A Fusion Approach for the Localization of Humans in Factory Environments

Fabian Hölzke, Peter Danielis, Frank Golatowski, Dirk Timmermann
Institute of Applied Microelectronics and CE
University of Rostock, Rostock, Germany
Email: fabian.hoelzke2@uni-rostock.de

Abstract—**Industrial automation increasingly relies on the automation and interconnection of formerly human operated transport machinery. Products are already moved by automated guided vehicles and machines like cranes may soon position themselves just in time based on context information. Human presence is however still required in some of these environments. This raises the question how to allow machines to sense a human's presence to enable context awareness functions and safety around autonomous machines. We propose a combination of Ultra-Wide Band (UWB) localization and Pedestrian Dead Reckoning (PDR) to achieve robust and reliable long- and short-term tracking of humans in an industrial environment. We highlight advantages and drawbacks of both localization methods, as well as current approaches to increase tracking accuracy of the individual technologies and their combination. Additionally, we present measurements using a Zero Velocity Update assisted PDR system and show that, under certain circumstances, the error of PDR can be reduced from 5% to 2% of the travelled distance. We also analyze the applicability of PDR correction methods in industrial environments. Our results show the potential of PDR for accurate short-term localization, supplanted by UWB to ensure long-term precision.**

I. Introduction

Industrial automation has been a driving factor for increased productivity and wealth since the first industrial revolution centuries ago. The initiative of *Industry 4.0* aims to enable a fourth revolution by increased digitization, inter-connectivity and data aggregation in industrial spaces. This enables machines to be context aware and to coordinate without the need of human intervention. Cranes or forklifts, for example, may be automated to position themselves to a given location without continuous human control or even move autonomously in anticipation of subsequent tasks. However, machines lack the multi-sensory perception of humans to move safely in a factory full of independent mobile actors, including humans. Mobile actors, especially human personnel, need to be reliably localized to enable real time orchestration and avoid collisions. Current infrastructure based approaches for localization have limited accuracy and are prone to disturbance (Bluetooth, WiFi fingerprinting) or require expensive specialized equipment, as is the case with Ultra-Wide Band (UWB) localization. Pedestrian Dead Reckoning (PDR) based methods are comparably inexpensive but exhibit degrading accuracy over time. We propose a combination of PDR and UWB based methods to achieve reliable, accurate and cost effective long- and short-term localization in a factory environment. In this paper we will outline the limitations of PDR based approaches in an industrial context and present our own measurements. We show an error of 5.11% relative to the travelled distance for PDR can be corrected to 2.02% through map matching under certain conditions. We also highlight current technologies and methods for a fusion of PDR with UWB localization, that may be used if map matching is not applicable.

This paper is structured as follows: Section II introduces position tracking using UWB. The fundamentals of position tracking by PDR are stated in Section III with a discussion of correction methods in Section III-A. In Section IV we present our findings regarding the feasibility of map matching correction methods for PDR in industrial areas and present a hybrid UWB and PDR approach as a viable alternative. Section V describes related work on the combination of PDR and UWB localization. Section VI concludes the paper.

II. Position tracking using UWB

Unlike received signal strength indicator (RSSI) based methods, UWB relies on short duration pulses which translates to an ultra-wide band signal in the frequency domain. This makes UWB localization comparably resilient to disturbances and therefore a candidate for industrial environment localization [1]. Single time instance localization with UWB relies on methods like maximum likelihood estimation of several noisy range or angle measurements between a moving target and several anchor stations. Such measurements are commonly known as Time of Arrival (TOA) and Time Difference of Arrival (TDOA) for range estimation and Angle of Arrival (AOA) respectively for angle measurements. At least four measurements to different base stations are needed for 3-D localization using TOA and TDOA.

The quality of localization can be improved by position tracking, utilizing past noisy measurements with a Extended Kalman Filter (EKF) [2]. The accuracy of tracking with an EKF is depending on update rate and target speed, outperforming other localization methods like particle filters or least-square methods at high update rates [3]. Continuous tracking requires a high enough sampling frequency to register sudden changes in motion. For battery powered base stations, this means a short interval for generated pulses which in turn leads to increased draining of the battery. Low update intervals are preferable to increase battery life time of base stations.

