MAP MATCHING BY USING INERTIAL SENSORS

Literature Review

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Abstract

This literature review aims to clarify what is known about map matching by using inertial sensors and what are the requirements for map matching, inertial sensors, placement and possible complementary position technology. The target is to develop a wearable location system that can position itself within a complex construction environment automatically with the aid of an accurate building model. The wearable location system should work on a tablet computer which is running an augmented reality (AR) solution and is capable of track and visualize 3D-CAD models in real environment. The wearable location system is needed to support the system in initialization of the accurate camera pose calculation and automatically finding the right location in the 3D-CAD model. One type of sensor which does seem applicable to people tracking is inertial measurement unit (IMU). The IMU sensors in aerospace applications, based on laser based gyroscopes, are big but provide a very accurate position estimation with a limited drift. Small and light units such as those based on Micro-Electro-Mechanical (MEMS) sensors are becoming very popular, but they have a significant bias and therefore suffer from large drifts and require method for calibration like map matching. The system requires very little fixed infrastructure, the monetary cost is proportional to the number of users, rather than to the coverage area as is the case for traditional absolute indoor location systems.

Keywords

Technology
Research
Center

Turun yliopisto
University of Turku

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Technology Research Center

Turun yliopisto University of Turku

1 Introduction

An augmented reality system (AR) must be able to align the augmented, virtual content with real world. For this the location of the system must be known with high accuracy. When an AR system is starting up, it must be initialized by determining the approximate location and then certain computer vision algorithms can be used to perform the exact matching of the real world to the virtual model in the system. For the approximate location, often a complex sensor network infrastructure is needed with sufficient coverage [11]. Alternatively, the inertial sensors (IMUs) utilization of dead reckoning underlines the advantages in such a scenario where being independent from any infrastructure and thus being immediately ready for operation is needed. The problem of signal multipath propagation in an indoor environment, which is common for sensor networks and decreases the accuracy, is completely irrelevant for the IMUs. The main problem for the low cost IMUs is the drift of acceleration or orientation over time. Because the dead reckoning system is continually adding detected changes to its previously calculated positions, any errors in measurement, even small, are accumulated from point to point, which leads to drift error. In order to limit this drift error, waypoints like RFID-tags and the inclusion of context information like map knowledge can lead to a significant improvement of localization accuracy. The use of dead reckoning for localization seems to reach at least room level precision in mission-critical, emergency or military indoor scenarios [P4]. Mission-critical indoor localization requirements that National Institute of Standards and Technology [3] concluded in 2008 suit well for environments under construction also to find the current position of a person or a device:

- localization accuracy of about 1 m
- functional within all types of buildings
- restricted to equipment that is brought on-site by the relief units themselves
- no site-specific training required
- stability against structural changes
- moderate costs

The target is to develop a wearable location system that can position itself within a complex construction environment automatically with the aid of accurate building model. The wearable location system should work at the same time on a tablet computer which is running an augmented reality solution and is capable to track and visualize 3D-CAD models in real environment. The wearable location system is needed to support the system in initialization of the accurate camera pose calculation and automatically finding the right location in the 3D-CAD model. The accuracy

of the system must be high enough. The system must be able to tell in which room or corridor the user is. Knowing also the direction where the camera is pointing or user is looking at would be very useful and make the camera pose initialization procedure faster. The system should not require a fixed localization infrastructure, the monetary cost should be proportional to the number of users, rather than to the coverage area. Also the environment is changing all the time during construction as new structures, modules and equipment, furniture are installed. This means additional challenge to all fingerprinting techniques i.e. those that are based on comparing the properties of radio signal propagation to a predefined map of such signals. An important requirement is that the system must be light, easy to carry with and the target is that no additional equipment would be needed [P13]. The scope of the literature review is utilization of map knowledge, map matching and data fusion with inertial sensors in indoor localization and possible complementary position technology. This paper is organized as follows: In Section 2, a brief introduction to localization is given, continued with inertial sensors and map matching in Section 3. In Section 4, the research method of the literature review and search results are described. The findings are discussed in Section 5 and the paper is concluded in Section 6. Terminology and abbreviations are listed in Appendix A, Glossary. Review papers and references are listed in Bibliography.

2 Indoor and Outdoor Localization

While there are solutions like global navigation satellite systems (GNSS) for the localization outdoors, problems arise in urban scenarios and indoors due to insufficient or failed signal reception. For indoor use, multiple alternative localization concepts exist that are suited for different use cases. Many of these encounter a series of challenges due to complex indoor environments, e.g. severe multipath effect, Non-Line-of-Sight (NLOS) conditions, high signal attenuations and noise interferences. In Time of Arrival (ToA) example in Figure 1, TX is transmitter to various receivers RX1, RX2 and RX3. The RX2 is in NLOS condition but the direct path (DP) is not completely obstructed. The propagation time of the signal depends not only upon the travelled distance, but also on the encountered materials. Since the propagation of electromagnetic waves is slower in some materials compared to air, the signal arrives with delay. The RX3 receives signal via reflector only. Several ToA estimators as well as ranging/localization schemes have been proposed in the literature to deal with these challenges [12]. A more robust system can be achieved with complementary localization method like inertial measurement unit, which is capable of detecting and rejecting multipath effects and NLOS.

A reliable indoor localization solution with high accuracy is still a challenge. Indoor localization methods can be divided into four main categories: triangulation, direct sensing, pattern recognition and dead reckoning [P21]. Triangulation-based e.g. WLAN and direct-sensing-based e.g. infrared localization approaches need infrastructure assistance and depend on the installation of beacons at known positions. Highest level accuracy can be achieved using Ultra Wide Band (UWB), Bluetooth Low Energy (BLE) or RFID (DASH7) beacons. UWB radio has several inherent advantages over narrowband radio (BLE, DASH7) in its use for calculating location by time-difference of arrival (TDOA) or time-of-arrival (TOA) measurements instead of signal attenuation (RSSI). First, the transmission bursts of wideband radio are shorter, so their starts and stops can be measured more precisely. But more importantly, UWB signals will be more readable in the presence of distortions [5, 2]. The huge UWB bandwidth coupled with a very low power level makes UWB signals appear more or less like background noise to other wireless communication systems. This allows them to coexist with other radio communication devices as well and make them immune to detection and interception by other narrowband wireless
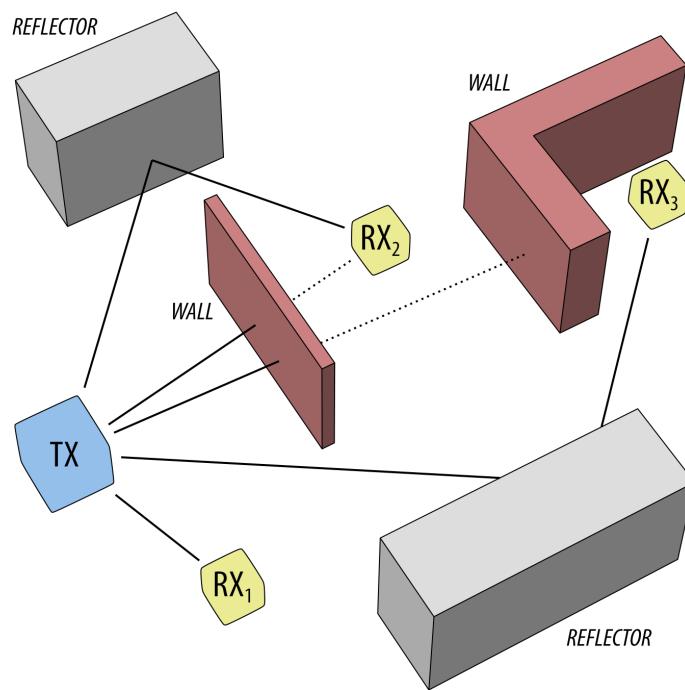
Figure 1: Multipath problems of traditional narrowband radio signal based positioning.

