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Virtual lifeline: Multimodal sensor data fusion for robust navigation in unknown environments

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ABSTRACT

We present a novel, multimodal indoor navigation technique that combines pedestrian dead reckoning (PDR) with relative position information from wireless sensor nodes. It is motivated by emergency response scenarios where no fixed or pre-deployed global positioning infrastructure is available and where typical motion patterns defeat standard PDR systems. We use RF and ultrasound beacons to periodically re-align the PDR system and reduce the impact of incremental error accumulation. Unlike previous work on multimodal positioning, we allow the beacons to be dynamically deployed (dropped by the user) at previously unknown locations. A key contribution of this paper is to show that despite the fact that the beacon locations are not known (in terms of absolute coordinates), they significantly improve the performance of the system. This effect is especially relevant when a user re-traces (parts of) the path he or she had previously travelled or lingers and moves around in an irregular pattern at single locations for extended periods of time. Both situations are common and relevant for emergency response scenarios. We describe the system architecture, the fusion algorithms and provide an in depth evaluation in a large scale, realistic experiment.

1. Introduction

Pedestrian navigation remains an open problem in environments where GPS is not available, such as buildings and obstructed locations. In this paper, we focus on this problem in the specifically challenging context of emergency response, where real-time location information can be crucial for saving lives. A wide range of location systems have been demonstrated for tracking in indoor environments but these require infrastructure to be pre-deployed and surveyed in the environment [1,2]. Advances have also been made in pedestrian dead reckoning (PDR) with inertial sensors [3] but such

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1 The work reported here was carried out while Widyawan was a researcher in the Cork Institute of Technology.

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systems perform well only for tracking of steady and smooth movement [4], or when detailed models of the environment are available for the evaluation of PDR estimates [5].

Our work builds on extensive user studies of firefighting undertaken in the European project *wearIT@work* [6,7].[2] It assumes a user (e.g., a firefighter) moving in an indoor environment with little or no visibility (e.g., due to smoke or dust), no GPS signals, no infrastructure that can be used for positioning (considering that the environment is unknown, and on fire or otherwise damaged), and conditions that are hostile to long range beacon based navigation (e.g., plasma explosions disturbing RF signals). Furthermore, the users will generally not move in a regular, steady pattern, continuously following a certain path. Rather, their movement through a building will typically involve interruptions (e.g., for inspection of facilities, or attention to victims); movement back and forth and in and out of rooms; and sharp turns and other movements that may be 'out of step' (e.g., to avoid obstacles). This makes PDR, which would otherwise be the technique of choice in infrastructure-less environments, difficult to implement reliably [4]. Considering the typical duration of a mission (20–30 min) and tendency of PDR systems to accumulate error with time, we suggest that robust navigation is not feasible with PDR alone (PDR shows 30 m of accumulated error in one of our experiments).

Based on the above findings, we have devised, implemented and evaluated a novel technique for pedestrian tracking that accounts for realistic conditions in emergency response. Our concept is to use PDR in combination with sensor nodes that users deploy as a *Virtual lifeline*, in analogy to the physical lifelines (aka. guidelines) that firefighters often use as 'safety rope'. The sensor nodes serve as 'ad hoc' beacons, placed or (automatically) dropped by users as they proceed with their mission, and provide relative position estimates which are fused with PDR data to track users. The role of the beacons is to effectively reduce the incremental error accumulation that is inherent in PDR estimates. In our experiments, we have used two types of 'lifeline' sensors: ultrasonic beacons that provide high accuracy ranging estimates over short distances, and RF beacons with low accuracy but larger range (such that several beacons can be detected from the same position).

An important aspect of our technique is that it relies solely on sensors that users carry into an unknown environment, and that lifeline beacons can be placed dynamically at a priori unknown positions. The position of the beacons is estimated from the navigation system itself, in a process akin to simultaneous localization and mapping [8]. A key insight from our experimental evaluation is that relative positioning with respect to the virtual lifeline of beacons significantly improves tracking performance, even though the beacon positions are not known in absolute terms. This effect is especially relevant when a user re-traces (parts of) the path he or she had previously travelled, or when their main trajectory is interrupted by other movement patterns, such moving in and out of rooms. Both situations are common and relevant for emergency response, and search and rescue operations.

1.1. Related work

Indoor location tracking of mobile users has been intensely researched, and systems have been demonstrated using a wide range of methods and techniques [1,2]. The prevailing approaches have been deployment of accurately surveyed sensor and/or marker infrastructure for geometric positioning [9,10], and location fingerprinting using environmental signals (e.g., WiFi, GSM) [11,12]. These approaches have in common that they require extensive preparation of the tracked environment (infrastructure deployment and/or fine-grained survey) and are therefore not applicable to emergency response in unknown environments.

Pedestrian navigation in unprepared "GPS-less" environments has been demonstrated with PDR systems using inertial sensing and dead reckoning. PDR systems exploit stance phases during walking to correct inertial drift for accurate tracking of smooth motion [3] but they are prone to failure in the context of disruptive movement such as sharp turns and jumps [4], and to significant heading errors caused by magnetic interference from structural features in the environment [13]. The inherent limitations of inertial tracking can be compensated when PDR is combined with other data sources. Woodman and Harle, for instance, have demonstrated a highly accurate system in which PDR is used in conjunction with a detailed map of a building [5]. Others have suggested combination of PDR with RFID [14], WLAN [15] and UWB [16]. The limitation of these fusion schemes is that they rely on either prior knowledge of the environment (maps) or pre-deployment of beacons at known positions. In contrast, we propose a technique that relies only on sensors carried and ad hoc deployed by the users of the system.

There are parallels in our approach to robot localization, in that we fuse multimodal sensor data using particle filters [8]. Particle filters have also been used in other location systems, to update the location of a user based on measurements received from a variety of different sensor systems [17,18]. However, these systems dealt with absolute measurements, whereas our approach is based on relative location data (PDR estimates, and relative position of beacons). Other work approaching pedestrian navigation with inspiration from robotics includes HeadSLAM, proposing integration of an inertial measurement and laser range finder in helmet-mounted gear [19].

The work described in this paper builds directly on previous research of the involved research groups. First, the emergency response scenario, including the concept and feasibility of firefighters deploying sensors as they enter a site, has been developed in a four year, iterative application design study performed as part of the *wearIT@work*project [6,7]. This research included observing, recording and analysing training sessions of professional firefighters of the Paris Fire

[2] http://www.wearitatwork.com.