Another factor for accurate tracking is the availability of base stations in line of sight (LOS) of the tracked target. Non line of sight (NLOS) base stations may lead to degrading accuracy due to signal degradation and multipath effects which affect the accuracy of range and angle measurements. Sophisticated NLOS detection and mitigation methods may not be suitable for resource constrained devices like wearable receivers. A measurement campaign featured in [4] shows that ranging errors above $2m$ occur in about 50% of NLOS cases. The authors use a machine learning approach on the received UWB waveform (namely support vector machines or SVM) for NLOS classification and mitigation. However this approach may not be feasible for resource constrained embedded systems in heterogeneous environments because of the high computational intensity of SVMs and the need for training data. Compared to RSSI based ranging, like utilizing Bluetooth beacons, UWB is still a good candidate technology for accurate indoor positioning as it is less prone to errors introduced by NLOS and multipath effects. However, localization with UWB may involve a considerable investment in hardware to ensure that multiple UWB anchors are in line of sight in every relevant part of the building.

III. Position tracking using PDR

Pedestrian Dead Reckoning (PDR) methods can be divided into two categories: Inertial Navigation Systems (INS or Strapdown Systems) and Step-and-Heading (SHS). Both methods utilize relatively inexpensive wearable inertial sensors and gyroscopes to derive the user's position relative to a given starting position and direction. While INS integrates the measured acceleration twice to calculate the user's displacement, SHS detects single steps and their direction. A gyroscope is used in both cases to measure a change of direction. There is no need for additional infrastructure [5], [6].

As an inertial sensor can only detect changes in acceleration and direction with respect to its own coordinate frame, the relation between sensor coordinate frame and real world coordinates has to be established. The direction of gravity as a low passed measurement of acceleration may be used to relate one axis (commonly the Z-axis) of both frames. The initial orientation around this axis remains to be established by either a magnetometer (compass), which may be unreliable indoors, or additional external knowledge like user input, alignment with map data or calibration through parallel location tracking, for example with UWB based localization. Permanent integration of noisy sensor values like in INS is subject to drift, degrading the accuracy of localization over time. This effect is mitigated through Zero-Velocity-Updates (ZUPT) with foot mounted sensors. This method uses the periods of standing when a foot touches the ground, to stop and reset the integration of sensor values or to analyze the accumulated error as the real change of position and orientation is temporarily zero. This method enables the detection of steps in any direction and their individual displacement, independent from speed or mode of walking [7], [8].

Instead of double integrating the acceleration between steps, SHS uses step detection and an estimation of step length through various heuristics. Like in INS, the step orientation is either determined by integration of angular velocity through a gyroscope or through a compass. Methods for step detection include analyzing the measured acceleration for peaks, exceeded thresholds, periodic patterns (auto correlation and frequency domain analysis) or a combination of these methods. The range of plausible step frequencies may also be considered to limit false detection of steps. Depending on the placement of the sensor node, an analysis of the angular rate may also be employed to recognize swinging arms or moving legs [6], [9], [10].

Step detection is prone to false detection or missing of steps through percussion of sensors or temporary unusual gait like side stepping, sliding or very slow walking. Additionally the gait of a person and therefore the acceleration pattern of a step varies between users and the sensors position on the user's body affects the characteristic acceleration pattern of a step. This may lead to decreased accuracy with predefined parameters. Depending on the employed method, the accuracy of step detection may be enhanced by parameter learning. Similarly, machine learning is employed for step detection. However, this requires an offline learning phase for each user and may be more computationally complex than other methods. A combination with parallel, independent localization may be used to establish an estimate of the ground truth to tune such parameters online [6], [11].

The estimation of step length when utilizing SHS is commonly done by analysing step frequency or acceleration magnitude. With additional Information of the user's height it is possible to get a reasonable estimate of current stride length [12], [13], [14]. Currently available commercial pedometers tend to underestimate step count while accuracy degrades with lowering walking speed. Hip mounted devices tend to be more accurate than wrist mounted ones or smartphone applications. While research publications report step detection accuracies of 97% and above in laboratory environments, studies of commercial devices tend to report accuracies of 90% and less. Detection accuracy tends to decrease with slower walking speeds [15], [16], [17], [18].

A. *Correction methods for PDR*

The accuracy of localization with dead reckoning techniques degrades over time as errors in step length and orientation and missed or falsely detected steps accumulate. Map matching methods can be employed to counter this effect. Here, the user's path is compared to a building map, eliminating trajectories that, for example, cross walls. A common method for map matching is the use of a particle filter. With each step a cloud of particles is propagated that models the uncertainty of the measurement. The particles are weighted depending on the plausibility of their trajectory, leaving only probable locations of the user. The user's position is then estimated as a combination of the weighted particles [19]. Some applications start at a known location and backtrack to eliminate sequences of particles that lead to dead ends. The remaining particles are then re-sampled. Another method distributes particles over the whole map and eliminates implausible particles while the user moves through the building. This way the user's location becomes more certain over time and parameters like step length can be derived from remaining particles [10]. These approaches require the propagation and validation of dozens to hundreds of particles with each step and are therefore computationally intensive. However, research shows that these methods work in real time on smartphones. Another limitation is the need for complex floor plans so that the users path through a building can be fit on a map without ambiguity [6], [20].