communication receivers [P25]. Figure 2 presents the Precision Personnel Locator (PPL) of the Worcester Polytechnic Institute (WPI) [6]. It is a UWB based system for the tracking of emergency agents within buildings and is independent from any previously installed infrastructure and includes IMU also. The signal is emitted by portable devices that are carried by the emergency agents and it is received by at least three beacons outside building, e.g. mounted on fire trucks that can be localized by using the GNSS. The position of each portable device is determined by first calculating distances using the time-difference of arrival technique and then fusing with IMU position estimation to have even more accurate position estimation. Quuppa [10] location tracking solution utilizes Bluetooth Low Energy and antennas that measure the angle-of-arrival (AoA) of a radio signal emitted by the tag. Benefit of this is that only two beacons are needed. DASH7 is an open source RFID-standard for wireless sensor networking, which operates in the 433 MHz unlicensed ISM-band and its biggest benefit is signal penetration of walls due low frequency [4]. Accuracy below 1 m has been reached in an office building using DASH7 system and Particle filter [8]. Visual pattern recognition based localization methods require high storage capacity and significant computing power. Magnetic distortions recognition requires fingerprint-maps and huge training before usage. Pedestrian dead reckoning (PDR) localization technique, which is based on inertial sensors, estimates a pedestrian's location with lower installation cost and computation over other localization methods. PDR localization techniques, however, have a main drawback that they are only able to provide required accuracy for a limited time due to the sensor errors arising from random zero bias and oscillation noise. For the low-cost inertial sensors specially, the accumulating errors grow rapidly with the travel distance of pedestrians. To handle this disadvantage, it is necessary to combine PDR techniques with other localization solutions or auxiliary information to correct the accumulating errors and achieve constant high-precision indoor localization. [P4]

Scattered Signal Reflections

Escape Route

Transmitter Badge- Firefighter

Incident Commander's Tactical Display

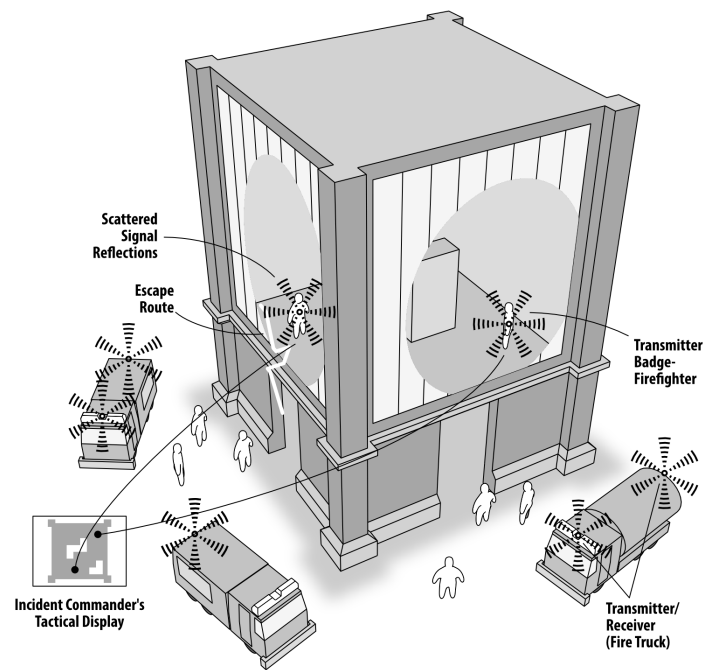**Transmitter/ Receiver (Fire Truck)**

Figure 2: The Precision Personnel Locator (PPL) of the Worcester Polytechnic Institute (WPI).

3 Map Matching By Using Inertial Sensors

The major advantage of inertial and motion sensors is that they do not require any setup of measurement devices or supporting sensors located at the site. Therefore, it is possible to conduct a position estimation in unknown terrain as the sensors are independent from any preinstalled infrastructure like transmitters, external satellites or other fixed reference points. Inertial and motion sensors are increasingly integrated as so-called inertial measurement unit (IMU) in end-user devices of the mass market like mobile phones and game controllers. An inertial measurement unit is an electronic device that measures and reports a device's velocity, orientation, and gravitational forces, using a combination of accelerometers and gyroscopes, sometimes also magnetometers. One way to get position is to make double integration over time. This yields the object's velocity in the first step and in the second step the distance travelled from the origin. Another, lightweight way, is to calculate steps, stride length and direction of a person. The inertial and motion sensors are used within the so-called dead reckoning (DR) navigation. The term dead reckoning describes the process of localization based on the continuous tracing of the measured direction and acceleration when starting from a known position. A general prerequisite for tracking the current position of an observed object using inertial sensors is the knowledge of the initial position and orientation. Localization is only possible relative to a known location, which leads to the main disadvantage of inertial sensors, measurement errors sum up over time. Thus, without an appropriate compensation, and increasing distance from the starting point, the inaccuracy of the localization may drastically increase. This is the reason that suitable compensation methods are required (see Section 2). The inclusion of context information like maps in the dead reckoning approach does not require any extra infrastructure. A detailed three dimensional building map is modeled as an input for a particle filter (PF) and map matching and fused to the inertial data from inertial sensor. PF is particularly useful in solving non-linear and non-Gaussian problems. The basic idea in using PF is to use random number generator to simulate the errors in position due to the noises in inertial sensors. Instead of single position estimate, there are multiple position estimates. These are called particles and whose form a cloud. With realistic state propagation and noise models, simulated particle states in the cloud provide good approximations of the statistical distributions of the true quantities represented by

the particle states. Inertial sensor can be placed for example a foot, a waist or keep in a pocket. Map matching methods are probably the most promising methods to aid DR. To make use of position information of personnel, an indoor map e.g. floor plan is needed. The idea of map matching is to utilize the map information for aiding the positioning. Corrections can be made to position and heading according to map information [P18].

4 Research Process And Search Results

A systematic literature study (SLR) is a systematic and repeatable approach to identify and study all relevant evidence on a specific research question or phenomenon [1]. Major publication databases and search engines were used that are available at our university. The search process was started by conducting several pilot searches using different search terms and search options. The following search string was used:

(IMU OR "inertial sensors" OR "inertial measurement unit" OR "MEMS INS") AND (localization OR positioning OR navigation OR tracking) AND (calibration OR "map matching" OR "particle filter" OR building OR maps OR layout OR RFID OR "Radio Frequency Identification")

The searches were done in November 2014. An article was selected if it was from the field of inertial sensor and localization and map matching. Only articles written in English were included. The article search was divided into three stages. In the first stage, the studies were included based on the title of an article. From 9729 hits, 292 were selected for the second stage. In the second stage, over half of the articles were dropped out based on the abstract. After the second stage, 110 articles remained to be analyzed in the third stage. In the third stage, short overviews of the articles were made and finally 25 articles were selected for the review. One person read the articles. In the categorization, the articles were categorized in terms of their content and type. The articles were divided to be either map matching (RQ1), inertial sensor (RQ2-4), complementary calibration method (RQ5) or another review. Finally the articles were read carefully and data was extracted from them and they were summarized.

16 articles were considered to belong to RQ1, map matching [P18, P19, P22, P11, P20, P25, P24, P20, P3, P23, P6, P5, P12, P1, P2, P9] and 7 articles were considered to belong to RQ2-RQ4, inertial sensors [P21, P14, P13, P7, P16, P17, P10]. Though, there were no direct borders between these, many times RQ1 articles included material reglated to RQ2-RQ4 and vice versa. None of the articles were considered to belong directly to RQ5, but often RQ1 articles included material related to RQ5. Among the selected articles two articles are considered as reviews or surveys [P8, P4]. Hashemi et al. [P8] present a review of real time map matching algorithms, current issues and future directions and Funchs et al. [P4] present a survey of indoor tracking
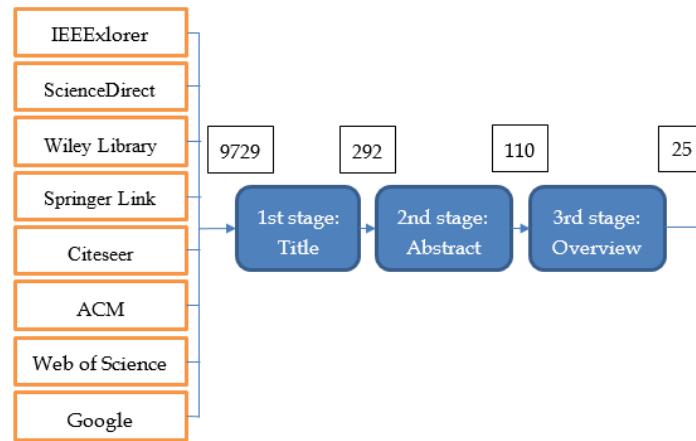
Figure 3: Search results.

for mission-critical scenarios. As mentioned in Section 1, mission-critical indoor localization requirements suite many times very well for construction environments also. Review articles contents are introduced shortly in Section 4.2 and discussed in Section 5. Accuracy of each papers method are listed in Table 1. The oldest article was from year 2004 [P5], the second oldest was from year 2008 [P24, P3, P23], while most of them were published in year 2014 [P18, P14, P13, P8, P7, P25, P20, P1, P2].