Brigade, and it established, amongst other results, the importance of supporting distinct movement patterns, in particular re-tracing of a path back to the entrance, and "lingering" in certain locations along the main trajectory for search and rescue. Secondly, the proposed system integrates an ultrasonic relative positioning system developed in the *RELATE* project[3] [20]. The RELATE system had been demonstrated for relative positioning of users, with bidirectional ultrasonic devices integrated in shoes and tracked relative to sensor nodes deployed in the environment [21]. The potential of the system to support PDR has previously been explored in simulations [13]. Thirdly, a fusion engine is adopted for this work that has resulted from long-standing indoor localization research at the Cork Institute of Technology.[4] The fusion engine is based on Sequential Bayesian Estimation [22] and comprises a Kalman filter, a particle filter and a backtracking particle filter [23]. The engine was initially developed for WLAN and Wireless Sensor Network localization [24], but later expanded for fusion of PDR and map information [25].

1.2. Contributions and organization

The work presented in this paper entails the following new contributions:

1. The introduction of a novel system concept for pedestrian navigation that combines pedestrian dead reckoning with use of an ad hoc deployed virtual lifeline of sensors (Section 2).
2. The description of the design, implementation and integration of a fully working system including the adaptation of our fusion methods to the specific needs of our application (Sections 3 and 4).
3. A detailed evaluation of the system focusing on the effect of various system configurations under different circumstances (Section 5). The evaluation has been performed in two buildings with varying characteristics (including in terms of magnetic interference observed), using two paths (80 and 400 m length) and multiple subjects. The paths were chosen to be representative of movement in an emergency response situation, which includes extended searches in rooms along the main trajectory. The system performance is evaluated both during deployment of the nodes and for re-tracing of a path back to the starting point.
4. The insight that relative positioning of beacons can significantly improve the performance of a pedestrian navigation systems even when these beacons are deployed in an ad hoc fashion at unknown positions.

2. System overview

2.1. Design considerations

The requirements for our system have been derived from a user-centred design process studying emergency response in the *wearIT@work*project [6,7]. The main considerations which were instrumental in the design of our system are as follows:

1. The availability of positioning infrastructure cannot be assumed. GPS is not available inside buildings, and in typical emergency response situations (e.g., building on fire, or earthquake) it is not reasonable to expect built-in infrastructure to work.
2. Movements of first responders do not follow a certain direction steadily, but are characterized by walking around rooms (e.g., checking for damage or survivors), by interruptions and localized movement patterns (e.g., as obstacles are moved out of the way), and by unconventional movement such as crawling. This makes the use of conventional PDR systems difficult. Over the typical time periods of such interventions (up to 30 min, limited by firefighters' air supply) irregular movement patters are likely to degrade the performance of a PDR system to unacceptable levels.
3. In most emergency response situations the ability of a navigation system to guide responders out of a building is key. Alternatively, the system might need to guide backup staff to join a team that has already gone into a building. Therefore any measures that increase system accuracy in the proximity of a previously taken path are of particular value.

2.2. System concept

Our system uses PDR as the main localization modality. PDR is fully independent of any supporting infrastructure. Reasonable accuracy can be achieved when movement is steady, but over longer distances and time, the system tends to drift to unacceptable levels.

To avoid such drift, the PDR system is periodically re-aligned using sensor nodes placed on the ground by the user. There are two types of sensor nodes. *Ultrasonic nodes* re-align the system with high accuracy over short distances of a few metres. They do so by relative position computation between the node on the ground and an identical node mounted on the shoe of the user. *Radio Frequency* (*RF*) *nodes* have lower accuracy but longer range so that several RF beacons may be detected from the same position.

The nodes are deployed in a dynamic, ad hoc fashion as the user enters a building. The node is assigned a coordinate that represents the user's current location. This coordinate is obtained from the PDR system. This means that a node's location

[3] http://eis.comp.lancs.ac.uk/relate/.

[4] http://www.aws.cit.ie.

is not known with absolute certainty. We therefore consider such nodes as being placed at ''unknown'' locations. The nodes serve three purposes:

1. As long as the user is in range of the node the error incurred by the PDR *since having placed the node* can be reduced using relative position information with regard to deployed nodes. For ultrasonic nodes this is a short-term, yet exact, correction. Because of their longer range, RF nodes can be used for a longer time, but with less accuracy.
2. When the user 'lingers around' a location the PDR system tends to quickly accumulate considerable error. If a sensor node is placed at the beginning of such a lingering phase then it can be used to fully correct this error when the user proceeds to the next location.
3. When the user wants to find the way back out of the building the placed nodes can be used to guide them. In this case we are not so much interested in positioning the user in absolute terms. Instead it is sufficient to determine their position relative to the way which they came in. Since the nodes have been placed on the way in, they can now be used to correct the position estimate (with respect to the way in) in an exact manner. As long as the PDR system is able to guide over the distance separating two nodes with an accuracy not exceeding the range of a node, the system can, in principle, accurately guide the user out of the building over arbitrary distances.

In addition to those nodes placed at unknown locations, we assume that some nodes can be pre-positioned at known locations (e.g. entry point, window, other known landmark) for which the exact position on the map is known. Such nodes can re-align the PDR system to the true position. However we make no assumption about the number of nodes that can be pre-positioned. Instead we investigate the influence of the number of pre-positioned nodes on the system accuracy during the empirical evaluation. Such an evaluation is especially interesting with respect to the RF nodes which have long range but poor accuracy. Thus, it is interesting to see if a few nodes placed at known locations can significantly improve the system performance. With respect to the ultrasonic nodes the effect of pre-placement is clear; when the user is close to such a node their position is reset to the correct value.

3. System components

3.1. Pedestrian dead reckoning

Pedestrian dead reckoning (PDR) is a self-contained navigation technique in which measurements provided by accelerometers and rate gyroscopes are used to track the position of a pedestrian given an initial position, orientation and velocity. Because it is self-contained this method is particularly suited to tracking search and rescue workers in places where there is little infrastructure or where the infrastructure is damaged. However because position information is computed incrementally based on potentially noisy sensor data the position error increases over time.

Our implementation uses an MTx measurement unit from XSens.[5] The proprietary algorithm embedded in the MTx computes real-time 3D orientation based on output from tri-axis gyroscopes, accelerometers and magnetometers. The rates of turn from the gyroscopes are integrated to track the rapidly changing orientation of the device. The accelerometers detect the direction of gravity and the magnetometers detect magnetic North; these directions are used to stabilize the orientation and to prevent errors accumulating without bound during the integration. Although the heading estimation is very good in open outdoor spaces it is strongly influenced by magnetic interference indoors.

The accelerations are rotated into the world coordinate space according to the orientation computed by the MTx and then double integrated to provide velocity and position. In order to reduce the accumulation of error due to the integration of accelerations our algorithm performs zero velocity updates at each step. We attached the MTx unit firmly under a user's shoe laces and every time the product of acceleration and rate of turn drops below a threshold we infer that the foot is in contact with the ground and therefore not moving. At this point the velocity can be reset to zero. This is illustrated in Fig. 1. Using a foot-mounted inertial measurement unit is more flexible and more robust than ''pedometer'' methods that explicitly estimate step length and require customization for different individuals and types of stride. The benefits of foot-mounted inertial sensors combined with zero velocity updates are described in more detail in [3,26,27].

