

## Towards a Rapidly Deployable Positioning System for Emergency Responders

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### Abstract

Ad hoc solutions for positioning and tracking of emergency response teams is an important and safety-critical challenge. The solutions based on inertial sensing systems are promising, but are subject to drift. Based on a brief characterization of the errors encountered in inertial-based dead reckoning estimates, we propose a solution based on a combination of foot-mounted inertial sensors and ultrasound beacons deployed as landmarks in an ad hoc fashion. This paper targets two important aspects within the context of providing positioning service for emergency responders namely on how to locate the deployed static beacons (using multidimensional scaling), and on how to track the responders by using a combination of ultrasound and inertial measurements (using a Kalman filter). We perform evaluation of both the ultrasonic beacon localization and tracking algorithm for data collected from real deployments for different trail topologies and our presented algorithms are benchmarked against an ultra-wideband (UWB) precision location system. Our approach of preventing the drift in inertial estimates by combining with ultrasound measurements are promising and offers a viable solution to providing positioning and tracking support to emergency responders.

**Keywords:** emergency-response, positioning and tracking algorithms, experimentation, multimodal, sensor fusion

### 1. Introduction

In this paper we focus on the use of a sensor network to provide *positioning* and *tracking* capabilities that can directly support firefighters. A recent survey (Fischer and Gellersen, 2010) on location and navigation support for emergency responders highlights the requirements of such systems and provides an extensive list of the state-of-the-art systems and prototypes that are specifically developed for this application. As quoted in the survey, although *pedestrian dead reckoning* (PDR) has been

applied to tracking and navigation of first responders with promising results, and is the *only* self-contained system currently available, the position error in a purely inertial system increases with time and thus requires correction from external sources (Renaudin et al., 2007a). A common practice is to periodically use GPS to correct position estimates, but for most indoor scenarios, GPS is not available. We address the problem of positional drift by having the responders themselves deploy beacons (referred to as *implicit deployment*), as they progress into an unknown environment (Fig. 1). In contrast to the previously published research (Renaudin et al., 2007b), our focus is on creating an ad hoc sensor network that *does not require any pre-deployment of infrastructure*.

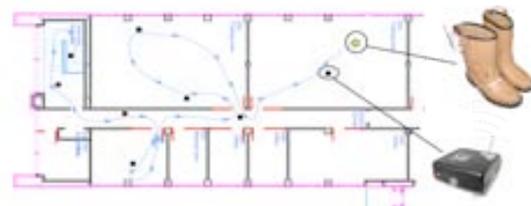


Fig 1. Breadcrumb trails, with deployed ultrasound nodes shown as black squares and boots equipped with equivalent ultrasound node and inertial sensor.

We use a combination of methods, namely ultrasound range/bearing and inertial measurements, as neither method is sufficient for the task independently. For instance, ultrasound measurements have limited precision (outlier measurements due to multi-path effects and noise) and reliability (signal loss between neighboring nodes due to communication or line-of-sight problems), and inertial tracking is prone to large drift with increasing distance. We strongly believe that such a combination of modalities can be extended to provide a fully functional ad hoc positioning system for tracking and navigating mobile users.

This paper examines several issues within the context of providing positioning capabilities to emergency responders -- (i) how to reconstruct the topology of the

network at the time of ultrasound beacon deployment, (ii) once the nodes are deployed, how to localize the static ultrasound nodes (deployed beacons) and (iii) how tracking can be achieved by fusing the multimodal data. The outline of the paper is as follows. In section II we review the related work pertaining to search and rescue missions. In section III we characterize the errors encountered in an inertial-based pedestrian dead reckoning solution and ultrasound range and bearing measurements in a mobile setting. In the section that follows, we highlight the beacon deployment strategy. We then present an algorithm for ultrasound beacon localization (using multidimensional scaling) in section V. In section VI we present a tracking algorithm (Kalman filtering based) for tracking the responder using a combination of ultrasound and inertial measurements. Section VII presents the performance of the presented algorithms based on traces of data gathered from real deployments. We validate the results using a commercially available precision UWB location system. Finally section VIII concludes the paper.

Our results show that using a combination of ultrasound and inertial measurements, the drift in the inertial estimates can be minimized and our study offers a viable solution for providing ad hoc positioning and tracking support to the emergency responders.

