a lower update rate which further reduces the computational complexity. Furthermore hip based approaches are easily portable to off-the-shelf smart phones (Gusenbauer et al., 2010), (Serra et al., 2010). This opens a wide range of consumer applications like navigation in exhibition halls or airports, but also seamless indoor/outdoor navigation in underground parking and shopping centers.

3 SYSTEM CONCEPT

3.1 Pedestrian Dead Reckoning

In this paper an IMU of the model MTi-G from Xsens Technologies B.V. was used. The IMU incorporates three-dimensional acceleration sensors, gyroscopes and magnetometers. An external GPS antenna can be connected to further improve the internal heading estimation algorithm. Also, when the GPS connection is used a pressure sensor stabilizes the height estimation. The IMU features an internal DSP which outputs the attitude based on a preconfigured preset. These presets influence the parameters of the attitude calculation. For example, it can be selected that sensor readings from the magnetometers should be incorporated in the calculation or not. The outputs of the IMU are calibrated sensor readings from all sensors and also the internally calculated attitude based on the chosen preset. This is a useful feature for the considered system because the sensor nodes MCU does not have to handle the complex calculation. A drawback

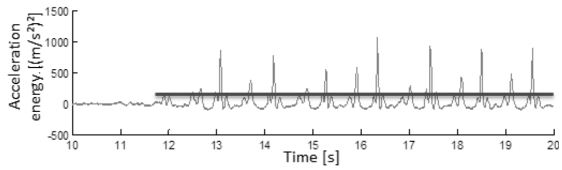


Figure 2: Acceleration energy and step detection threshold.

of this approach is that the algorithms on the sensor node have to rely on the attitude and no further corrections (like HDR, tuning of sensor readings depending on the application) on the attitude can be applied.
As stated in Section 2 already, current MEMS IMU do not provide the accuracy needed for strapdown algorithms when it is placed somewhere on the human body. Our approach to determine the user's position is based on step recognition which updates the position estimation at each detected step. Therefore, it is also necessary to know direction and length of each step. These three issues will be covered in the following sections after a short clarification on the used coordinate frames has been introduced.

3.1.1 Coordinate Frames

The resulting position estimation is with reference to the navigation frame (n-frame) which represents a local tangent plane (LTP) on the earth's surface. However, sensor measurements from the IMU are in body frame (b-frame)-coordinates of the IMU. To quantify the pedestrian's step direction an additional coordinate frame is introduced. This is referred to as human frame (h-frame) in which the x-axis describes the forward-walking direction, the y-axis is perpendicular in the horizontal plane (sidewards) and the z-axis is perpendicular to both other axes and roughly aligned with the human body (up-direction).

3.1.2 Step Recognition

The detection of successive steps is based on a peak and threshold analysis. The acceleration energy $E(\vec{a}_k)$ is calculated in every time step k from all three dimensions of the acceleration signal $\vec{a}_k$.

$$E(\vec{a}_k) = a_{x,k}^2 + a_{y,k}^2 + a_{z,k}^2 \tag{1}$$

Figure 2 shows the acceleration energy pattern with the threshold applied. Additionally, multiple peaks within a time-frame of 300 ms after a successfully detected step are rejected. This has a similar effect as filtering the signal with a low pass filter beforehand and prevents multiple detections of the same step.
The threshold is set to a value of 10 $(m/s^2)^2$ which applies for slow walking patterns, but also holds for faster walking and running.

3.1.3 Steplength Estimation

For an on-line estimation of the users step length there exist a number of different approaches. However, they all perform very similarly (Jahn et al., 2010). Some approaches need a calibration for each particular user which is not desired for ad-hoc localization (Zhao, 2010). For the purpose of this paper the Weinberg Algorithm is chosen because of its simplicity and missing calibration procedure (Weinberg, 2002). The step length SL is calculated from the maximum and minimum measured acceleration a in z-direction of the n-frame. A constant parameter W can be set for unit transformations.