There are two major types of error in the position estimated by our dead reckoning system. First, the estimated linear distance travelled is affected by small errors in the orientation matrix which cause some forward motion to be interpreted as vertical motion for instance. Second the estimated heading is affected by magnetic interference. This type of error is difficult to analyse because it depends not only on the environment but also on the speed at which the person is walking and the particular acceleration and rotation patterns experienced by the sensors and processed by the MTx real-time algorithm. Both types of error cause the estimated position to drift over time although short segments of a path will each be estimated correctly.

3.2. The Relate ultrasonic nodes

The Relate ultrasonic sensor network is a set of nodes capable of estimating distance and angle to neighbour nodes, and a bridge node connecting a laptop to the node network. These are shown in Fig. 2.

[5] http://www.xsens.com/.

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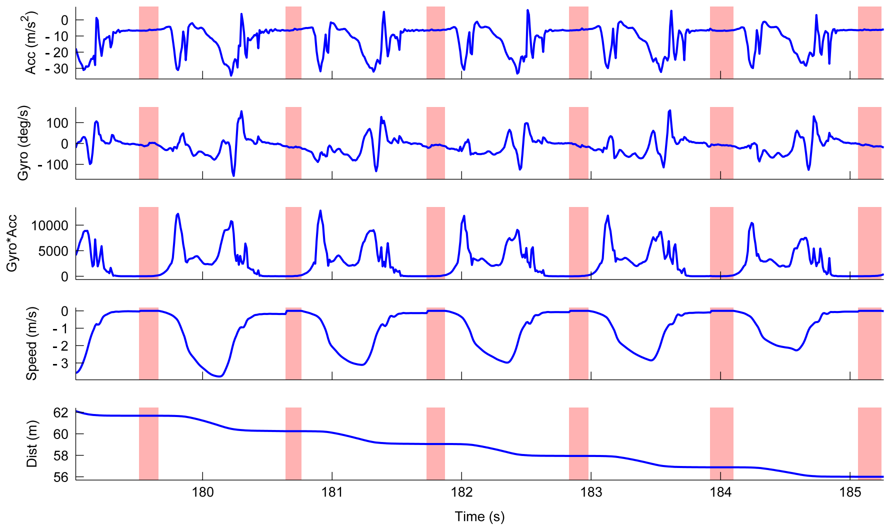

Fig. 1. Zero velocity updates in pedestrian dead reckoning: each step has a stance phase (shaded) and a swing phase. Velocity is reset to zero during the stance phase, acceleration is double integrated during the swing phase.

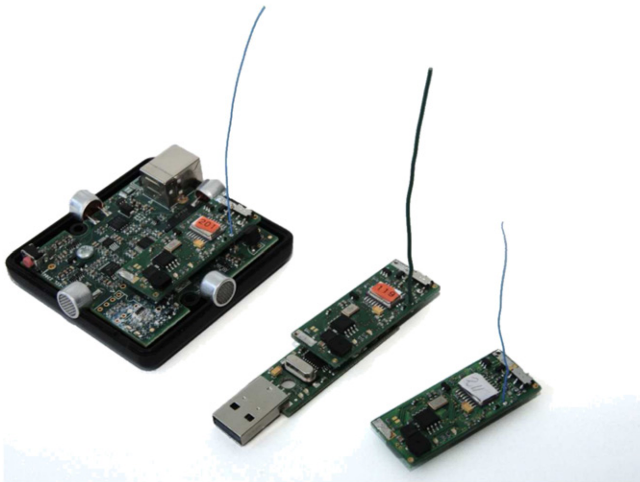

Fig. 2. Components of a Relate sensor network. From left to right: Relate node—ultrasound distance and angle of arrival estimation, USB bridge—interface between node network and laptop software, particle—core communication and processing board.

The current Relate node version (which is used in the experiments) is only able to process 2D ultrasound pulses in a plane. These nodes are based on the same sensing hardware as described in [20] where the transmission range is 3 m and the error is reported as 11 cm and 48° with 90% confidence.

A Relate node consists of two parts, a core processing and communication board, and an ultrasound amplification and transmission board. The microcontroller (Microchip PIC 18) on the communication board samples the incoming ultrasound pulses from neighbours and broadcasts the measurement results via a radio interface module. The radio module has an indoor transmission range of approximately 15 m at 868 MHz.

In the experiments we attach a Relate node to user's shoe. The node periodically emits ultrasound pulses. All nodes in the ultrasound transmission range of the emitter node return the measured relative distance and angle. These measurements are then stored in a log file (time stamp, neighbour node id, distance and angle from the node to the user).

3.3. Radio frequency based localization

Received Signal Strength Indication (RSSI) is a measure of the signal power in the radio link while a packet is being received. Given a model for the path loss in the wireless environment, RSSI values can be used to estimate distances. However, the relation between distance and RSSI can be difficult to estimate in specific settings. While simple radio propagation models can estimate path loss with reasonable accuracy in outdoor environments, for indoor environments

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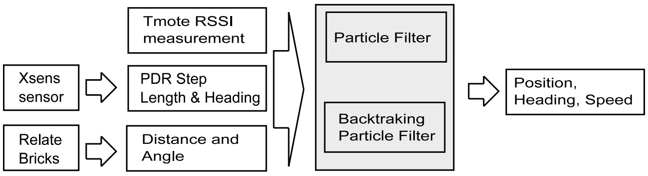

Fig. 3. Block diagram of the data fusion process: RSSI, PDR and ultrasound sensor data as inputs, and position, heading and speed as outputs of the fusion engine.

phenomena like reflection of obstacles, diffraction around obstacles, and transmission (accompanied by refraction) into the obstacle or medium, considerably reduce the reliability of distances computed from RSSI values. To cope with these phenomena, our RF nodes send beacons at different transmission powers. As this results in a range of different signal strengths and radio ranges, a more accurate position of the receiver can be computed.

We use three transmission power levels in our experiments, with low transmission power at −22 dBm, medium transmission power at −9 dBm, and high transmission power at 0 dBm, to distinguish distances in the close vicinity, intermediate range and far away. Since these ranges overlap, using more than three power levels does not improve the performance. Furthermore, using higher number of power levels increases the time it takes to gather the measurements, thus delaying the position estimation. The transmission level and RSSI were collected from the RF node. The difference between those values is the path loss which is used to estimate the distance (see Section 4.1 for further explanation).