## 2. Related Work

In this section we review some of the related work on positioning, tracking and navigational systems that were developed specifically for search and rescue missions. For more detailed information on this topic, we refer the reader to the recent published survey published (Fischer and Gellersen, 2010). Following their classification criteria, we mainly differentiate the existing systems in terms of *deployment methods* (pre-deployment, strategic or implicit) and *infrastructure reliance* (infrastructure support required or not required).

**(i) No deployment:** Dead reckoning is the only completely self-contained location technique that requires no prior knowledge of the environment. The position provided by the inertial sensors invariably drifts over time—the drift can be reduced by using shoe-mounted inertial sensors and resetting the velocity to zero at each footfall (Ojeda and Borenstein, 2006) and by combining the inertial measurements with data from an electronic compass through a Kalman filter in order to avoid drift in heading (Foxlin, 2005). HeadSLAM (Cinaz and Kenn, 2008) is a recent work that uses a combination of dead reckoning and measurements from a laser scanner (for detecting direction and distance to obstacles) for building the map of the environment and for positioning purposes. The main idea of this work is to develop a system that can perform Simultaneous

Localization and Mapping (SLAM), a well-researched topic in robotics. As indicated in (Fischer and Gellersen, 2010) SLAM can be quite effective when a particular area is scanned several times but it is not clear how this system might perform in the event of an emergency. It has been shown that disruptive motion (typical to search and rescue) produce scaling errors and thus the estimated position drifts even more than during normal walking. Despite these limitations, there is no other self-contained location technique available. This is why we, and others, attempt to address these limitations by combining dead reckoning with other complementary technologies.

**(ii) No deployment aided by map-matching:** (Widyawan et al., 2008) have used floor plans to ensure that the successive dead reckoning estimates do not pass through walls using an algorithm based on particle filters. The idea is to discard the particles, which pass through the walls, and their results are obtained using building outlines. This work relies on the building plan detail to function effectively.

**(iii) Strategic deployment:** Strategic deployment refers to infrastructure deployed at strategic points upon responders arrival either outside or inside the building. The navigation system developed by (Renaudin et al., 2007b) combines PDR with map matching in order to prevent drift in the dead reckoning estimates. Inertial measurement units (IMUs) on the chest and legs are used to measure movement and posture. The first team to enter the building place an RFID tag on each door frame they pass through. The position computed by the inertial navigation system (INS) can then be corrected according to a database of the coordinates and directions of all doors in the building. The second team is equipped with an RFID reader and can therefore determine their positions as they scan each tag. This is an attractive solution since it is entirely ad hoc. Nevertheless it requires floor plans of the building and will fail in areas with few doors such as open plan offices or airport terminals. The indoor positioning system developed by Thales (Graham-Rowe, 2007) works similar to GPS but it is operational indoors: firetrucks parked around a building act as “satellites” that use UWB RF signals to locate firefighters inside a building by means of time of arrival measurements. Although this system might perform well for lightweight residential buildings, UWB may not penetrate larger structures that extend underground for instance. For this reason we choose to deploy a physical chain of sensors that can create a link to the outside both for positioning and communication purposes.

**(iv) Pre-deployment or pre-installation:** The Fire project (Steingart et al., 2005) has developed SmokeNet, a wireless network of smoke detectors that are pre-deployed in the buildings. When a firefighter node enters

a SmokeNet enabled building, the SmokeNet will identify the firefighter based on the node ID and route messages to the node pertaining to the firefighter's location, the location of other firefighters, location of the fire, etc.,. Since this work is based on the notion that sensors must be pre-deployed in the environment, the system is not useful when the infrastructure is severely damaged due to the advent of fire.

**(v) Implicit deployment:** Infrastructure that is deployed by the emergency responders implicitly as part of their mission is referred to as implicit deployment. In (Fischer et al., 2008) a navigational support system based on a combination of foot-mounted inertial sensors and ultrasound beacons is proposed. The idea is to allow the emergency responders deploy the ultrasound beacons as they progress into the unknown environment. A SLAM approach using a combination of inertial and ultrasound measurements have been addressed in our recent work (Fischer et al., 2011).

Our work falls under the category of *implicit deployment*. We extend the prior work (Fischer et al., 2008) which focused on providing the navigation assistance by displaying an arrow on a head-mounted display unit, to help a person retrace a path by providing the *positioning* and *tracking* capability in this paper.