$$SL = \sqrt[4]{max(a_z^n) - min(a_z^n)} \cdot W \tag{2}$$

3.1.4 Step Direction

The step direction, i.e. the alignment of the IMU to the human body, needs to be known in coordinates of the b-frame so that it can be transformed to the n-frame. Assuming the user is walking forward, the step direction is given in the h-frame by the vector $[1,0,0]^T$. For normal and fast walking the step direction is characterized by a larger acceleration in movement direction than the sidewards acceleration. It can be obtained by a principal component analysis (PCA) over these two components of acceleration (Kourogi and Kurata, 2003). From the raw-acceleration data in the b-frame the gravitational component g and the acceleration $a^n_{z,k}$ has to be removed. These can be obtained with the direction cosine matrix (DCM) $C^b_{n\,k}$ directly.

$$g^b_k = C^{b\,T}_{n\,k} \cdot [0,0,g]^T \tag{3}$$

$$a^b_{z_n,k} = C^{b\,T}_{n\,k} \cdot [0,0,a^n_{z,k}]^T \tag{4}$$

Applying the PCA to the remaining two components of acceleration yields the step direction $\vec{sd}$ in b-frame coordinates.

$$\vec{sd}^{\,b}_k = PCA(\vec{a}^b_k - g^b_k - a^b_{z_n,k}) \tag{5}$$

It can, however, not yet been distinguished between forward and backward direction. Similar to (Kourogi and Kurata, 2003) the alternation of maximums in x- and z-components of the h-frame acceleration is used to determine the step direction completely. With this kind of step direction estimation, also the relationship, i.e., the transformation matrix between the b- and h-frame is given by the three principal component vectors returned by the PCA.
Because calculating the step direction puts a heavy workload on the MCU, the procedure is done for initialization only. Also, the PCA delivers unreliable results if the person to localize is running or moving slowly. For these walking patterns accelerations in other than the walking direction become more dominant. This results in a noisy step direction which has a great influence on the position estimation.
For the intended use cases it is sufficient to call the procedure once after the device is attached to the user. For other applications (e.g. smart phones), the forward direction can change if the device is taken out of the pocket and being put back in. This implies a recalibration procedure whenever a reliable walking pattern is recognized.

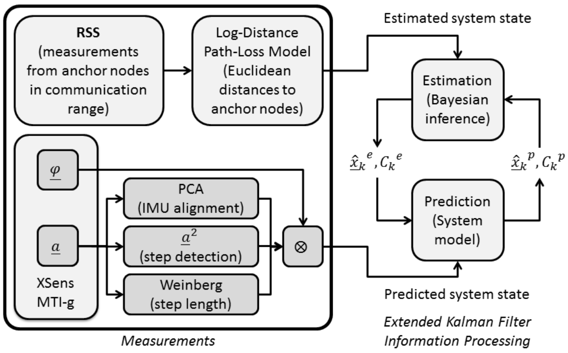


Figure 3: Overview of the measurements and data processing.

3.2 System and Measurement Model

To model the system and the measurement inputs, a modified version from (Schmid et al., 2011b) is used. Incoming measurements are processed by means of a Kalman filter. Figure 3 shows an overview of the considered measurement inputs and information processing. In contrast to (Schmid et al., 2011b) PDR position updates are considered as an external input $\vec{u}_k$ to the system and hence are part of the system model.

$$\hat{\underline{x}}^p_k = A \cdot \hat{\underline{x}}^e_k + B \cdot \hat{\underline{u}}_k + \hat{\underline{w}}_k \tag{6}$$

Position updates from the WSN are considered as measurement inputs and are processed in the update step of the Kalman filter. For localization without an IMU a system model which assumes a constant speed between each time-step is used. Therefore, the state vector $\hat{\underline{x}}_k$ models position and velocity. To prevent drifting away very fast when no sensor readings are present at all a velocity prediction factor smaller than 1 is chosen in the system model. This is established by setting the corresponding elements of the system matrix A to a value smaller than 1, i.e., 0.99.

Fusing PDR position updates with the system model increases the covariance matrix of the overall position estimation which represents the typical behavior of any PDR system.

Figure 4: IMU sensor node combination (Xsens MTi-G and ITIV LocNode).

Additionally, to achieve long term stability RSS measurements to anchor nodes (with known positions) are used upon availability. As soon as the on-body node receives a broadcast message from an anchor node, distance information is deduced from the RSS value of the received packet. This information is fused to the current position estimate in the filter step of the Kalman filter. The relationship between distances and corresponding RSS values has been evaluated experimentally and is modeled by the log distance path-loss model (Schmid et al., 2011a). As these measurements are non-linear an extended Kalman filter is used for linearization. Complementary to the PDR covariance model feeding of RSS position estimations decreases the covariance matrix of the system.