It is important to note that RSSI values are useful to complement the positioning information provided by PDR and RELATE nodes, but are by themselves insufficient for accurate indoor localization. RSSI information (transmission range of 15–20 m) is particularly useful when the ultrasonic receiver is out of range (which only have a range of 3–4 m) and is the only available information to fuse with the PDR measurements. For simplicity, in our experiments we used separate Tmote Sky nodes for the RF measurements, but in practice, all these modules should be integrated in a single small sensor node.

3.4. The fusion engine

The fusion engine receives RSSI data from Tmote Sky nodes, step length and heading from PDR, distance and angle measurements from Relate nodes. This data is provided as input to the filtering estimator. The output of the fusion engine is an object state: position, orientation and speed. The engine combines two filtering algorithms: particle filtering and backtracking particle filtering, as shown in Fig. 3.

4. Fusion algorithm

Particle Filtering (PF) is a technique that implements a recursive Bayesian filter using the Sequential Monte-Carlo method [28]. The particle filter directly estimates the posterior probability density function (pdf) of the state using the following equation [29]:

$$p(\mathbf{x}_t|\mathbf{z}_t) \approx \sum_{i=1}^{N} w_t^i \delta(\mathbf{x}_t - \mathbf{x}_t^i) \tag{1}$$

where $\mathbf{x}_t^i$ is the ith sampling point or particle of the posterior probability and w_t^i is the weight of the particle.

4.1. Particle filter implementation

During the prediction stage, each particle will have dynamics implemented by incorporating PDR displacement estimates into the particle transition function.

For each stride,[6] a new particle state $\mathbf{x}_t^i$ is generated from the stride length and stride heading estimated from the inertial calculations and is governed by the following transition function:

$$\mathbf{x}_t^i = \begin{bmatrix} x_t^i \\ y_t^i \end{bmatrix} = \begin{bmatrix} x_{t-1}^i + s_t^i \cos(\theta_t^i) \\ y_{t-1}^i + s_t^i \sin(\theta_t^i) \end{bmatrix} \tag{2}$$

where s_t^i is the stride length of the ith particle at time t, sampled from a normal distribution $N(s_t, \sigma_s)$, with mean stride length s_t and standard deviation σ_s. Particle heading θ_t^i is sampled from a normal distribution $N(\theta_t, \sigma_{\theta t})$ with mean stride heading θ_t and standard deviation $\sigma_{\theta t}$. Mean stride length and heading are the actual estimations by PDR system. Standard deviation σ_s and $\sigma_{\theta t}$ are constant values valid over a wide range of stride lengths and headings. Values of 0.15m and 0.5π were used for σ_s and $\sigma_{\theta t}$, respectively. They are constants that are obtained from experiments reported in [23,25,30].

[6] Since the motion sensor is on one foot only, the PDR algorithm calculates the distance between footfalls for the same foot. This is the definition of a stride. For adults, one normal stride is between 1.2 and 2.0 m in length.

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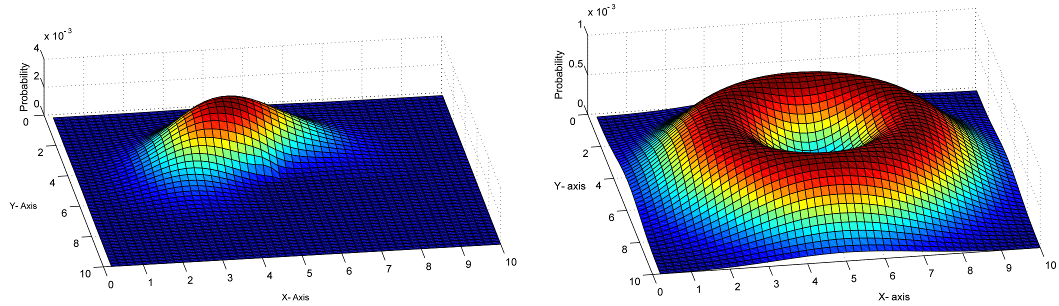


(a) Relate ultrasound measurement. (b) Tmote RSSI-to-distance measurement.

Fig. 4. Likelihood functions or Relate and Tmote measurement in a 10 m × 10 m horizontal plane.

The data fusion of PDR, building plan information, Relate ultrasound and Tmote RSSI sensor data is formally performed during the calculation of particle weights with the likelihood function. The particle weight w_t^i is changed according to the following rule:

$$w_t^i = \begin{cases} 1/N, & \text{for PDR} \\ p(\mathbf{z}_t|\mathbf{x}_t^i), & \text{for ultrasound or RSSI} \end{cases} \tag{3}$$

where N is the number of particles, $p(\mathbf{z}_t|\mathbf{x}_t^i)$ is the likelihood function.

The likelihood function $p(\mathbf{z}_t|\mathbf{x}_t^i)$ describes the probability of taking a certain measurement from a certain location and is governed in our model by a Gaussian distribution. The likelihood function of $p(\mathbf{z}_t|\mathbf{x}_t^i)$ for Relate node measurements is given by:

$$\begin{aligned} p(\mathbf{z}_t|\mathbf{x}_t^i) = {} & \frac{1}{\sigma_d\sqrt{2\pi}} \exp\left[-\frac{(X_{z_t} - X_{x_t^i})^2}{2\sigma_d^2}\right] \cdot \\ & \frac{1}{\sigma_a\sqrt{2\pi}} \exp\left[-\frac{(\theta_{z_t} - \theta_{x_t^i})^2}{2\sigma_a^2}\right] \end{aligned} \tag{4}$$

with X_{z_t} being the ultrasound distance measured from a Relate node, $X_{x_t^i}$ the actual distance of the ith particle at time step t from the Relate node, σ_d the distance measurement standard deviation, θ_{z_t} being the angle measured from the Relate node, $\theta_{x_t^i}$ the actual angle of the ith particle at time step t from the Relate node, and σ_a the angle measurement standard deviation. Values of 1 m and 60° were used for σ_d and σ_a, respectively. Fig. 4(a) illustrates the Relate node measurement likelihood function.[7]