4.1 Review Questions

In this literature review, the main objective was to find out the current state of indoor map matching by using inertial sensors, accelerometer and gyroscope. Review questions are:

RQ1 What is currently known about map matching by using inertial sensors?
RQ2 What are hardware requirements for inertial sensors?
RQ3 What are pedestrian dead-reckoning algorithm requirements?
RQ4 What are inertial sensors placement requirements?
RQ5 What could be complementary calibration method for inertial sensors?

4.2 Review Articles

4.2.1 Map Matching Articles

Leppäkoski et al. [P15] presented results of field tests where extended Kalman filter was used to fuse signals from WLAN strengths and waist-mounted inertial sensor unit including one gyro and an accelerometer. The inertial sensor was used to determine traveled distance and heading. A particle filter was used to combine the inertial

data with map information. The results showed that both the map information and WLAN signals can be used to improve the quality of pedestrian dead reckoning estimates. The WLAN based positioning is complementary with map information, because map information is relatively useless in open areas, where walls and obstacles cannot guide the particles. There is a lot of disturbances present in WLAN signals in areas that contain dense obstacles, which distort positioning algorithms using fingerprints, while in open areas the quality of WLAN based position estimate is better. In the system, the maximum position error was 3 m in 17 min walk and can be obtained even without WLAN, however tests were done in one test area only, in a library. This emphasizes the benefit that usage of heading information can provide in an indoor positioning system. The utilization of indoor maps in pedestrian navigation differs from the way how street maps are used in car navigation. In car navigation, the roads represent the possible locations of the car, and the task of the positioning algorithm is to estimate to the most probable road segment where the car is located. In indoor navigation, instead of defining possible routes, the indoor map gives information about impossible locations and movements. The positioning algorithm uses information about walls and obstacles that the pedestrian is not able walk through. The walls and obstacles are presented by line segments defined by the coordinates of starting and ending nodes. The map information about the walls and obstacles is difficult to formulate so that it could be applied with Extended Kalman Filter (EKF). Particle filters can utilize such information easily. After each propagation step, particle filter algorithm can check whether the particles ended into obstacles or out of the room through the walls. If either of these happened the particles weight can be set to zero that in the next resampling those will not survive. The computational load of this process is significant if the number of obstacle lines is large. However, the number of intersection tests can be reduced, if the obstacle lines close to each other are grouped, which minimizes the run time of the particle filter processing. Then, instead of checking intersections with all the lines, the algorithm first searches the line groups in the area where the particle transition happens, and checks the line crossing only with the lines of these groups.

Tofthjaer et al. [P22] evaluated the impact of sensor errors and building structures on the positioning accuracy using a waist-mounted system and a particle filter. Tofthjaer et al. analyzed results of regular and open spaced office buildings as well as a shopping mall environment. The results showed that accuracy differences can be explained by sensor errors and the constraints provided by building structures. The noise of the inertial sensors is the major source of positioning errors. Doors that have to be passed change a pedestrian's movement pattern because a couple of sidesteps, maybe even a backwards step have to be made for every closed door. As sensors are less accurate for such types of steps, the presence of doors will increase the error. The evaluated system provides a median accuracy of 2.5–8.6 m depending on the sensor errors and building structures compared to 8.0–25.3 m with pure inertial positioning. GPS was also used to provide at least the initial position and to correct particles. For correction, the particle filter updates the particle weights according to their distance from the GPS position.

Kirkko-Jaakkola et al. [P12] presented a method for indoor pedestrian navigation based on low-cost inertial sensors and building plan information initialized with

Global Navigation Satellite System (GNSS). The body mounted inertial sensor is utilizing a step-detecting technique. Position is estimated with the Monte Carlo approximation of the Bayesian filter called Particle Filter (PF). Kirkko-Jaakkola et al. evaluated a system which is capable of indoor localization without availability of local infrastructure. The most common approach is to scan Wireless Local Area Network (WLAN) signals, since wireless Access Points (APs) usually stay in the same location for a long time. Medium Access Control (MAC) addresses of APs allow estimation of the location of the user. Cellular network and Bluetooth signals are also popular, but those have certain limitations. Despite the global coverage, cellular triangulation yields a relatively imprecise position solution. Bluetooth signals work at short ranges, but using them for positioning requires the presence of dedicated transmitters. Bluetooth has the advantage over WLAN that its signal power is lower, which decreases the probability of outlier observations. Initialization was made with high-sensitivity (HS) GNSS receiver that is capable of acquiring and tracking signals that are significantly weaker than nominally, well below 10 dB-Hz which is a typical level indoors, corresponding to a signal that has propagated through a brick roofing or a concrete wall. Even high-sensitivity receivers designed for acquiring and tracking weak signals cannot typically resolve the user position accurately. For example, identifying the room where the user is located depends on the surroundings of the antenna and on the available assistance information.

Perttula et al. [P18] made a system which consists of an inertial measurement unit (IMU) connected to a radio. Step length and heading estimation is computed in the IMU and sent to the server that is connected to another radio. On the server side, the position is estimated using particle filter-based map matching. The benefit of the distributed architecture is that the computational capacity can be kept very low on the user side, which leads to long operation time as power consumption remains very low. For accurate WLAN positioning, methods based on signal strength measurements and triangulation are not sufficient because fingerprinting are needed. The accuracy of localization is proportional to the density of reference points. The time consumption of the measurements is directly proportional to the number of the reference points. Although WLAN networks exist nowadays almost everywhere, most of them are not sufficient for accurate positioning. Another radio technology used in indoor positioning is ultrawideband (UWB). It is more reliable technology than other radio network-based positioning systems as the reference points can be located outside the building. Extremely short pulses are transmitted using low transmit power which overcomes the multipath problems of traditional radio signal-based positioning techniques. The reference points can locate themselves using GPS, and thus the tracked personnel's relative position to reference points can be converted to absolute coordinates. The advantage of this approach is that no preinstalled infrastructure is needed. Because of limited transmission power, the method is not suitable for large buildings. Perttula et al. used low-cost accelerometers and gyroscopes in a torso-mounted IMU although the advantage of foot-mounted sensors is that Zero Velocity Updates (ZUPTs) can be used to reduce error growth of double integration. In some studies, this has been found to be more accurate than PDR methods which are based on step detection and step length estimation. In addition, ZUPTs do not assume normal walking to the forward direction. Also, ZUPTs are

not as practical as body mounted sensors where no extra interfaces are needed. Perttula et al. also mentioned that a system that uses a digital compass, is very vulnerable for magnetic distortions. When the user walks, every step introduces a distinctive pattern to the accelerometer output. Therefore, it is assumed that the user is moving on a flat surface such as on the floor indoors. The positioning problem reduces to two dimensions when the motion is estimated by detecting steps from the acceleration signals. Waypoint corrections and map matching are techniques used to aid PDR to prevent unbounded error accumulation. According to some studies, the error of basic PDR in torso-mounted system is larger than error of double integration based ZUPT foot-mounted system. Both of these aiding techniques can be used to keep the localization error at a reasonable level. The gyroscope and accelerometer measurements of a torso mounted IMU are preprocessed in the microcontroller of the IMU to produce step length and heading change estimates and sent to the server for map matching. The average distance errors of the PDR system were 9.9 and 10.3 m, while the average distance errors were 1.4 and 1.7 m with the PF map matching.