Localization based on PDR alone comes to use whenever no or too few anchor nodes are available. For example if the person to localize leaves the WSN-covered area or arrives at a place where the anchor node density is low. In such situations the PDR system has to overtake until the person once again receives radio packets and the position can be corrected.

4 IMPLEMENTATION AND EXPERIMENTAL SETUP

The presented evaluation is based on real data but carried out offline. This method allows to evaluate various parameter settings of data processing concepts without having to re-run each experiment several times and modify the MCU's source code. On the hardware side, a PDR unit to be carried on the hip of a person to be localized has been developed. The sensor nodes are also based on our own design. The sensor network software is based on a proprietary ZigBee stack implementation. The developed system was used to record data in various environments including in- and outdoor scenarios.

4.1 Hardware

Figure 4 shows the developed PDR-unit consisting of the Xsens MTi-G IMU and an ITIV LocNode sensor node(Schmid et al., 2011a). The casing is designed to fit into a standard camera bag which can be attached to a belt and carried on the hip of a test person. This PDR unit allows storing the RSS values of received radio packets as well as the IMU's attitude estimation and acceleration data on an SD-card.

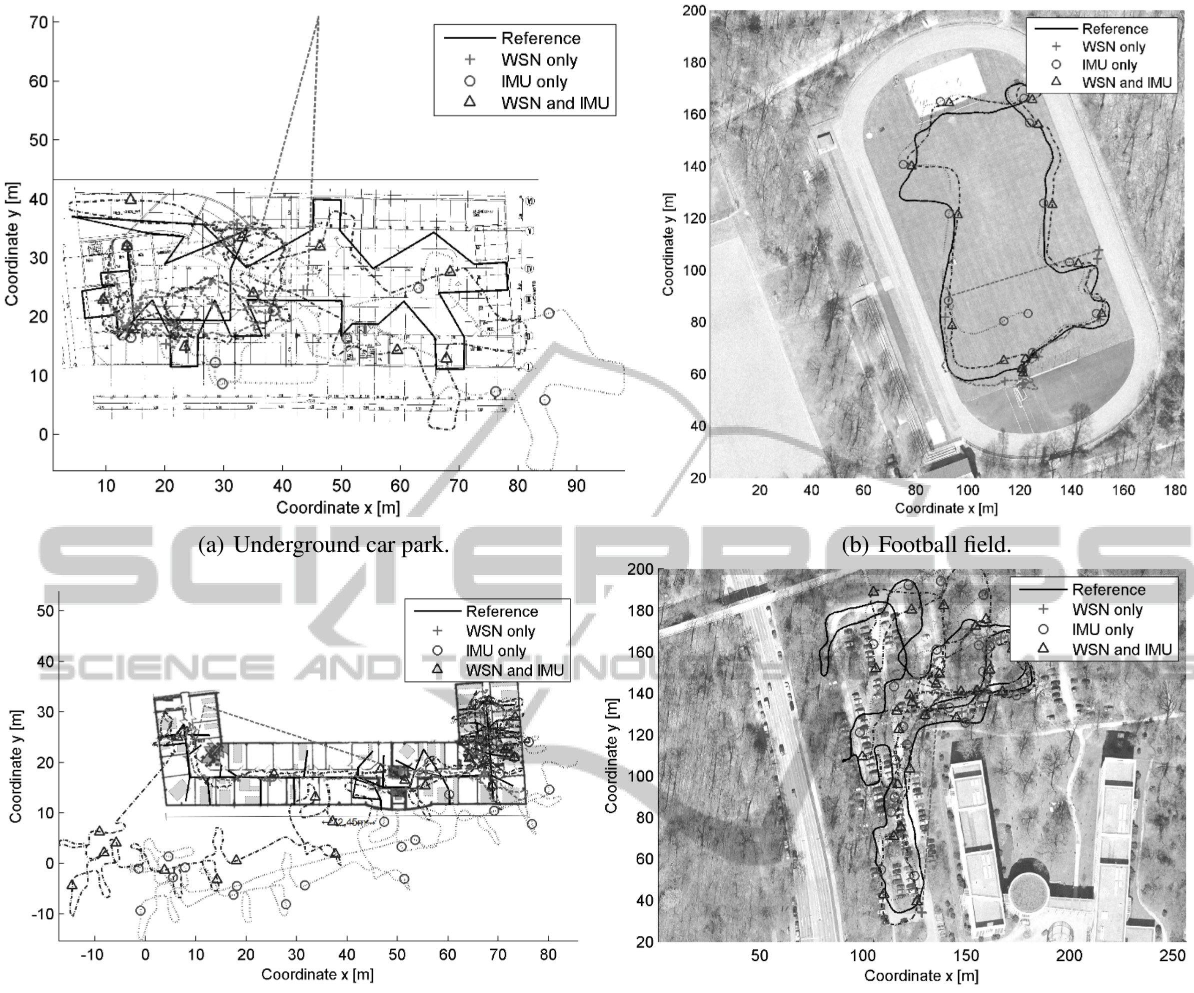
The incorporated Xsens MTi-G IMU provides calibrated data from acceleration, gyro and magnetic field sensors and also includes a DSP to fuse this data for attitude estimation. The DSP's data processing can be tuned with predefined profiles according to the scenario in which the unit is used. For the undergone experimental study, the "aerospace" profile was used. This profile results in an inclusion of data from the magnetic field sensors into the attitude estimation for long term heading stabilization. Although magnetic field sensors can be disturbed in indoor environments, they are the only possibility to obtain reliable long term stability. Because fusing turn rates from the gyro sensors with magnetic sensor readings, these magnetic field disturbances can be partially corrected. Also, the IMU's incorporated GPS receiver and the barometer were disabled and not used for this work.