### 3. Sensor Platform and Characterization

In this section we give a brief overview of the platform that have been used for this work and report their error characteristics.

#### A. Sensor Platform

**Ultrasound Sensor:** The ultrasound sensors that we use are from (Relate project). The sensor board consists of four 40 KHz narrow band ultrasound transducers, a temperature sensor, and a battery. The ultrasound transducers act both as receivers and transmitters. When the brick is in the receiving mode, it uses data from transducers on which they detect ultrasonic pulses of sufficient strength and measure peak signal values and the *time-of-flight* (TOF) of the ultrasonic pulses sent by the transmitting device. The smallest TOF is then used to estimate the range. The *angle-of-arrival* (AOA) estimate is calculated from the relative spread of peak signal values measured across these transducers. More details on the range and bearing estimation algorithms from these ultrasonic devices have been previously published (Hazas et al., 2005).

**Inertial Measurement Unit:** The MTx (Xsens Technologies) *inertial measurement unit* (IMU) comprises of a tri-axis accelerometer, gyroscope and magnetometer. In order to convert the MTx measurements into meaningful positions, the raw

accelerations are rotated from the sensor coordinate system into the world coordinate system using the rotation matrix computed by the MTx. In our prior work (Fischer et al., 2008) we have presented the *pedestrian dead reckoning* algorithm, which uses shoe-mounted IMU's and applying periodic *zero-velocity updates* (ZUPT). The accelerations are double integrated to yield position estimates. In order to reduce the position error (which increases quadratically with time) we reset the integrated velocities to zero at each stance phase resulting in linear error with distance covered. More details can be found in (Fischer et al., 2011).

#### B. Sensor characterization

**Characterization of ultrasound sensor:** In this subsection we briefly characterize the raw range and bearing measurements of the ultrasound nodes. The ultrasound nodes are deployed as in Fig. 6 (Sec. VII) and a commercially available precision ultra--wideband (UWB) system (Ubisense Technologies) is used as a groundtruth for characterizing the range measurements obtained from the ultrasound nodes. Our measurement campaign is different from the previous work (Hazas et al., 2005) in the sense that we collected the ultrasound data while the device was *moving*; the earlier work characterized the ultrasound range/bearing measurement error for a static case, reporting typical range errors of 10 cm and bearing errors of 30 degrees respectively. Several experiments were performed (refer to Sect: VII A), and the ninetieth percentile of the range samples exhibit an error below 1 m and the ninetieth percentile of the bearing errors were observed as 60 degrees (Fischer et al., 2011). This is in contrast with the ultrasound range measurement campaigns performed in static setups, where the observed errors were significantly smaller. As with any ultrasonic ranging device, limited line of sight conditions (more caused due to mobility) cause performance degradation. When the line-of-sight between two devices is fully or partially blocked (much more due to the placement of the device on user's foot), several factors contribute to the measurement error. Firstly, the tendency of ultrasonic waves to bend around obstructions can slightly lengthen the measured TOF, reduce the received signal strength, and cause the received pulse shape to vary from the expected shape of a direct-path pulse. Secondly, the receiver is more likely to identify multipath signals (i.e. reflections) as a valid ranging pulse.

**Characterization of Pedestrian Dead Reckoning:**In this subsection we report the performance of the PDR algorithm. In all the experiments the IMU was firmly attached under the laces of the user's shoe. The experiment was run in the office corridors and the user followed the trajectory as represented by the groundtruth in Fig. 2. These paths were traversed several times each

and in all the experiments the user returns to the starting point.

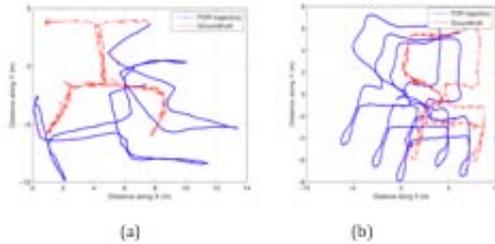


Figure 2. Depiction of progressive degradation of heading using only PDR. In Path 1, the inertial estimates are severely impacted by the error in heading right from the starting point. Path 2 starts off well, but drift is pronounced when repeating the trajectory multiple times.