Woodman et al. [P24] developed a localization system which used a foot-mounted inertial unit, a detailed building model, and a particle filter. Woodman et al. pointed out environmental symmetry and scalability problems that are commonly faced during particle filter localization task. Translational symmetry is a problem for buildings where each floor has a similar layout. In such environments, locating the pedestrian in a single floor is difficult due to translational symmetry in the vertical direction. The number of particles required during the early stages of localization can be reduced by identifying the area. WLAN signal strength can be used to reduce the initial complexity and to locate particle filter area. Woodman et al. point out that the main cause of drift are small errors in the gyroscope signals. These errors cause growing tilt errors in the tracked orientation. Together with acceleration signals double integration this causes an error in position which grows cubically in time. By using Zero Velocity Updates (ZUPTs) the drift problem can be reduced by detecting when the foot is in the stationary stance phase, i.e. in contact with the ground. Woodman et al. used 2.5 dimensional description of the building map where each object has a vertical position but no depth. The map is defined to be a set of planar floor polygons. Each floor polygon corresponds to a surface on which a pedestrian's foot may be grounded. Each edge of a floor polygon is either an impassable wall or a connection to the edge of another polygon. Connected edges must coexist in the (x,y) plane. However the connected edges may be separated in the vertical direction to represent stairs. The use of a 2.5D format avoids complexity that would be required if fully 3-dimensional maps would be used. The evaluated post-processed system is able to track a user throughout a 8725 m2 building in three floors to within 0.5 m 75% of the time, and to within 0.73 m 95% of the time.

A floor plan is needed for map matching. The idea of map matching is to utilize the map information to aid the positioning. Corrections can be made to position and heading according to map information. In construction engineering it is highly unlikely that a person crosses walls, but it is possible in case all walls are not the same as on map information. In sophisticated systems, crossing walls in maps should not be fully restricted, but then parallel RF-based indoor localization method and radio frequency tags would be needed for initialization. Map matching is used as an

aid for PDR system [P5], possible routes consist of nodes, curves and connectivity information. Constraining the position estimates only to predefined routes, i.e. nodes and curves, makes that type of map matching impractical. A more sophisticated map matching algorithm is based on particle filtering as in [P6]. This algorithm corrects the IMU-based estimate by fitting the shape of the estimated trajectory to the shape of the areas defined in the map. The system [P6] uses double integration of the acceleration signals over time to calculate the distances. Furthermore all three Euler-angles (roll, pitch, yaw) are calculated by integration of the angular rate over time. Unfortunately, small measurement errors could induce large errors to the estimated position if additional sensors or methods are not used. Therefore an Extended Kalman Filter (EKF) is used to stabilize the measurement of the IMU's orientation. Also the earth's magnetic and gravitational field are measured and utilized. The distances to the three axes are calculated using one footstep.

In [P19] Pinchin et al. introduced a heuristic heading approach. The method uses a particle filter approach where particles that cross walls are removed. Previously the particle filter approach has been computationally intensive process and has required many particles to effectively model the navigation errors. Pinchin et al. recognized that heading is the primary source of navigation error and therefore a heuristic heading information was incorporated into the particle filter design. By weighting particles according to their heading the number of particles required to maintain a small failure rate was reduced. There are two key problems with foot mounted inertial navigation system (INS) according Pinchin et al.. Firstly, the INS heading errors are poorly observable using ZUPTs. Secondly, in order to achieve stable filter performance, especially when using an Extended Kalman Filter (EKF), the INS must be initialized with an accurate position and attitude. Pinchin et al. demonstrated "CHAIN method" to improve positioning performance in areas where only few map constraints are present. The system showed significant reduction the filter failure rates, ranging from 44% to 14% when a small number of particles is used and the initial position is poorly known.

The Simultaneous Localization and Mapping (SLAM) principle can be used to generate a suitable map of the visited areas. In [P20] Puyol et al. introduced Foot-SLAM that is an algorithm based on the simultaneous localization and mapping principle. It relies on human odometry, i.e. measurements of a pedestrian's steps with foot mounted inertial measurement unit to build probabilistic maps of human motion for such environments using crowdsourcing. The approach employs a particle filter and partitions of the map space. The partitioned map space is a grid of adjacent hexagonal prisms with eight faces in multistory building. An AutoRegressive Integrated Moving Average (ARIMA) model is used to model vertical component of the odometry errors. Tree based data structure is used to efficiently store the probabilistic map, allowing real time processing. The FootSLAM is a suitable for massmarket applications where data collected by traveling pedestrians are used to create navigable maps in heavily frequented areas. The FootSLAM map of a building could help optimize the building's operations to identify usage and identify hot spots, bottlenecks and alternative routes. The paper raises the future possibility of crowdsourced indoor mapping and accurate navigation by using the low-cost sensors of a handheld smartphone.

In [P11] Kaiser et al. introduced a foot-mounted indoor positioning system which is using the knowledge of floorplans in the localization algorithm. A new motion model based on floorplans is introduced that is capable of weighting the possible headings of the pedestrian as a function of the environment. The motion model benefit is that it can more effectively represent the probability density function of possible headings that are restricted by floorplans than a simple binary particle weighting. The simple binary particle weighting eliminates only those that crossed walls and keeps the rest. The following situations result a very large and probably permanent position error until a second source of location can be obtained (e.g. GNSS, wireless localization). 1) Pedestrian walks in area of differently sized rooms and structures. 2) Pedestrian walks past a door at an angle and a certain fraction of the particles walk through the door as well. A good human motion model will not just eliminate particles that cross walls but rather reward those that follow a trajectory compatible with the building layout. The demonstrated motion model worked better than a simple PF that only uses knowledge of walls to constrain particles and can fail above example situations.

In [P3, P23] Beauregard et al. introduced a novel Backtracking Particle Filter (BPF) that can utilize different levels of building plan detail to improve PDR performance. The BPF takes advantage of trajectory histories and longrange geometrical constraint information. The BPF yields excellent positioning performance with detailed building plan information. For indoor positioning, building plans are very useful information that can be used to enhance location accuracy and reduce uncertainty of walking trajectories. Particle Filters (PF) can utilize building plan information during the indoor positioning. This technique is called Map Filtering. It is usually possible during even short ZUPs (Zero Velocity Updates) at footfalls to estimate the gravity vector from accelerometer readings and thereby determine roll and pitch angles. These can be exploited by a KF to correct gyro drifts around these two axes. Gyro drift around the yaw axis is typically controlled via magnetometer readings. Unfortunately, magnetic disturbances can make magnetometer based orientation estimates very problematic in indoor environments. It is wise to give more weight to the yaw gyro measurements than to the magnetometers. The system utilized foot mounted inertial sensors and showed that BPF technique can give better results than a standard Particle Filter technique. BPF takes advantage of longrange geometrical constraint information that the estimated path is always backtracked. That means that the particles proven to be unsuitable are eliminated in previous steps. In this way, the localization results of the previous steps are improved, which improves localization accuracy. The system got 0.74 m mean 2D error with detailed building plan information and BPF.

In [P1, P2] Bao et al. introduced step counting based dead reckoning algorithm which utilizes map matching. Inertial sensors are put on trousers pocket simulating mobile device and step is detected by the pattern of the acceleration. To compensate for the accumulating error in a dead reckoning tracking system, some other method needs to be fused to form a hybrid system. The paper compares different compensation methods with dead-reckoning. Pure Map Matching (MM), Map Matching enabled Particle Filter (MMPF) and improved PF are compared. The improved PF underlines the uncertainty in the step direction estimation. The particles with the

wrong direction estimation are more likely to be the ones with the wrong location estimation and can be eliminated by map constraints. The improved PF calibrates the location estimation, as well as step direction estimation, while keeping the computational complexity the same as the original PF. Unlike PF, which is executed at every step, the MM algorithm is triggered only when a pedestrian is considered to be walking along a certain corridor. The MM takes 1/6 of the CPU time compared to the PF (100 particles). Although the MM algorithm provides reliable results with less CPU cost, the required narrow corridors may not always exist in an indoor environment. Experimental results shown that in a dense map with corridors, MM, MMPF and improved PF outperform the original PF. When only partial map constraints are applied, the advantage of using the improved PF is shown, which returns more accurate and robust results.