4.2 Software

A ZigBee framework is used to setup a WSN with self-organization and multi-hop capabilities. Localization functionality is implemented in this framework. For the purpose of an off-line evaluation, the framework also allows to store all received radio packets on the sensor nodes' SD-card. Each anchor node is configured to broadcast its own position reg-

Table 1: Overview of lengths of the experiments.

	Institute	Under-ground	Football field	Parking lot
mean length [m]	700	450	750	1320
mean length [s]	560	290	480	900
max. length [m]	1120	510	910	1920
min. length [m]	390	370	570	1000



(a) Underground car park.

(b) Football field.

(c) Institute building.

(d) Parking lot.

Figure 5: Surroundings, ground truth and reconstructed trajectories for exemplary runs in the 4 experimental setups.

ularly at a rate of 4 *Hz*. The on-body node processes acceleration and attitude data at a rate of 10 *Hz* and radio packets upon availability.

4.3 Experimental Setup

For a quantitative experimental evaluation of the proposed hybrid PDR WSN localization approach, a lot of data had to be collected. The goal of the undergone experimental campaign was to prevent an over-fitting of the proposed fusion approach to a specific environment. For this purpose, four experiments in the institute office building, an underground car park, a football field and a parking lot were carried out. In each experiment, several runs of a couple of minutes were conducted. Figure 5 shows an overview and an example trajectory of one run in each environment.

A WSN with 62 sensor nodes was deployed in each environment. To limit the influences of too many parameters, one person carrying the IMU-equipped sensor node was walking more than 20 *km* in all experiments and corresponding data from the IMU and WSN was collected. In each experiment multiple runs with a length between 370 *m* and 1920 *m* were performed. The mean lengths in meters and seconds for each experiment are given in table 1. It can be seen that the experiments differ in these characteristics. That means, that different walking speeds and different trajectories have been evaluated. Additionally to the experiments presented in this paper the PDR concept was also evaluated experimentally with different users, but with shorter runs and without WSN data available. A comprehensive analysis of different users walking patterns are part of our current research.