Figure 1: The cased IMU mounted on a shoe.

IV. Investigation of PDR feasibility depending on building geometry

To investigate if map matching is useful as a method of long-term correction for PDR in an industrial context, we conducted our own experiments. In the following section we present experimental results obtained by our own map matching correction methods.

A. Experimental setup

Six users are asked to walk a given course through a single floor of a University building. The users are equipped with an Inertial Measuring Unit (IMU) that is strapped to the bridge of one foot as seen in figure 1. The IMU periodically transmits acceleration and angular velocity to a smartphone via Bluetooth. The smartphone runs an implementation of the zero velocity update (ZUPT) method, using a Madgwick filter to calculate the foots orientation. This ZUPT with Magdwick fusion generates a three dimensional vector modelling the propagation of the user's foot between steps, which we call the step vector. The user's starting orientation and position are predefined. The current position is determined by stringing together the calculated step vectors. Only the horizontal components of the step vector are considered in this experiment (ignoring the Z-axis).

The smartphone application is capable of correcting a new step vector with information about known paths through the building. This correction method forces a step vector on a nearby path if the user walks in parallel to the path (within a range of acceptable deviation). Otherwise, if the user walks perpendicular to the path, the step vector is not corrected. As angular drift is a significant source of error, drift is also corrected by comparing the orientation of parallel steps with the orientation of a known nearby path, for example along a corridor.

Two test courses are examined. Course *Corridor* consists of a straight section through a corridor and back to the start, including one 180° turn. The length of this course is $77m$. Course *Hall* consists of a round trip along the perimeter in a hall with a length of $69m$.

B. Experimental results

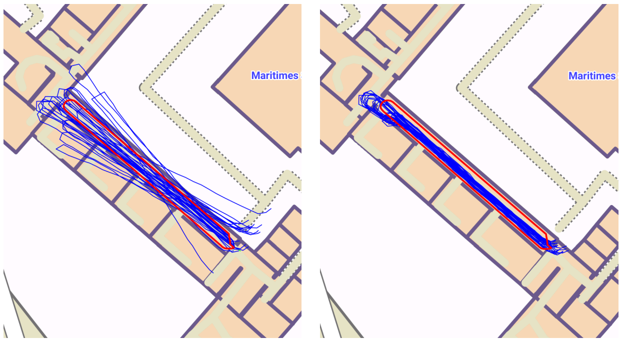
The results of the experiment are shown in Table I. The course length and position error between start and end point are stated as absolute values. The error is calculated as the mean distance between start and end of 18 test runs in total, by 6 test persons. The relative error is calculated as the mean absolute error divided by the course length. Figures 2 and 3 show the recorded test paths as thin blue lines and the ground truth as a thicker red line in a map of the test floor.

The uncorrected error between start and end of the test course averages to about 5% of the course length. The correction by a known path along the test corridor improves the average error to $1.55m$ or 2.02%. Figure 2a shows the distribution of the recorded uncorrected user paths along the corridor. Figure 2a shows the respective corrected user paths. The spread of uncorrected user path end points and the contraction by our correction method suggests that drift is a significant source of error here. Errors in the initial orientation can be discounted as they influence the angular fit to the map but shouldn't influence the accuracy of the return to the starting position. The remaining error after correction can be attributed to the measuring error of step length. Another source of error may be the drift correction due to altering a steps measured direction and therefore altering the traveled distance along the corridor.

Figure 3 shows the uncorrected user paths from and to the entry of a lecture hall. The test path leads around the perimeter of the hall with a semicircle shaped deviation. Like in course *Corridor*, permanent drift and deviations in the starting orientation lead to a significant spread of the user paths. However, small scale movements like the semicircle portion of the path and 90° turns at the corners are recorded accurately. The deviation of the recorded start and endpoints average to $3.47m$ or 5.03% of path length which is comparable to the results of course *Corridor*.

TABLE I: Error of PDR measured as distance between start and end point.