In [P25] Xiao et al. introduced a fresh MM method for indoor localization. The MM method is computationally efficient and tracks very well even with noisy inertial sensor data. Key to the method is to handle the tracking problem as a Conditional Random Field. The CRF is a technique which has had great success in areas such as natural language processing. The system demonstrated how it is able to accurate track the position of a user using accelerometer and magnetometer measurements only. The system is energy efficient because gyro is not needed at all. Xiao et al. compared the CRF-method against other state of the art map matching methods in three buildings. The novel method outperforms competing algorithms in all three buildings. The room level accuracy is above 90% in all buildings.

In [P9] Holcik Master's Thesis work presents a mobile system which combines pedestrian dead reckoning and absolute localization methods. Pedestrian dead reckoning uses a step detection filter and the device orientation is measured by combining inertial sensor signals from gyroscope, magnetometer and accelerometer. WLAN is used as absolute localization method. WLAN signal strength is used for the initial location initialization and location correction. Signal strength fingerprint method is used for the computation of the location probability density function. The function is added to the one of the particle filter, together with a wall collision model for building map matching. Before particle filter was selected, Grip based method was found out to have too high computation load requirements for handheld device. Evaluation test measured the median error distance of 2.3 meters, 90th-percentile is at 5.6 meters.

In [P8] Hashemi et al. presented a review of real time map matching algorithms, current issues and future directions. The review concentrated on outdoor map matching which allows drivers to keep track of their precise whereabouts and provide optimal routes to reach specified locations. It was found out that most map-matching algorithms make an unbalanced trade-off between performance and accuracy and that "weight-based" map-matching algorithms balance simplicity and accuracy and "advanced" map-matching algorithms provide high accuracy but with low performance. The review pointed out that most "weigh-based" map-matching algorithms divide their logic into different parts for identifying the correct segment in different situations: when the movement starts, before crossing an intersection and after crossing an intersection. This approach is proven to be efficient because it improves the percentage of correct segment identification without making the algo-

rithm complicated or computationally intensive.

In [P4] Fuchs et al. presented a survey of indoor tracking for mission critical scenarios among first responders like firemen. The survey pointed out requirements for this kind of system, already mentioned in Section 1. The survey grouped systems as signal based and non-signal based systems. The survey points out that as a radio signal is not following a defined propagation model indoors, using signal attenuation for position estimation is only feasible when preceded by an extensive fingerprinting phase of the received signal strength. Even then, an accuracy of below 1 m is not achieved with current systems. Signal delay is only an imprecise distance estimate in an indoor environment because of effects like reflection and multipath propagation. Different approaches try to improve the accuracy by using wideband signals or statistical methods in order to alleviate the disturbances of multipath propagation. The most promising concept, according to the survey, seems to be the use of ultra-wideband signals (UWB). On the other hand, the lateration with signal delay and attenuation alone delivers unacceptable results for a reliable and precise indoor localization in difficult conditions. The method of dead reckoning holds the decisive advantage of being independent from an existing infrastructure. It is not influenced by structural changes of the environment. The only disadvantage is the increasing error over time due to imprecise measurements. Thought, there are multiple approaches to reduce the impact of imprecise sensor measurements with methods of data fusion like Kalman or Particle Filters. As a summary the survey proposed a system which would combine the data of several different localization methods that complement one another as much as possible.

4.2.2 Inertial Sensor Articles

[P17] presents a novel orientation algorithm designed to support a computationally efficient, wearable inertial human motion tracking. The Kalman filter (KF) has become the accepted basis for the majority of orientation algorithms and commercial inertial orientation sensors. Xsens, Microstrain, VectorNav, Intersense , PNI and Crossbow all produce systems founded on its use. However, it has a number of disadvantages. It can be complicated to implement and requires high sampling rates which can far exceed the subject bandwidth. The article introduces orientation estimation algorithm that is applicable to both IMU and MARG (Magnetic Angular Rate and Gravity) systems. Orientation estimation algorithm is also known as Attitude and Heading Reference System. The key difference between an inertial measurement unit (IMU) and an AHRS is the addition of an on-board processing system in the AHRS. The on-board processing provides solved attitude and heading solutions versus an IMU which just delivers sensor data to an additional device that solves the attitude solution. AHRS is able to provide a complete measurement of orientation relative to the direction of gravity and the earth's magnetic field. Results indicate that the algorithm achieves levels of accuracy matching that of the Kalman based algorithm. The low computational load and ability to operate at small sampling rates significantly reduces the hardware and power necessary for wearable inertial movement tracking. These enable the creation of lightweight, inexpensive systems capable of functioning for extended periods of time. The algorithm is available as

an open source software.

In [P10], Jimenez et al. compared several of the most relevant algorithms for step detection, stride length, heading and position estimation. Some PDR approaches assume a smooth walk on horizontal surfaces, and others are valid for uneven terrain with complicated gait patterns. Foot inserted inertial measurement unit is used to first compare step detection methods. Best method is based on accelerometers (0.1% error), second gyroscopes (0.2 % error) and third magnetometer (0.94 % error). The step detection is very reliable at continuous walk, but it is more difficult to detect steps robustly at the beginning/end of walk, and at very low speeds (e.g. museum-like style of walking). Tests continued to stride length estimation, where "Weindberg" and ZUPT stride length methods and ZUPT double integration method were tested. The ZUPT double integration positioning method is normally considered as the most powerful PDR method, since it is able to satisfactorily estimate the position while running, with lateral walk or on uneven terrain. However Jimenez et al. showed that in smooth surfaces, positioning method based on stride length plus foot orientations can be superior and more computationally efficient.

In [P21], Jiuchao et al. presented indoor localization method based on a smartphone inertial sensors, combined with a floor plan and a particle filter. To address the challenges of low sampling frequency and limited processing power in smartphones, a step detection technique is developed. The precision of the stride length estimation is influenced by pedestrian different kind of motions. An adaptive stride length estimation algorithm based on the motions classification is developed. Heading estimation is carried out by applying the principal component analysis (PCA) to acceleration measurements projected to the global horizontal plane, which is independent of the orientation of a smartphone. The heading determination is one of the most challenging parts of a PDR system, because the error of heading leads to a fast growth of localization error. It is difficult to achieve reliable heading determination specifically in indoor environments where magnetometer may become invalid due to various interferences. For indoor localization on a smartphone, there exists another problem that the smartphone heading may be different from the pedestrian's heading. Therefore, two main tasks need to be finished before implementing an indoor localization. One is to obtain the heading of a smartphone, and the other is to infer the heading offset between the smartphone and the pedestrian. Jiuchao et al. argued also that as particle filtering has been regarded as a computationally intensive algorithm, and the goal is to achieve real-time operation on a platform of a commercial smartphone. Two methods are implemented to reduce the computational load of particle filter. One is binary weight, the other is reduction in particle number. When particle's weight is binary, the computation of state update and resampling is lighter. The system mean error is 0.74 meters and 95th percentile error is 1.71 meters.

Li et al. [P16] presents a system which utilizes a smartphone inertial sensors. Li et al. developed an algorithm for detection of steps and heading direction, and integrating these to an indoor map using a particle filter. The algorithm provides an adaptive estimate at every step, and it is position and orientation free on the user body. A 3-axis accelerometer is used instead of its vertical and horizontal components because a mobile phone can be at any position on the user body. The position of the phone, such as in a hand or in a pocket, can affect the sensor readings. This

makes reliable detection across positions challenging. The step length can vary quite a lot over time, due to speed, terrain, and other environmental constraints. That is why Li et al. developed a personalization algorithm that adapts the stride length estimation to each user on the fly. Another challenge for the system is to have reliable heading direction, despite the fact the phone can be at any heading on the body. The phone heading may be different from the user heading during walking. Here one source of constraints is the indoor floor map, which constrains the motion with corridors and walls. Li et al. utilized the particle filter algorithm, a nonparametric form of Bayesian estimation, to compute the overall position. The algorithm integrates information from the step length estimator and heading estimator, in addition to the constraints from the floor map. Every time a step is detected, the system acquires the step length based on step model and infers the heading direction of that step as well. Both step length and heading direction are fed into the particle filter module together with the map information. Each particle filter particle moves according to the dynamics of the model step by step and is constrained by the map. If a particle hits a wall, it will die, and a new particle is generated around another live particle. Particles whose trajectories align with the observation will have a higher probability to live. Thus, the position of live particles reflect the estimated position of the user. Tests are carried out in Windows phone and the map is loaded as XML file and is divided into small tiles. Each tile is labeled as pathway, room or wall. Manual method is used for localization initialization. Two phones are evaluated. One in the hand and the other in the pant pocket. Evaluation results showed that the system can achieve a mean accuracy of 1.5m for the in-hand case and 2m for the in-pocket case in a 31m×15m testing area. Li et al. pointed out that heading direction inference from magnetometer is the major cause for error, and they are looking methods to calibrate the readings to compensate for the error.