Two major sources of errors are observed in the dead reckoning estimates - error in distance and error in heading. The error in distance and heading together will lead to a large error in the position (as can be seen in Fig. 2). The path shown in Fig. 2 (a) starts well but severely drifts off after one loop of walk, while from Fig. 2(b), we observe that the inertial estimates are severely impacted by the error in heading right from the starting point. Although some distance drift is inevitable due to the integration of noise and offsets in the raw sensor data, we believe that most of the distance error is due to the MTx incorrectly estimating its orientation as explained by (Foxlin, 2005). Thus we might interpret some of the forward motion as vertical motion, or vice-versa. Since MTx is a commercial product we have very little information about how the different sensors are used in computing the orientation, and almost no control over any of the internal parameters. Based on our experiments in different environments, as reported in our earlier work (Fischer et al, 2008) we assume that most of the heading errors are due to metallic objects or magnetic fields interfering with the MTx magnetometers. However, in both cases (Fig. 2(a) and (b)) we observe that the individual steps are not subject to huge drifts, as the shape of the trail adheres to the true distances, and the drift in inertial estimates occurs incrementally.

#### 4. Deployment Strategy

In order to solve the positioning and tracking problem in the emergency response scenario, our solution requires the firefighters to deploy ultrasonic beacons along their path as part of their normal search operation. The deployment of these beacons has two main goals: to track the location of the firefighters by creating an estimate of the deployed beacon positions and secondly, to allow the firefighters to navigate along a previously deployed path.

The beacon deployment algorithm needs to be simple (for practical reasons) and at the same time needs to take into account the physical limitations of the devices (ultrasound transmission range is limited to 5 m for our hardware (Relate project) and slightly more for the Cricket devices (Priyantha et al., 2000)). At every single moment, a firefighter walking along the path determined by the beacon needs to be in contact with at least the two beacons at both ends of the segment of the path on which he/she is.

Although the deployment of beacons is an added task to the firefighters, this is the minimal cost to be paid for setting up an ad-hoc infrastructure that can provide position and navigational assistance, which can in turn save lives. In reality, the beacon placement may be automatic (assuming a dispensing mechanism and using an audio triggering system that dictates when to deploy beacons) or strategic (e.g. at turns). We set three rules for deploying the beacons: (i) a beacon needs to be deployed at the entry point of the building, (ii) a beacon needs to be deployed at the point in which the last deployed beacon signal drops below a receiving threshold and (iii) a beacon needs to be deployed each time the firefighter takes a major turn.

The first rule is straightforward: it defines the root of the graph created by the beacons. The second rule is triggered in case the firefighter walks in a straight line and gets outside the transmission range of the last deployed beacon. The last rule is introduced due to two reasons: on the one hand, by deploying beacons at major turns reduces the noise introduced by the inertial estimates and on the other hand, this assures that the firefighter will be in contact with at least two beacons (by mitigating the non-line-of-sight effects introduced by turns in corridors). The last rule is also based on the simplifying assumption that the geometry of the buildings is somewhat rectangular and the firefighters will move mainly alongside walls. Since the normal search operation carried out by firefighters covers the whole building where all the rooms are searched, this rule also increases the density of deployed beacons there by giving enough constraints to solve for the beacon position estimation.

Deploying the beacons in the above manner has the advantage that it offers an alternative to navigation alongside the deployment based on computed position only. The deployment of the beacons can be done by marking the order in which the beacons have been deployed (assuming synchronized low-resolution timers on the beacons and a button being pushed at the moment of deployment). This way, each beacons receives an ID, based on the deployment time (the first beacon deployed having the lowest ID). In case of emergency, the firefighters can follow the ultrasound signals and

navigate to reach the exit (Souryal et al., 2007) (by moving always towards the beacon with the smallest ID they can hear).

## 5. Static Beacon Localization

When all the beacons have been deployed, we can employ a static localization algorithm to compute their positions. Once the position of the beacons is computed, this information can be used to track the firefighters by enabling mechanisms such as the use of Kalman tracking (Sect. VI).