The likelihood function $p(\mathbf{z}_t|\mathbf{x}_t^i)$ for a Tmote RSSI measurement is given by the following expression:

$$p(\mathbf{z}_t|\mathbf{x}_t^i) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(X_{z_t} - X_{x_t^i})^2}{2\sigma^2}\right] \tag{5}$$

with X_{z_t} being the RSSI-to-distance measured from a Tmote, $X_{x_t^i}$ the actual distance of the ith particle at time step t from the Tmote, σ the RSSI-to-distance standard deviation. The simple One-Slope model [31] is used to estimate distance from RSSI:

$$L = L_1 + 10n\log(d) \tag{6}$$

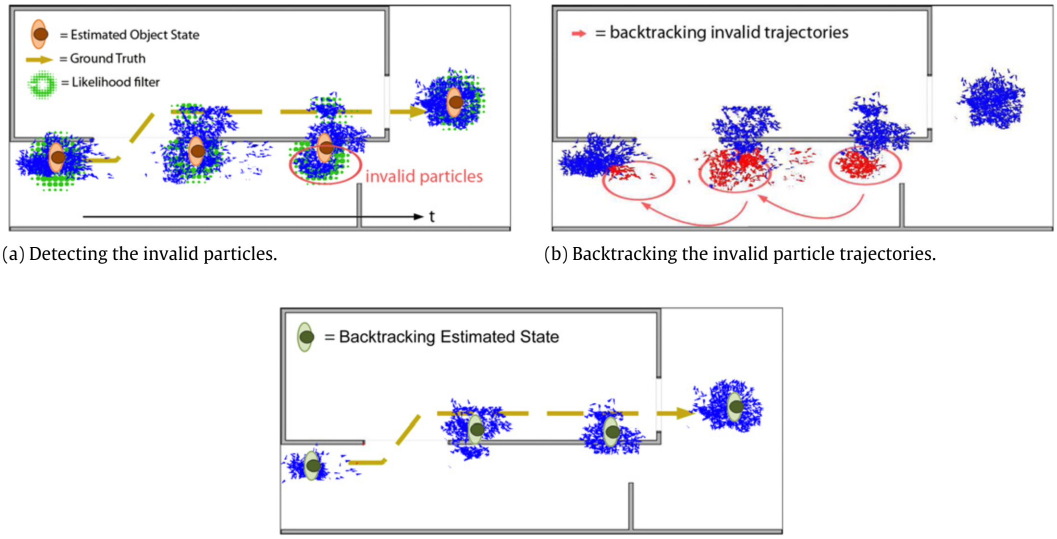
where L (dB) is a power loss, L_1 (dB) is a reference loss value of 1 m distance, n is a power decay factor (path-loss exponent) defining slope, and d is the distance in metres. Taken from [32], the values of $L1$ and n are 40 dB and 4, respectively. It is known that path-loss prediction has low reliability in indoor environments. To cope with this, a relatively high value for of σ was used. This value is a fix percentage of the RSSI-to-distance measurement (0.5 of d), chosen based on the result of several trials. The three transmission powers (see Section 3.3) are used separately to obtain three likelihood functions (Eq. (5)).

The L_1 and n values have been experimented in six buildings [23–25,33]. These buildings are typical office and campus buildings (many walled rooms, corridors, equipped with tables and cabinets). It can be suggested that these values is valid in this type of structure. However, for different kind of indoor structures (e.g.: large open space, metal structures) the validity needs further investigation.

Fig. 4(b) illustrates the Tmote likelihood function.[8] It is a ring shape with Gaussian cross-section.

7 Relate node is positioned in the centre of the plot, 2 m of measured distance (1 m of σ_d), 210 of degree angle measurement (45° of σ_a).

8 Tmote node is positioned in the centre, 2 m of RSSI-to-distance measurement (1 m of σ).



(a) Detecting the invalid particles.

(b) Backtracking the invalid particle trajectories.

(c) Backtracking the estimated states.

Fig. 5. Conceptual operation of the backtracking particle filter for data fusion.

4.2. Backtracking particle filter

The Backtracking Particle Filter (BPF) is a technique for refining state estimates based on particle trajectory histories. If some particles x_t^i are not valid at some time t, the previous state estimates going back to x_{t-tail} can be refined by removing invalid particle trajectories. This is based on the assumption that an invalid particle is the result of a particle that follows an invalid trajectory or path. Therefore, recalculation of the previous state estimation $\hat{x}_{t-tail}$ without invalid trajectories will produce better estimates. In order to enable backtracking, each particle has to remember its state history or trajectory.

The BPF implementation for the data fusion is illustrated in the following figures. Fig. 5(a) shows a typical phenomenon when a standard particle filter is used for the fusion of PDR, Relate and Tmote data. It illustrates the posterior density of particles at four time steps. The position estimates and the ground-truth are shown in the figure as well.

The likelihood functions categorize some particles as invalid between the 3rd and 4th step and the invalid particles are not subsequently resampled. Fig. 5(b) shows how the backtracking particle filter removes the invalid trajectories. Fig. 5(c) illustrates the recalculated state estimates after backtracking. It can be seen that under certain conditions backtracking can improve state estimates relative to a normal particle filter. Further explanation of the BPF can be found in [23].

5. Experimental evaluation

5.1. Setup

5.1.1. General

For the evaluation of our indoor navigation technique, we collect data for off-line processing in two different walking modes: normal walking and extended search. In the extended search the person enters one of the dedicated rooms and randomly moves around in this room. The random movement mimics fire fighters during search and rescue operations.

The experiments were conducted at Passau University, Germany (FIM building for normal walking and ITZ building for extended search). We start at a given position and head along a path defined by waypoints until the retreat point is reached. We then turn around and return to the start point.

The positions of the points are chosen so that the test person is able to walk in straight lines between them. The ground-truth lines were recorded in our floor-plan software. During the walks, we recorded various sensor measurements which in turn were used for estimating the position. Using the recorded estimation together with the known positions of the ground-truth points we can evaluate the quality of our fusion algorithms.

The beacon nodes (Tmote Sky for RSSI measurements and Relate for ultrasound distance and angle measurements) are dropped in pairs at each of the waypoints (Fig. 6). Because of the size and casing of the sensor nodes, they are currently still deployed by hand. But a device for automatic deployment and smaller ruggedized sensor nodes are under development.

Together with the MTx inertial measurement unit (IMU) an ultrasound node is attached to the test person's shoe. He carries a laptop equipped with a Relate bridge, a Tmote Sky bridge and a USB connection to the IMU. The laptop logs the data for each sensor modality into a separate flat file. Each data entry includes the exact time stamp.

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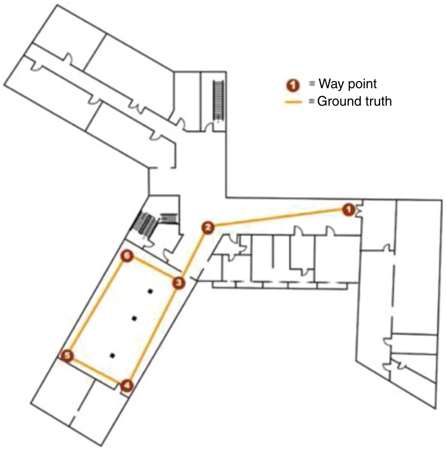
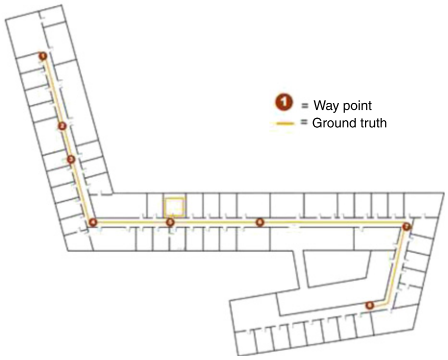


(a) Floor plan of the basement of the FIM building. The room containing points 3, 4, 5, 6 has metal lockers attached to the walls.