In [P14] and [P13] Lan et al. introduced a new method to estimate user's step length with a waist mounted mobile phone. The method utilizes the height change of the waist based on the Pythagorean Theorem. Similar is used in Weinbergs method and also mentioned in [P10]. Lan et al. proposed a new zero velocity update (ZUPT) method to address sensor drift error. Simple harmonic motion and a low-pass filtering mechanism is combined with the analysis of gait characteristics. Exploiting the geometric similarity between the user trajectory and a floor map is proposed for map matching. The map matching algorithm includes three different filters to calibrate the direction errors from a gyro using the building floor map. The sliding-window-based algorithm detects corners. The floor plan is characterized by using a link–node model, also mentioned in [P5] and [P18]. Lan et al. stated that while waist-mounted systems are implementable on a hand-held device, their step length estimation accuracy is typically worse than foot-mounted systems. On the other hand foot-mounted systems performs poorly with regard to orientation accuracy. Lan et al. pointed two type of errors that can be observed due to PDR sensor hardware: 1) Systematic, such as sensor bias, sensitivity, and drift. 2) Random such as environmental changes. The system 98th percentile error is 0.48 meters.

In [P7] Hardegger et al. introduced "ActionSLAM", a wearable system that can track people in previously unknown multi-floor environments with sub-room accuracy. There are two common PDR approaches, Step-and-Heading (SH-PDR) and

Zero-Velocity UPdaTes (ZUPT-PDR). Step-and-Heading, SH-PDR, which is relying on hip- or belt-mounted IMUs or they do not make any assumption regarding the on-body location of the sensors. SH-PDR combines step detection rules, step length heuristics and heading estimators to derive the user's trajectory. For regular, straight step, the error accumulation for SH-PDR may be less than 2 % of the distance travelled. In recordings with more complex foot motions such as jumps and walking in place, SH-PDR however fails. Zero velocity update, ZUPT-PDR integrates the raw acceleration and rotation velocity data of a foot-mounted IMU, and corrects the velocity whenever the foot is on the ground and therefore not moving. Outside and in wooden buildings where magnetometers provide reliable information about the sensor's heading, the error accumulation can be as low as 0.3 % of the distance travelled. In particular, in steel-framed constructions, the magnetic field close to the ground is strongly disturbed. ZUPT-PDR without magnetometer correction achieves a tracking accuracy of 0.6–1.2 % of the distance travelled. To perform frequent zero-velocity updates, ZUPT-PDR requires that the feet are on the ground and not moving at regular intervals. Aside from that, ZUPT-PDR is independent of the user's motions on territory and therefore better suited for real-world deployment than SH-PDR. SLAM is a family of techniques in which one set of sensors estimates the user trajectory (e.g., through PDR), while another set of sensors recognizes landmarks in the environment. By adding these landmarks to a map, future observations of the same landmarks will compensate for errors in the user trajectory. Action-SLAM stands for action-based simultaneous localization and mapping. It fuses dead reckoning data from a foot-mounted inertial measurement unit with the recognition of location-related actions to build and update a local landmark map. Simultaneously, this map compensates for position drift errors that accumulate in open-loop tracking by means of a particle filter. The system utilized a foot mounted inertial measurement unit, similar as the OpenShoe project (openshoe.org). The algorithm is computationally light-weight and runs in realtime in a mobile phone, enabling immediate location-aware feedback. The algorithm robustly (93 % of runs) mapped the areas with a mean landmark positioning error of 0.59 m.

Article	PDR method	MM method	Accuracy	IMU placing
P9	SH-PDR	PF	3 m	Waist
P7	SH-PDR	PF	2.5–8.6 m	Waist
P20	SH-PDR	PF	good	Waist
P1	SH-PDR	PF	1.4-1.7 m	Torso
P13	ZUPT-PDR	PF	0.5 m 75%, 0.73 m 95%	Foot
P8	ZUPT-PDR	PF	1.33 m	Foot
P15, P17	ZUPT-PDR	BPF	0.74 m	Foot
P22, P23	SH-PDR	PF	1.19 m	Pocket
P12	SH-PDR	CRF	1.14 m, 2.37 m 97 %	Hand
P24	SH-PDR	PF	2.3 m, 5.6 m 90 %	Hand
P21	SH-PDR	-	4.15 m	Foot
P3	SH-PDR	PF	0.74 m, 1.71 m 95%	Pocket
P11	SH-PDR	PF	1.5 m hand, 2m pocket	Hand/Pocket
P4, P5	SH-PDR	Three filters	0.48 m 98%	Waist
P10	ZUPT-PDR	PF	0.59 m 93%	Foot

Table 1: PDR and MM methods and accuracy.

5 Discussion

The paper presents a study about indoor localization by using the map matching and the inertial measurement sensors. Target is to collect knowhow about map matching and complementary calibration methods (RQ1, RQ5) and inertial sensors requirements, like hardware (RQ2), algorithm (RQ3) and placement (RQ4). First there is discussion about the map matching and complementary methods findings and then, in the following chapter, about the inertial sensors findings.

5.1 Calibration Method Discussion

5.1.1 Complementary Method

A particle filter was used in many papers to combine the inertial data with map information, when Extended Kalman filter was used to fuse together some other localization method, like WLAN. Leppäkoski et al. [P15] pointed out that map information is relatively useless in open areas, where walls and obstacles cannot guide the particles. Same open area issue was found by Tofthjaer et al. [P22] when they analyzed results from deploying the system in regular and open spaced office buildings as well as in a shopping mall. WLAN is a good complementary method for inertial sensors, but it is not sufficient for accurate positioning due normally low density of reference points and signal multipath [P18]. Bluetooth has the advantage over WLAN that its signal power is lower, which decreases the probability of outlier observations. RFID DASH7 is a standard which operates in the 433 MHz unlicensed ISM band and penetrates walls better than more high frequency Bluetooth or WLAN [P12]. Main issue on the above methods is that they are based on signal strength measurements and fingerprinting is needed for adequate accuracy. In some papers GPS was used for providing the initial position and to correct particles, whose weights are updated according to their distances from the GPS position. HS-GNSS is capable of acquiring and tracking signals that are significantly weaker than nominally. Signals are able to propagate through a brick roofing or a concrete wall. The UWB uses extremely short pulses and signal is spread over a large frequency range to overcome the multipath problems of traditional radio signal based positioning techniques and it looked as most promising in mission critical review [P4]. Because of limited transmission power, the UWB is not suitable for large buildings if only three beacons/anchors are used. For example, DecaWave [5] DW1000 UWB chip (Figure 4) has 40 meters of
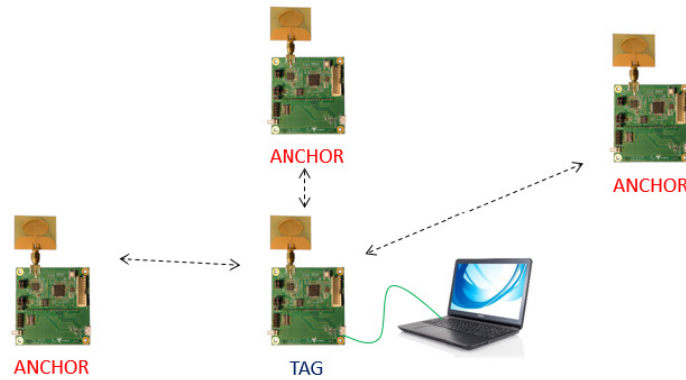
Figure 4: DecaWave UWB localization system SDK [5]

range Non Line Of Sight (NLOS, through walls) and up to 300 meters of range Line Of Sight (LOS). Accuracy of the chip is 10 cm both indoors and outdoors. For small building it is possible to add three beacons/anchors outside the building. Thus, it is possible to locate beacons/anchors by using the GNSS and the tracked personnel's relative position to beacons/anchors can be converted to absolute coordinates [P18] . The system could also enable algorithm for assisted placing of beacons/anchors according the 3D map, thus supporting an optimal deployment. Also for inertial measurements initialization complementary localization method would be good to reduce particle filter particles needed in the beginning. Although many times particle filter can fix the location later on based on movements. In construction engineering it is highly unlikely that person crosses walls, but it is possible in case all walls are not the same as on the map. In sophisticated systems, crossing walls in maps should not be fully restricted, but then parallel RF-based indoor localization method and radio frequency tags would be needed for initialization. Woodman et al. [P24] pointed out two problems commonly faced during particle filter localization task: environmental symmetry and scalability. For correcting these two above problems Woodman et al. proposed complementary absolute position method which could locate the particle filter area.