To allow for an evaluation, a reference (ground

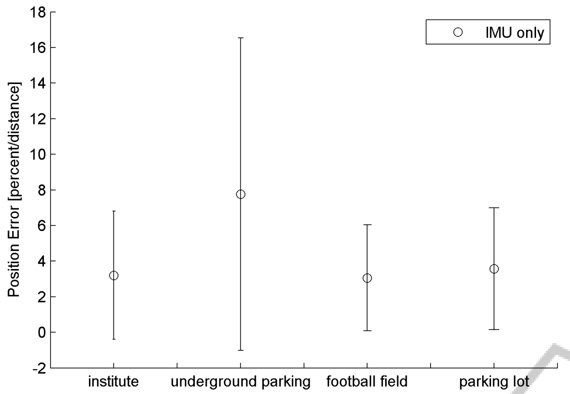


Figure 6: Stand-Alone PDR Error evaluation for all runs in each experiment.

truth) was recorded with a differential GPS (DGPS) in the outdoor experiments. Indoors, the user walked various predefined trajectories. A sequence of way points was set up and the time between reaching each of them was measured. For every segment between the way points a constant speed was assumed. This method of predefining a trajectory cannot guaranty the quality of a GPS recorded reference trajectory but is still an adequate way to obtain a ground truth. For the purpose of this paper a constant IMU alignment on the test person's body (step direction) has been assumed for all runs in all experiments. To allow for a comparison between in- and outdoor experiments they are set up in 2D only. However, the calculations are done in 3D and the height of the sensors can be easily tracked by barometric sensors.

5 DATA EVALUATION AND DISCUSSION

The gathered data were evaluated off-line with the methods described in Section 3. The evaluation concentrates on the effect of a short-time accurate localization system (PDR) to bridge time intervals in which no other localization system is available. At first, the developed stand-alone PDR solution is evaluated and the resulting errors are analyzed. After that it is shown how this PDR system can be used to stabilize a WSN localization system if it is assumed that the person to be localized leaves the WSN or the WSN breaks down. When the person enters the WSN again, the position errors can be corrected.

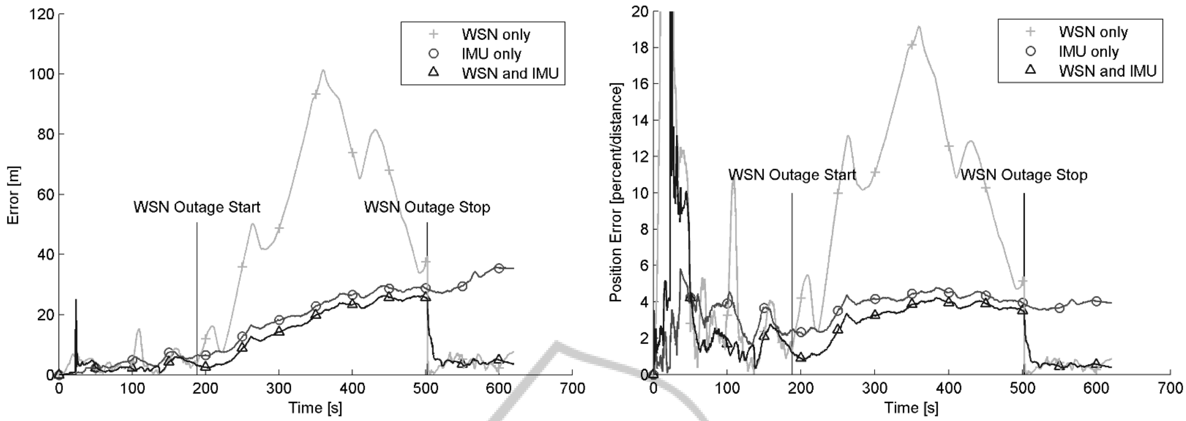
5.1 Stand-alone PDR Error Analysis

For the developed PDR system, the following error sources are dominant. From figure 5 (circle line) it can be seen that heading estimation indoors is not as reliable as in the outdoor scenarios. This error is expected to be introduced by magnetic disturbances in the indoor environments. As heading is calculated internally on the Xsens MTi-G's DSP it cannot be corrected and parameters of the filter cannot be adjusted. Alternatively heading could be calculated from the raw measurements from the IMU, but this would require a fast processor on the sensor node. To allow for an implementation on a widely used WSN platform and achieve long battery lifetimes this option is not considered in this paper.

The other errors are introduced by the calculations described in Section 3. Each falsely detected step introduces an error of one step length, although the step recognition is very robust. A more influencing error is the step length calculation which adds a small distance during each step. Assuming a wrong but constant step direction, results in a heading offset which turns the whole trajectory in n-frame coordinates by a certain angle around the starting point. This error can be observed in figure 5 (c) in the institute experiment and is the most critical part in the system. Instead of analyzing each of the error sources alone, a general analysis of the system's performance in resulting position accuracies is undergone.