(b) Floor plan of the basement of the ITZ building. Floor-plan dimension is 100 m × 80 m.

Fig. 6. Floor plans for the experiments.

In the experiments the initial position is specified by the starting point S and the initial orientation is the first measurement by magnetometers. The initial velocity is assumed zero. In a real emergency situation the starting point will typically be the entry point such as a door or window or any other known landmark. The initial orientation and velocity will be estimated similarly to the experiments.

5.1.2. Experiments with normal walking

The basement floor of the FIM building was used to collect data with normal walking mode. The overall test-bed dimension is 65 m × 65 m (4225 m^2). The basement floor contains a 220 m^2 locker room, an area with reinforced concrete stairways up to the ground floor and a corridor to the storage areas of the building. All rooms can only be entered by fireproof metal doors. This test-bed is chosen to see the influence of the metal structure on the magnetometer of the MTx sensor. Three people did two 80 m-walks or 6 walks in total in this building (Fig. 6(a)).

5.1.3. Experiments with extended search inside rooms

Another data set was recorded on the second floor of the ITZ building. The overall test-bed dimension is 100 m × 80 m (8000 m^2). Two people each did four 400 m-walks for this data set or 8 walks in total. We used the path described in Fig. 6(b). Ultrasound nodes were not placed in the rooms, but deployed on the corridor partially covered the adjacent rooms instead. Therefore a person walking inside the room can occasionally be located.

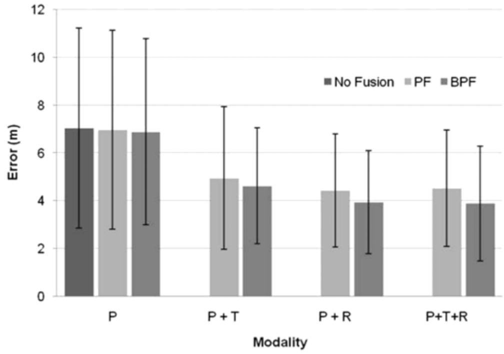
On each of the four different runs the person enters one of the dedicated rooms and randomly moves around in this room for at least one minute. The PDR location estimate is expected to drift significantly during this type of movement in a confined space. However, the nearby ultrasound nodes (and the Tmote RSSI proximity measurements) will be used to correct the position error.

5.2. Results

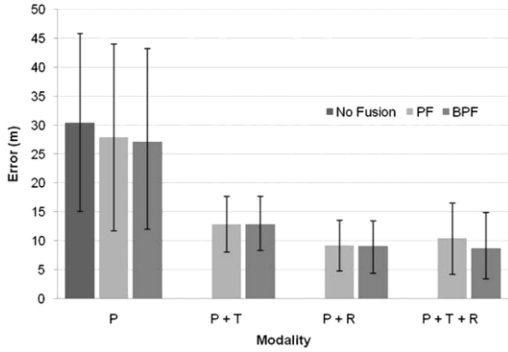
The Lifeline performance is evaluated together with the data fusion algorithm, i.e.: Particle Filter (PF) and the Backtracking Particle Filter (BPF). Several combinations of sensory data, PDR only (P), PDR + Relate (P + R), PDR + Tmote (P + T), PDR + Relate + Tmote (P + R + T), are used to evaluate the performance and contribution of each modality. For evaluation of the fusion process, the error calculation was performed off-line. The ground-truth and measurements were saved in files and subsequently input to the filtering algorithm.

The default system configuration is that the lifeline nodes (Relate and Tmote) are dropped by the user in unknown locations (in absolute location terms) and are used to re-align the PDR path in and out (for finding the way out of the building). Therefore, we are also interested in seeing the positioning performance when entering the building and then retreating to the exit. The lifeline system is evaluated with both normal walking mode and extended search inside rooms. The beacon nodes were dropped in pairs at each of the waypoints. There are 6 and 8 pairs of nodes in normal and extended search mode, respectively. The average distances between nodes for normal and extended search mode are 15 m and 24 m, respectively.

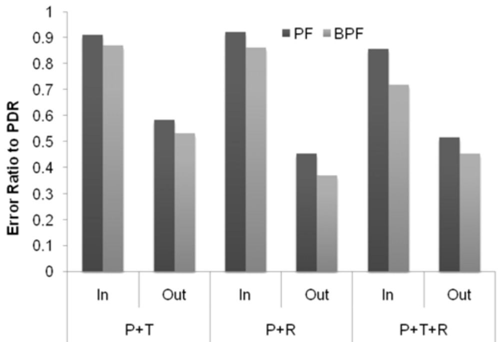
The positioning accuracy for normal walking mode in the FIM building is summarized in Fig. 7(a) and for the extended search mode in the ITZ building in Fig. 7(b). From the results of both experiments it can be seen that the overall accuracy increases in proportion to the number of modalities being used. BPF fusion of PDR + Tmote + Relate provides the best



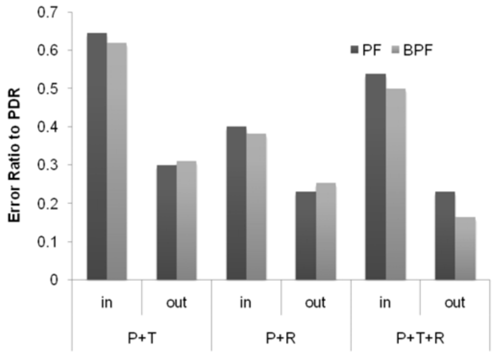
(a) Accuracy and standard deviation in normal walking mode.



(b) Accuracy and standard deviation in extended search mode.



(c) The *in-out* path positioning accuracy in normal walking mode.



(d) The *in-out* positioning accuracy in extended search mode.

Fig. 7. Positioning accuracy with normal and extended search walking mode.

accuracy (3.88 m mean error in normal walking mode and 8.66 m mean error in extended search mode) while the PDR only mode is worst with 7.04 m mean error in normal and about 30.45 m mean error in extended search mode.

The numbers also confirm the assumption that our system is particularly useful to compensate irregular 'lingering' motion patterns during extended search. The absolute value of positioning accuracy in the extended search mode is not as good in the normal walking mode. However, accuracy improvement (in ratio to the baseline PDR error) is larger in the extended walking mode. While the improvement in position accuracy for normal walking is with factor 2, this increases to a factor of about 4 for the extended search mode.