5.1.2 Map Matching

In [P4] Fuchs et al. presented a survey of indoor tracking for mission critical scenarios among first responders like firemen. Fuchs et al. argued that for signal based localization, the most promising concept seems to be the use of ultra-wideband signals (UWB). Fuchs et al. argued also that the method of dead reckoning holds the decisive advantage to be independent from an existing infrastructure, disadvantage is the increasing error over time due to imprecise measurements. Though, there are multiple approaches to reduce the impact of imprecise sensor measurements with methods of sensor data fusion like Kalman or Particle Filters. In [P15] Leppäkoski

et al. mentioned that the map information about the walls and obstacles is difficult to formulate so that it could be applied with Extended Kalman Filter (EKF). Particle filters (PF) can utilize this kind of information easily. Several papers concentrated on improving original Particle Filter. Pinchin [P19] and Kaiser [P11] weighting particles according to their heading. That way they reduce the number of particles required to maintain a small failure rate and improve system performance in more open areas where there are few mapped walls to aid navigation. A good human motion model will not just eliminate particles that cross walls but rather reward those that follow a trajectory compatible with the building layout. In [P3, P23] Beauregard et al. introduced a novel Backtracking Particle Filter (BPF), which is a technique where different levels of building plan detail can be combined to improve PDR performance. The BPF technique can give better results than a standard Particle Filter technique. The BPF takes advantage of long-range geometrical constraint information that the estimated path is always backtracked. That means that the particles proven to be unsuitable are eliminated in previous steps. In [P1, P2] Bao et al. introduced improved PF. Bao et al. compared pure Map Matching (MM), Map Matching enabled Particle Filter (MMPF) and improved PF. The improved PF underlines the uncertainty in step direction estimation. The particles with the wrong direction estimation are more likely to be the ones with the wrong location estimation and can be eliminated by map constraints. The improved PF calibrates the location estimation, while keeping the computational complexity the same as the original PF. Experimental result shows that in a dense map constraint environment with corridors, MM, MMPF and improved PF outperform the original PF. The computational load of the particle filter process is significant if the number of obstacle lines is large. However, the number of line crossing checks can be reduced, if the obstacle lines close to each other are grouped, which minimizes the run time of the particle filter processing [P18]. To reduce the computational load of a particle filter two methods are implemented in [P21], one is binary weight, the other is reduction in particle number. In [P25] Xiao et al. introduced a fresh approach which is computationally efficient and power efficient because gyro is not used. Key of the approach is expressing the tracking problem as a conditional random field (CRF). Xiao et al. argued that their novel method outperforms competing algorithms like PF. In [P8] Hashemi et al. compared outdoor map matching which allows drivers to keep track of their precise whereabouts and provide optimal routes to reach specified locations. Hashemi et al. found out for example that most map-matching algorithms make an unbalanced trade-off between performance and accuracy and that "weight-based" map-matching algorithms balance simplicity and accuracy.

5.2   Inertial Sensors Discussion

5.2.1   Hardware

There is a clear trend towards low power digital motion processors (DMPs), e.g. InvenSense MPU-6000/MPU-6050 is able to task and process inertial data in bursts, while the system processor remains in a low power sleep mode. Many ultra low

Figure 5: Intel® Curie™ module - button-sized prototype [7].

power chips (KMX61, LMS303C) are not equipped with power hungry gyroscopes, allowing always-on positioning for wearable device market. Positioning uses accelerometer and magnetometer only in [P25]. Intel came out with its first platform for wearable technology market on January/2015 (Figure 5). Intel has developed a tiny size of SoC-module called Curie that is ideal for always-on applications, including motion sensors, application processor, Bluetooth, battery charging circuitry and a low-power integrated DSP sensorhub with a proprietary pattern matching accelerator. The module runs on open source RTOS. Intel starts to sell the module on the second half of 2015 [7]. [P17] presents a novel open source orientation algorithm that is computationally efficient and competes with the Kalman filter. [P17] results indicated the algorithm achieves levels of accuracy matching that of the Kalman based algorithm, but with lower computational load. It is possible to buy a development kit that includes proprietary AHRS algorithm (Attitude and Heading Reference System) also and ZUPT-PDR demo [13]. Another open source project is the OpenShoe project [9]. OpenShoe is an open source embedded foot-mounted inertial navigation system (ZUPT-PDR) implementation, including both hardware and software designs.

5.2.2   Step Detection / Double Integration And Placement

There are two common PDR approaches, Step-and-Heading (SH-PDR) and Zero-Velocity-Update (ZUPT-PRD). Step-and-Heading, SH-PDR, is relying on hip- or belt- or torso-mounted IMUs. To address the challenges of low sampling frequency and limited processing power in mobile device, a step and heading detection technology seems to be adequate method. It is more difficult to detect steps robustly at the beginning/end of motion, and at very low speeds [P10] or more complex foot motions such as jumps and walking in place [P7]. Tofthjaer et al. [P22] mentioned that the presence of doors that have to be passed will change a pedestrian's movement pattern because for every closed door a couple of sidesteps, maybe even backwards steps have to be made. As the step detection method is less accurate for such type of steps, the presence of doors will increase the error. Several articles presented different ways to measure step length and heading. It is showed that on smooth

surfaces, which is expected for SH-PDR, positioning method based on stride length plus foot orientations, can be superior and more computationally efficient than double integration [P10]. The position problem reduces to two dimension when the motion is estimated by detecting steps from the acceleration signals. It also allows distributed architecture where computational capacity can be kept very low on the user side, which leads to long operation time as power consumption also remains very low [P18]. Zero velocity update ZUPT-PDR on the other side integrates the raw acceleration and rotation velocity data of a foot-mounted IMU, and corrects the velocity whenever the foot is on the ground and therefore not moving. Since it is able to satisfactorily estimate steps while running, with lateral walk or on uneven terrain, ZUPT-PDR is independent of the user's motions and therefore better suited for real-world deployment than SH-PDR [P7]. Although the error of SH-PDR in torso-mounted system is larger than error of double integration based ZUPT-PDR foot-mounted system, according to some studies, both of these aiding techniques can be used to keep the error at reasonable level [P18] (See Table 1)

5.2.3 Algorithms

Several papers presented algorithms for PDR, many of them for the SH-PDR, but also for the ZUPT-PDR. In [P10] Jimenez et al. found out that best method for step detection is to use accelerators (0.1 % error). Many papers argued that heading determination is one of the most challenging parts of a PDR system because the error of heading leads to a fast growth of localization error. The reliable heading determination is difficult to achieve specifically in indoor environments where magnetometer may become invalid due to various interferences. These errors from gyroscope or magnetometer causes growing tilt error in the tracked orientation. Together with acceleration signals double integration this causes an error in position (drift) which grows cubically in time [P24]. By using Zero Velocity Updates (ZUPT-PDR) and sophisticated filters [P17, P6] the drift problem can be reduced. Xiao [P25] mentioned that the system is energy efficient because power hungry gyro is not needed at all. Xiao argued that the novel conditional random field based system beat other state of the art map matching methods. On a smartphone, there exists another problem that the smartphone heading may be different from the pedestrian's heading and that needs to be solved first. Some papers also presented adaptive personal step algorithms that adapt the stride length estimation to each user. Couple of papers [P11, P7] raise the future possibility of crowdsourced indoor mapping and accurate navigation by using low-cost inertial sensors. The Simultaneous Localization And Mapping (SLAM) principle can be used to generate a suitable map of the visited areas. The map compensates for position drift errors that accumulate in tracking by means of a particle filter. [P17] presents a novel open source orientation algorithm that is computationally efficient and competes with the Kalman filter. [P17] results indicated the algorithm achieves levels of accuracy matching that of the Kalman based algorithm, but with lower computational load. Anyway, before algorithms can be selected it needs to be decided if the system which will be developed is relying on SH-PDR or ZUPT-PDR. Another decision is related to open areas [P22, P15], like large open halls where inertial sensors aid with map matching is not the most accurate solution

and where complementary absolute position system is more accurate.