To quantify the errors of the PDR system, the relative deviation to the traveled distance of the reference trajectory is taken into account. Therefore the PDR system is analyzed without the WSN localization. The errors in every run of each experiment are summed up and the overall relative error for each experiment is calculated. Figure 6 shows the mean error and standard deviation for all runs of each experiment. The mean error is between 3.5 % and 10 % of traveled distance. The relative error is characterized by very high values in the beginning of each run as the total traveled distance is short and small displacements result in high error quantities. At the end of each run the relative error typically stabilizes around 5 % of traveled distance. The highest error and standard deviation is found in the underground parking experiment. This might be due to higher disturbances of the magnetic field and the resulting attitude estimation difficulties.

However, if the developed hip-mounted PDR unit is solely considered, the presented method allows for error rates on the order of a few percent of traveled distance.



(a) Total error in meters. (b) Error in percent of traveled distance.

Figure 7: Error over time for exemplary run.

5.2 Unavailability of WSN Localization

If long term accurate reference data from a WSN is available, the absolute error remains more or less constant and the relative error converges to zero with operation time of the system. Person localization in environments where a dense WSN is deployed allows for room-level accuracies (Schmid et al., 2011a). However, in realistic scenarios it cannot be assumed that the person to localize always remains in the area that is covered by the WSN. Also, it has to be considered that the WSN could fail during the operation. In such situations, localization can be continued by means of dead reckoning.

To evaluate this concept the hybrid solution as described in section 3 is considered. Then, it is assumed that the WSN fails at $t_{down,start} = 0.3 \cdot t_{run}$ and recovers at $t_{down,end} = 0.8 \cdot t_{run}$ in each run with length t_{run}. During this time, no RSS packets are received and the IMU is used for PDR alone.

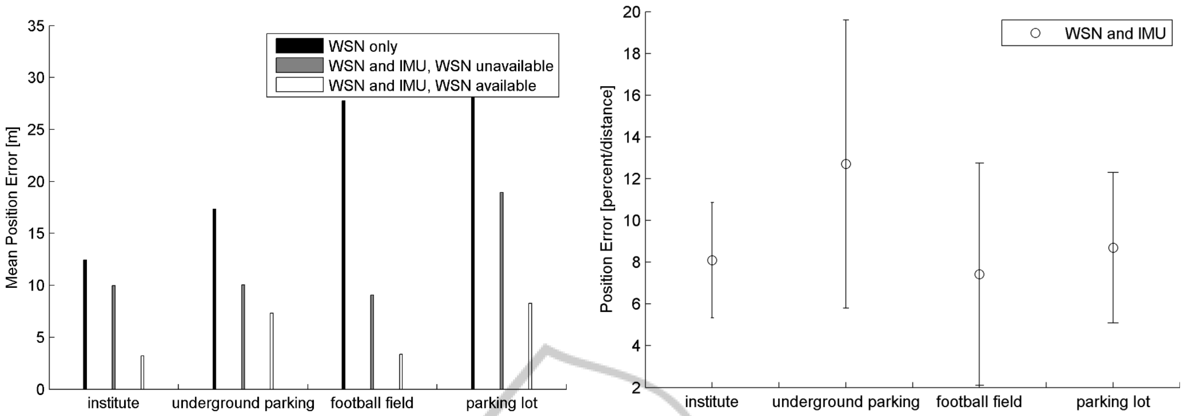
Figure 7 shows how the error evolves over time during one example run from the experiments. It can be seen that the total error of the position estimation increases during the run if only IMU data are considered for the localization (circle line). Naturally, the error remains more or less constant on a relative scale and the downtime of the WSN does not affect its accuracy as these data are not used. The cross line shows localization based on data from the WSN alone. When the network fails at $t \approx 200\ s$ the position sticks close to the coordinates where the last measurements were received. However, the considered position-velocity model (Section 3) draws the position estimation away. The mentioned velocity prediction factor in the system model lets the position converge.