Course	Length	Without correction		With correction	
		Abs. error	Rel. error	Abs. error	Rel. error
Corridor	$77.00m$	$3.94m$	5.11%	$1.55m$	2.02%
Hall	$69.00m$	$3.47m$	5.03%		



(a) No correction. (b) Correction with map information.

Figure 2: Corrected and uncorrected user paths of the course *Corridor*.

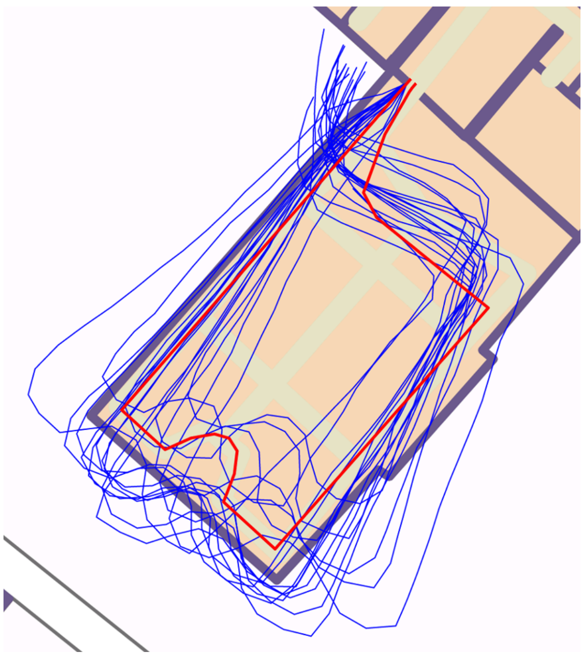


Figure 3: The uncorrected user paths of the course *Hall*.

C. Discussion

The examined map based correction methods are particularly useful regarding building sections and movement patterns that leave little room for speculation regarding the user's true path. A string of parallel steps along a corridor can be corrected easily regarding orientation drift, leaving only ambiguity regarding the true travelled distance. Map based correction fails however, when users can walk freely in any direction in a wide open space - as is the case in a factory hall. Orientation drift soon degrades the reliability of position tracking through PDR. However, small scale movements like turns are recorded accurately per step. In respect to open spaces like factory halls, this highlights the need for additional localization technologies like UWB to correct the degrading accuracy of PDR and the potential for improved accuracy in the short term by PDR. If an industrial space features geometries like narrow corridors, map matching is a feasible correction method for PDR. This reduces the need for UWB infrastructure in certain building parts.

Figure 4 shows an exemplary scenario of a factory building which benefits from a hybrid localization strategy: A production area and a storage area are connected by a corridor. A gate is separating corridor and storage area. The production and storage areas are fully covered by UWB anchors (A1 - A4 and A5 - A8). The corridor is only partially covered by two (A1, A2) UWB anchors in LOS, with one section not covered at all.

To enable accurate UWB localization in the corridor, four additional UWB anchors would need to be installed. However, a combination of localization by PDR, the ranging information of the remaining anchors in line of sight and map matching may provide sufficient accuracy when transitioning from the storage to the production area. This eliminates the need for additional UWB anchors. Additionally, the assumption of full UWB coverage at all times in the production and storage areas may not be attainable in reality: Large equipment, moving machinery or shelving may temporarily block line of sight to an UWB anchor, introducing NLOS in an otherwise fully covered area. In this case as well, fusion with PDR helps to improve short-term localization reliability and accuracy, even without map based correction.

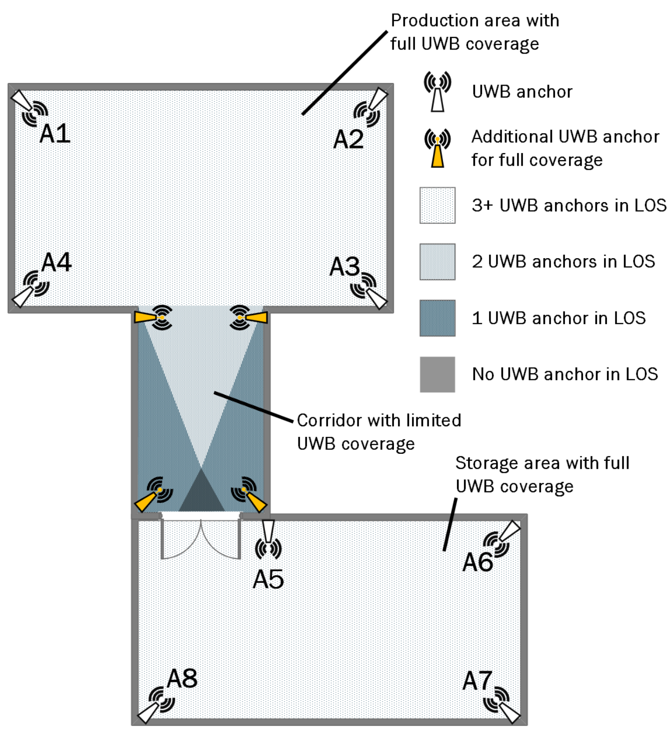


Figure 4: Schematic view of a factory space with limited LOS in the corridor section.