6 Conclusions

For mobile tools in general, lightweight equipment and reasonably low processing power and data storage needs are essential. Visual tracking methods are essential for camera tracking, but they alone are typically not capable of defining the indoor location. On the review it was found that a particle filter is a good choice for map matching by using inertial sensors and there is enough information available for the start and it is accurate enough. Before inertial measurement unit algorithms can be developed it needs to be decided if the system is relying on the SH-PDR or the ZUPT-PDR. Because the system which will be developed requires quite a heavy picture recognition processing and rendering to be done at the same time with localization, the SH-PDR looks like a better choice because of low computation requirements. Accuracy of the SH-PDR with map matching is suitable for the system. Also digital motion processor hardware platform of Intel's Curie [7], which will be available 2H/2015, looks promising for the SH-PDR. Another decision is related to open areas, like large open halls where inertial sensors aid with map matching is not the most accurate solution and where complementary absolute position system is more accurate. Also for localization initialization, a complementary absolute position system would be beneficial. All of these absolute position systems require special hardware, beacons network. DASH7 and UWB should penetrate walls better due to signal characteristics and already have lower interference and BLE is in mobile devices. Each of these have certain benefits and would need a separate review and construction site tests of the features and limitations. However, the need to have an installed beacon network, as well as the possible need of an initialization phase every time the radio map changes, makes signal attenuation based (BLE, DASH7) on systems problematic for construction time use. UWB technology offers the potential of achieving high ranging accuracy through signal time-of-arrival (ToA) measurements even in harsh construction environments due to its ability to resolve multipath problem and penetrate obstacles. The IEEE 802.15.4a is the first UWB-based standard for low-rate wireless personal area network with localization capability. Ranging accuracy is expected to be one meter or sub-meter at least 90 % of the time. However, the big challenge is to achieve ranging accuracy also in non-ideal conditions, i.e. when the ranging measurements are affected by large errors. In the integrated UWB + INS system, a position error is calculated from the difference in the position estimation from both systems. When UWB measurements are not available or some of the measurements are of low confidence because of multipath radio propagation, the inertial measurements are used for the position

calculation. A combination of these two systems compensates for the shortcomings of each and yields a better performance when compared to individual subsystems. The most essential contribution of INS positioning is the direction. In a pure UWB systems it is impossible to determine the direction. It is only possible to calculate the heading by subsequent position fixes. The beacon based absolute position system should not need a computing resource hungry particle filter, which is needed for the map matching. This would give more computing power for other applications on the tablet computer, like AR tracking and rendering. In the construction site, a beacon network infrastructure cannot be assumed for the whole big building. Instead removable beacons installed according the required AR area looks reasonable. An additional benefit is that the placed beacons can serve as AR markers also and form a communication network. The system could inform a user each time when the algorithm detects that the user is leaving the signal range of the beacons and asking to add beacons so that localization is again possible. The system could also enable algorithm for assisted placing of beacons according the 3D map, thus supporting an optimal deployment. It would be natural to combine several position methods i.e. use UWB based absolute localization method and fuse it with SH-PDR localization method and particle filter based map matching to have optimal accuracy. In case computing power on the tablet is found to be insufficient for map matching, a backend server for calculations is one solution, but makes the system more complicated. The integration of UWB and inertial measurement units only (SH-PDR) has three primary benefits. Firstly, IMU data can be employed to compute the travelled trajectory when UWB measurements are absent due to range limitations or adverse non-line-of-sight (NLOS) conditions. Secondly, UWB-based positioning can supplement IMU data to discriminate between accurate measurements and data corrupted by noise and drift. Thirdly, because of map matching is not needed, a lot of computing power is saved. Assisted placing of removable UWB-beacons and automatic range calibration looks reasonable for construction environment.

Appendix A Glossary

AHRS

> An Attitude and Heading Reference System consists of sensors on three axes that provide attitude for vehicle, including heading, pitch and yaw. The key difference between an inertial measurement unit (IMU) and an AHRS is the addition of an on-board processing system in an AHRS which provides solved attitude and heading solutions versus an IMU which just delivers sensor data to an additional device that solves the attitude solution.

AoA

> Angle of Arrival.

AR

> Augmented Reality. According to the definition by Azuma, an augmented reality system has three capabilities: combination of real and virtual imagery, registration (alignment) of computer graphics with the objects in real 3D environment and interactivity in real time.

DASH7

> An open source RFID-standard for wireless sensor networking, which operates in the 433 MHz unlicensed ISM band.

DP

> Direct Path.

DR

> Dead Reckoning, a process of calculating one's current position by using a previously determined position.

EKF

> Extended Kalman Filter. In estimation theory, the extended Kalman filter (EKF) is the nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance.

FP

> Fingerprinting means mapping based on received signal strength in a location. FP is often used in radio frequency positioning, but it is possible to apply it also to visual or audio signals. Fingerprinting maps can be measured empirically,

or calculated analytically based on models. In operation, the measured signal strengths are compared to the maps and the best match is searched.

GNSS

Global Navigation Satellite System (GNSS) receivers: GPS, GLONASS, Galileo or Beidou system

IMU

Inertial Measurement Unit. A device that measures velocity, orientation and gravitational forces, typically using a combination of three orthogonally arranged accelerometers and three gyroscopes, possibly also magnetometers.

INS

Inertial Navigation System. A device that provides an estimate of velocity, orientation and (possibly) position based on the data from an IMU. Position and orientation can be tracked from measured data if the initial position and orientation is known.

ISM

The industrial, scientific and medical (ISM) radio bands.

KF

Kalman filtering is an algorithm that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone.

MARG

Magnetic Angular Rate and Gravity. A MARG sensor is a hybrid IMU which incorporates a triaxis magnetometer. An IMU alone can only measure an attitude relative to the direction of gravity. MARG systems are able to provide a complete measurement of orientation relative to the direction of gravity and the earth's magnetic field.

NFC

Near Field Communication. A very short range radio communication standard, based on RFID technology.

PAN

Personal Area Network. A local, wireless networking system that can be used e.g. to connect mobile devices and accessories. Bluetooth is an example of a PAN technology.

PDR

Pedestrian Dead Reckoning. In navigation, dead reckoning is the process of calculating one's current position by using a previously determined position, or fix, and advancing that position based upon known or estimated speeds over elapsed time and course.

PoA

Phase of Arrival.

Pose

The exact location, with an accuracy of a few centimeters or better, and direction of view.

Position

Determining the approximate location, meaning an accuracy of less than a few meters or better. Same as location.

RSSI

Received Signal Strength Indication (or Radio Signal Strength Indication). Measurement of the received signal strength can be used for estimation of the distance between transmitter and receiver.

SH-PDR

Step and Heading-Pedestrian Dead Reckoning. Measures stride length plus heading for PDR.

SLAM

Simultaneous Location and Mapping. A technique used to build up a map within an unknown environment, or to update and fill in a map within a known environment, while at the same time keeping track of their current location.

TDoA

Time Difference of Arrival.

ToA

Time of Arrival.

Tracking

Following the pose in (practically) real time, so that the system can keep updating the virtual view without significant delay.

UWB

Ultra-Wide Band. A radio technology which uses a very low energy level for short-range, high-bandwidth communications using a large portion of the radio spectrum. A valuable aspect of UWB technology is the ability for a UWB radio system to determine the "time of flight" of the transmission at various frequencies. This helps overcome multipath propagation, as at least some of the frequencies have a line-of-sight trajectory.

WLAN

Wireless Local Area Network.

ZUPT-PDR

Zero Velocity UPdaTe-Pedestrian Dead Reckoning. Integrates the raw acceleration and rotation velocity data of a foot-mounted IMU, and corrects the velocity whenever the foot is on the ground and therefore not moving.

Acknowledgements

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