On an absolute scale this results in an increasing error which can also be observed in the trajectories in figure 5. As the estimated position stays roughly at the last known position the error becomes larger when the person moves further away from that spot. In the presented scenarios the test person did not move too far away from the test field so the error stays within the bounds of the experiment's area. Especially because the trajectories come full circle in most cases the errors become smaller again after a certain point in time. This implies a maximum value for the total error. If the developed hybrid information processing approach is used, the PDR system allows continuous localization as long as no WSN data are available and bridges the gap until the WSN covered area is re-entered (triangle line). This behavior can be observed in the trajectories in figure 5 and in the error analysis in figure 7. Compared to the reconstructed trajectories from PDR (circle line) or WSN (cross line) alone the hybrid information processing approach allows for a much better localization accuracy if an outage of the WSN is assumed (triangle line).

5.3 Robustness Issues and Evaluation

Figure 8 compares the resulting mean errors based on all collected data from the presented experiments. It shows the mean errors for failing WSN-only localization and the hybrid solution with and without the WSN failing.

With the WSN failing it can be seen that the WSN-only solution cannot provide sufficient localization accuracy anymore. Compared to that, for the hybrid solution, the resulting localization accuracies in figure 8 (a) are in the range of a few meters depending on the surroundings. If the WSN is not available anymore



(a) Error in meters. (b) Error in percent of traveled distance.

Figure 8: Mean error and standard deviation over all runs in all experiments.

the mean errors increase but still allows for reasonable localization accuracy. The much higher errors in the parking lot experiment are due to very long runs compared to the other experiments and following longer times without WSN localization. To further quantify the localization accuracies the relative errors are taken into account. Therefore, relative errors during the unavailability of each run are given in figure 8 (b). It can be seen that the relative errors of the parking lot experiment are comparable to the other experiments. In this analysis the underground parking experiment exhibits higher values which are introduced by very high relative errors in the beginning of each run. Because the underground parking experiment is characterized by a series of relatively short runs these higher errors in the beginning contribute to the high values shown in figure 8 (b). The high relative errors in the beginning are introduced because a very short distance has yet been covered but the initial absolute error is comparably high. Theoretically this results in infinite large errors. Compared to the stand-alone error analysis from section 5.1 it can be seen that the relative errors are higher in the analysis with a failing WSN. As mentioned before, relative errors in the beginning of the WSN outage are very high and thus affect the overall error. Additionally, the covered distance is shorter compared to the stand-alone analysis which also has an impact on the mean relative error.

In general, the PDR approach delivers a vital complementary solution to localization in ad-hoc WSN scenarios.

6 CONCLUSIONS

This paper evaluated a person localization approach for WSN by combining RSS localization with PDR.

A hip-mounted IMU, integrated with a wireless sensor node is used for step detection and step length estimation of the user. Additionally, the orientation of the IMU in relation to the body of the person is estimated by means of a PCA. The paper evaluates the system under different environmental conditions and presents the performance of the system also when the sensor network is left for a while.

The focus of the evaluated implementation lies on algorithms which can be carried out on a typical WSN MCU. Relative errors are on the order of 5 % to 10 % of traveled distance. This is comparable to state of the art approaches, but considering the low computational complexity it allows for WSN integration and longer battery lifetimes. the performance does not allow for long term navigation without any stabilization by an absolute positioning system. But, the method presented carries the potential for localization and navigation applications where generally an absolute positioning system is present but not very reliable at all times. PDR guaranties short-term accuracy, while WSN measurements provide long-term stability. It has been shown that the presented PDR approach allows to bridge outages of the WSN or also helps the user to navigate through uncovered areas for some time. Possible applications for the presented person localization approach include firefighters or security scenarios but also construction sites and hospitals. Also, the principal portability on many smart phones opens a wide range of consumer applications like navigation in large buildings (e.g. airports, exhibition halls, shopping centers or others). The contribution of this paper is an efficient approach to PDR with low processing capabilities and a comprehensive experimental analysis of the system under varying environmental conditions.

7 FUTURE WORK

For the next future, it is planned to further study the attitude estimation done by the integrated DSP inside the IMU. Therefore, we are currently working on a new design for a hip-mounted PDR unit. Furthermore, in terms of algorithms design, we are working on a classification of typical movement patterns to improve and optimize the performance for a specific application scenario. Based on the movement classification the alignment procedure of the IMU will be further improved. Also, the initialization process of the anchor nodes and cooperative approaches will be evaluated further.

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