In this scenario, the combination of PDR and UWB would reduce the need for UWB hardware from 12 to 8 anchor stations - cutting initial hardware investment cost by 33% (excluding a low cost inertial sensor node for PDR). The following chapter will examine related work regarding the fusion of localization technologies with PDR, focusing on UWB as a candidate technology.

V. Related work

A promising approach to increase long-term tracking accuracy and to lessen the need for high frequency ranging updates and sophisticated NLOS mitigation is the combination of UWB and PDR. Short term movements are accurately detected by PDR which allows lower frequency UWB updates and range measurement outliers due to NLOS may be mitigated with the additional positioning information of PDR. Additionally UWB mitigates the long term accuracy degradation of PDR [5], [2]. The following examples shall give an overview of current research regarding hybrid PDR approaches.

[21] employs RSSI based localization fused with PDR by an Extended Kalman Filter (EKF). The authors demonstrate a covariance matrix tuning method suited for large spaces, similar to factory halls, based on the estimated distance to base nodes and the respective estimated accuracy statistics. They are able to improve localization accuracy in a $8.6m$ x $18m$ round trip inside a hall from $2.65m$ with an untuned EKF to $1.7m$.

The authors of [22] use step counting and step length estimation fused with low frequency UWB localization updates. The authors do not employ tracking of the UWB positions by Kalman filter because of the low sampling frequency. Instead, the UWB derived position is fused with PDR data that is sampled per each step of the user. UWB is only used to mitigate the accumulated positioning error by PDR. The drift of PDR orientation is not mitigated because of the low frequency of UWB updates. This may still lead to a decreasing reliability of the PDR data over time.

Another system fusing PDR and UWB data is presented in [23]. The trilateration of UWB TOA data is realized as a least-squares solving problem within an EKF that also uses acceleration and rotation data of an IMU. UWB nodes that exhibit NLOS behaviour are detected by comparing the predicted (Kalman prediction step) error distribution of the measurement of a node with the actual measurement, disregarding measurements that lie outside of a certain confidence interval. The least-squares solving approach increases the reliability with an increasing number of TOA measurements from different nodes.

Drone localization via EKF-fused GPS, IMU, Vision and UWB range measurements is presented in [24]. Measurement outliers, like UWB NLOS measurements, are rejected by doing a Chi-Squared test on the measurement residuals.

[25] presents an approach to optimize step detection parameters based on past sensor data and Kalman filter innovation parameters. Past inertial data with available GPS measurements is used to minimize a cost function of Kalman innovation and innovation co-variance. The goal is to find the optimal step detection parameter that minimizes the discrepancy of inertial and GPS data that is expressed in the Kalman filter innovation and innovation co-variance. This approach is only tested on offline batch data. It is however feasible to use this approach for an automated PDR configuration at the beginning of UWB assisted localization.

VI. Conclusion

Range based tracking techniques like UWB provide robust long-term localization while PDR is accurate in the short term and may be realized with no infrastructure and low priced hardware. However, PDR suffers from degrading accuracy with travelled distance and UWB requires specialized infrastructure in line of sight with high update rates which limits battery life. The fusion of PDR and UWB localization using a Kalman filter combines the advantages of both technologies and enables accurate localization at reasonable cost in industrial environments: The short term accuracy of PDR allows lower update rates for range measurements and compensates temporarily degraded ranging accuracy due to NLOS. Additionaly, PDR reduces the need for UWB infrastructure in suitable building geometries. In turn, UWB localization is used to compensate the degrading long term accuracy of PDR. A hybrid approach also enables the online tuning of step detection parameters when using SHS by providing an estimate of the ground truth, continuously improving the accuracy of PDR.

We will publish a detailed description of the algorithms used in our experiments regarding map matching for PDR and additional experimental results in the near future. Additionally, we will conduct experiments with UWB and PDR hybrid localization.

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