The positioning accuracy when entering the building and retreating to the exit is summarized in Fig. 7(c) for normal walking mode and in Fig. 7(d) for extended search mode. The accuracy was the error of the estimated positions to the ground-truth. It was obtained from averaging 73 and 176 measurements for normal walking and extended search mode respectively.

The error shown is the ratio between the error value and the corresponding *in* or *out* no-fusion PDR error. The absolute value of the positioning accuracy can be seen in Tables 1 and 2 for normal walking mode and extended search mode respectively. It can be seen that in normal walking mode the improvement on the "way in" way is small (around 15% for PDR and ultrasound nodes). As expected the effect is larger (around 50%) for the extended search scenario. However the main improvement (around 60% less error for the normal walking and around 80% for the extended search) can be seen for the "way out", as the system benefits from the path being re-aligned when the user comes back to previously placed nodes.

The effect of our system on the "way out" accuracy is illustrated by the trajectories as shown in Fig. 8(a) and (b) for normal walking and extended search mode respectively. The end of the pure PDR trajectory is way off (by tens of metres) compared to the starting point. If used to guide a first responder back out of the building the system would obviously fail. On the other hand, our system is off track only between the Relate/Tmote nodes so that the trajectory ends right at the starting node.

The effect of placing different number of beacon nodes is shown in Fig. 9(a) and (b) for normal walking and extended search mode respectively. The beacon nodes are varied (1, 2, 3, 4, 5, 6, 7 and 8). It can be seen that the accuracy increases as more nodes are used. The effect is more evident in extended search mode. This is due to the fact that the PDR error, which accumulates over time, will be corrected more frequently.

The final results concern the effect of positioning some nodes at predefined locations for which the exact coordinates are known. Such nodes can re-align the system to the true position. The number of pre-deployed nodes are varied (2, 3, 4, 6 and 8) with the average distances between pairs of nodes are between 15–93 m (depend on the number of used nodes).

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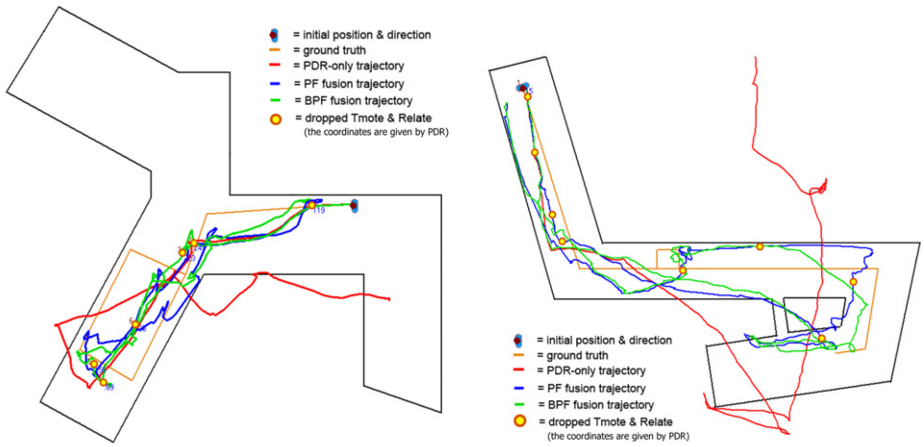
Table 1
Positioning accuracy of the *in* path and the *out* path in normal walking mode (metres).

	PDR		PDR + Tmote		PDR + Relate		PDR + Relate + Tmote	
	In	Out	In	Out	In	Out	In	Out
No Fusion	$\mu = 5.17$ $\sigma = 2.47$	$\mu = 8.95$ $\sigma = 4.68$	–	–	–	–	–	–
PF	$\mu = 4.68$ $\sigma = 2.11$	$\mu = 9.27$ $\sigma = 4.44$	$\mu = 4.71$ $\sigma = 2.25$	$\mu = 5.21$ $\sigma = 3.57$	$\mu = 4.76$ $\sigma = 2.27$	$\mu = 4.06$ $\sigma = 2.57$	$\mu = 4.43$ $\sigma = 1.88$	$\mu = 4.61$ $\sigma = 2.89$
BPF	$\mu = 4.89$ $\sigma = 2.16$	$\mu = 8.93$ $\sigma = 4.20$	$\mu = 4.50$ $\sigma = 2.00$	$\mu = 4.75$ $\sigma = 2.77$	$\mu = 4.46$ $\sigma = 2.16$	$\mu = 3.31$ $\sigma = 1.76$	$\mu = 3.72$ $\sigma = 2.05$	$\mu = 4.06$ $\sigma = 2.70$

Table 2
Positioning accuracy of the *in* path and the *out* path in extended search mode (metres).

	PDR		PDR + Tmote		PDR + Relate		PDR + Relate + Tmote	
	In	Out	In	Out	In	Out	In	Out
No Fusion	$\mu = 21.74$ $\sigma = 13.09$	$\mu = 39.16$ $\sigma = 12.19$	–	–	–	–	–	–
PF	$\mu = 19.44$ $\sigma = 14.01$	$\mu = 36.27$ $\sigma = 13.59$	$\mu = 14.03$ $\sigma = 5.34$	$\mu = 11.68$ $\sigma = 4.22$	$\mu = 8.69$ $\sigma = 4.02$	$\mu = 9.06$ $\sigma = 4.64$	$\mu = 11.72$ $\sigma = 6.00$	$\mu = 9.04$ $\sigma = 6.06$
BPF	$\mu = 19.75$ $\sigma = 14.61$	$\mu = 34.52$ $\sigma = 11.66$	$\mu = 13.48$ $\sigma = 4.77$	$\mu = 12.17$ $\sigma = 4.16$	$\mu = 8.31$ $\sigma = 4.54$	$\mu = 9.91$ $\sigma = 4.75$	$\mu = 10.86$ $\sigma = 5.95$	$\mu = 6.41$ $\sigma = 3.19$



(a) Trajectories for normal walking mode.

(b) Trajectories for extended search mode.

Fig. 8. Trajectories for different walking mode and fusion algorithm with PDR + Relate + Tmote modality.

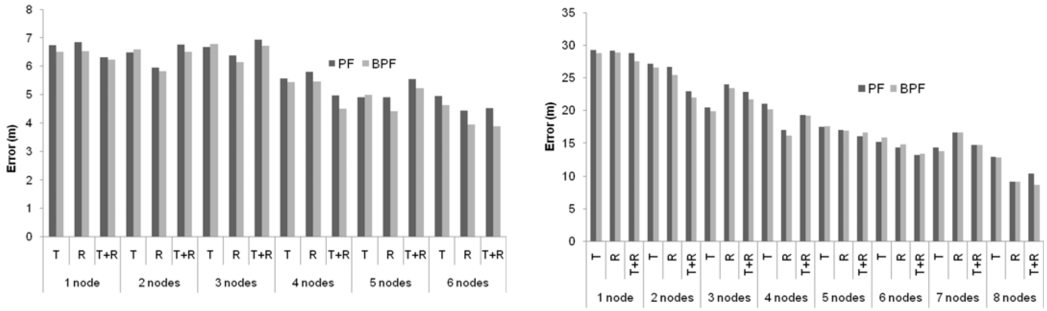
The location accuracy for different number of pre-positioned nodes (with different distances) is summarized in Fig. 10(a) and (b) for normal walking and extended search mode respectively.

Two effects can be seen. First, as expected, the accuracy increases as more nodes are pre-positioned. For a combined RF and ultrasonic system the error is reduced from around 5 m (in the normal walking case) when no nodes have been pre-positioned to around 2 m with all nodes in known positions. Secondly, the impact of pre-positioning is less significant for the extended search scenario. This is due to the fact that in this case the improvement mostly comes from re-alignment after the 'lingering' phases. Such re-alignment does not depend on the knowledge of absolute position, merely on being able to reset to the point at which the "lingering" phase started.

5.3. Discussion

The main conclusion of our experiments is that even if the position of the RF and ultrasound beacons is not known, they significantly contribute to the positioning accuracy. This is due to two effects.

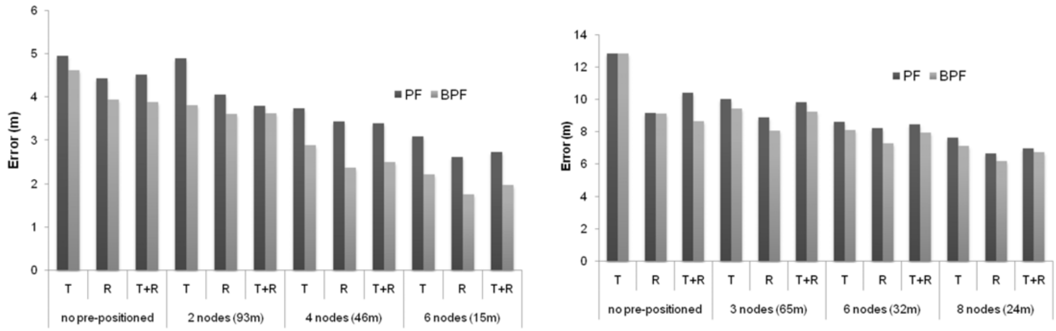
1. As the user moves away from a newly placed node the beacon signal can be used to correct the path estimate relative to the node. This explains why even for the normal walking mode and the 'going in' path there is an improvement in accuracy. For the ultrasound nodes this effect is limited by the small range of the nodes. For the RF beacons the limitation



(a) Number of beacon nodes and accuracy in normal walking mode.

(b) Number of beacon nodes and accuracy in extended search mode.

Fig. 9. Influence of the number of beacon nodes on the accuracy in normal walking and extended search mode.



(a) Pre-positioned nodes and the accuracy in normal walking mode.

(b) Pre-positioned nodes and the accuracy in extended search mode.

Fig. 10. Influence of the pre-positioned nodes on the accuracy in normal walking and extended search mode.

is due to the poor accuracy of this particular positioning method. Therefore, the effect is relatively small for normal walking and the ‘in’ part of the path.

2. As the user encounters a node that has been previously placed the path estimate is reset. This means that all errors incurred by the system since placing this node cease to contribute to further position estimates. Depending on how far the user has gone since placing the node and how much error has been incurred on the way this can be a significant effect. It accounts for the large performance gain in the extended search mode and on the ‘out’ part of the path.

In addition to the above improvements in absolute position accuracy, it is also worthwhile to consider the effect of the system on applications that require re-tracing of a path rather than information about absolute position. This is a common requirement in search and rescue scenarios where getting units back out or getting reinforcements into the building is a major concern. As shown in the trajectories in Fig. 8(a) and (b) when re-tracing a path our system produces errors only between the nodes, and perfectly re-aligns the position close to the nodes. This is due to the ultrasound nodes being highly accurate over short distances. It means that our system can be used to accurately navigate a person out along the way they came in (or reinforcements along the way the original unit used) as long as the PDR error (potentially reduced by the RF information) is small enough to bridge the gap between the ultrasound beacons of two neighbouring nodes.

Assuming node placement every 15 to 24 m (as done in our experiments) and node range of around 3 m (the range of our current ultrasound nodes) this is clearly trivial. Note that the combination of PDR and RF beacons achieves an average error of 4.5 m (Table 1) over the entire “way in” path which is 80 m long. This suggests that node spacing well in excess of the 15 to 24 m should be feasible. The influence of the beacon nodes density is summarized in Fig. 9. The nodes also should be deployed close to a room entrance, especially when the firefighter would like to search inside.

In some cases, PDR + Relateultrasound + RSSI seem to perform slightly worse than PDR + Relate ultrasound (see Fig. 10(a) and (b)). The electromagnetic signal naturally provides noisy RSSI measurements due to the influence of indoor environment and by themselves insufficient for accurate indoor localization. This factor makes the RSSI localization sometimes contributes as an adverse effect to the fusion and has to be compensated with a high value of standard deviation in the filtering algorithm. However, Tmote localization based on RSSI information is particularly useful when the ultrasonic nodes is out of range and become the only available information to fuse with the PDR measurements. PDR fusion with any measurement is clearly better than PDR alone.

The implementation of the system in the firefighter scenario is investigated in a different study within the project. In the study, a node launcher is used to automatically dropped ultrasound and RF beacons [6].

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6. Conclusion and future work

We have presented an indoor navigation system based on a combination of Pedestrian Dead Reckoning (PDR) with relative position information from a "Lifeline" of RF and ultrasound beacon nodes. A significant aspect of our system is that it works in unknown environments where map information is not available, a fact that is usually encountered in emergency situations, and does not require precise location information for the "Lifeline" of RF and ultrasound beacon nodes.

While our system does not completely solve the general indoor positioning problem, it however produces a demonstrable improvement over PDR only systems. Under assumptions relevant to search and rescue missions ('lingering around', re-tracking) this improvement is of a significant magnitude (2 to 4 times less error). In fact, if being able to re-trace a path is the only requirement then our system does indeed provide a solution. Notably, our solution works independently of the length of the travelled path and depends only on the distance between neighbouring nodes.

Having shown that the positioning accuracy of the system is in principle adequate for re-tracing long paths we are now progressing towards implementing and evaluating a complete navigation solution. We will also continue work on improving the fusion algorithms including for example more intelligent, adaptive use of the RF and ultrasound system and fusing data from different users whom we know to be walking together.

With respect to the RF systems the use of directional antennas is a promising direction that will also be explored. Another potential improvement is the extension of the range of the ultrasound nodes which is currently limited by technical constraints of our hardware.

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