Many algorithms have been developed for locating a static network. Centralized approaches such as *multidimensional scaling* (MDS) (Shang et al., 2003) and *convex position estimation* (Doherty et al., 2001) or distributed ones such as *distance vector* (DV) based techniques (Niculescu and Nath 2003) and *robust quadrilaterals* based techniques (Moore et al., 2004) solve the same problem with different methods. We decided to use the MDS approach, as the algorithm does not rely on *beacons* and provides results close to the achievable optimum (Costa et al., 2006). MDS has as a drawback the fact that traditionally it is a centralized algorithm, although distributed variants have been proposed (Ji and Zha, 2004). For our application scenario, both approaches will work (the main disadvantage of the centralized approach - high traffic needed - is counteracted by the low connectivity of the network and the delay tolerance of the network - beacons are deployed slowly).

MDS takes a global view of the information available in the network (the measured or estimated distances between all devices). MDS provides a representation of the network topology, accurate up to a translation, rotation and flip. This uncertainty is usually solved by choosing three nodes with known positions in a 2D setup, effectively *anchoring* the setup. In the case of our scenario, this uncertainty is easily reduced by making use of the map of the building or the communication between the firefighters and the incident commanders outside.

One issue arising with the static localization algorithm (and with MDS in particular) is that the connectivity of the network is very low; in the worst-case scenario each beacon only has two neighbors. The missing distances needed for MDS to run can be replaced in at least two ways: using the distance computed on the shortest path (Ji and Zha, 2005) or by employing a separate radio on each beacon. The second approach is less preferred because radio communication can provide only a very rough estimation of distance indoors (e.g. based on received signal strength indication). This comes at the

cost of a more complex beacon hardware platform and the need of a radio communication protocol stack.

## 6. Tracking Algorithm

In this section we present our use of a Kalman filter to track a mobile user along a trail of ultrasound nodes pre-deployed at “known” locations using both inertial and ultrasound measurements. Kalman filtering based approaches have been used for several tracking applications (Djugash et al., 2005). The tracking algorithm we present here, highlights how measurements from two different sensing media (ultrasound and inertial measurements) can be fused by a Kalman filter. The algorithm presented is inspired by SCAAT tracking as proposed by (Welch and Bishop, 1997) where incomplete data can be used for location, as opposed to methods where measurements are processed in batches. The SCAAT method blends individual measurements that each provide incomplete constraints into a complete state estimate.

The user wears an ultrasound node on the toe of their shoe and an inertial sensor is attached to the foot. The ultrasound node emits pulses approximately three times per second and inertial measurements are sampled at 100 Hz. The inertial measurements are recorded in “step length” i.e. the distance moved per time step and “step heading” i.e. the difference in heading between two time steps. Based on our observations reported in Sect. III where individual steps are not subject to huge drifts and the drift in inertial estimates occurs incrementally, we use the Kalman filtered ultrasound measurements to correct for the drift in inertial sensors.

We formulate an EKF using a state vector  $x_k$  with four variables, two position variables  $u, v$ , and two correction variables  $\psi$  and  $scale$ , where  $\psi$  refers to the correction factor to be applied to heading estimate and  $scale$  refers to the correction factor to be applied to distance estimates of the inertial sensors. After any discrete time step, the filter has an idea of its state and how confident it is in that state. The filter then corrects the predicted state based on the most recent measurements and its internal state. The measurement function here represents the range and bearing converted to position estimates. While it is also possible to use range-only and bearing-only ultrasonic measurements, we found that the best result is achieved using both the modalities.

The filter is initialized with a posterior state estimate  $x_k$ - and uncertainty  $P_k$ - We set the initial state estimates based on the real position measurements reported by the Ubisense system deployed in the same test area. Alternatively, one could set the initial state estimates based on averaging the first few ultrasound

measurements through non-linear regression (Hazas et al., 2005). Since we use a SCAAT implementation, we order the measurements based on the recorded timestamps as to whether the current measurement is an ultrasound measurement or inertial measurement. Each ultrasound measurement consists of a timestamp, the position of the deployed node that took the measurement, and the relative range and bearing to the mobile node. Each inertial measurement consists of a timestamp, the step distance (difference between the current and previous position) and step heading (difference between the current and the previous heading).

If the current measurement is an ultrasound measurement, the position and correction to be applied to the heading i.e.  $\psi$  and the error in distance is estimated i.e. *scale* and updated as part of the filter estimates. If the subsequent measurement is an inertial measurement, it uses the  $\psi$  and *scale* estimated by the filter when the previous ultrasound measurement was received and add this correction factor to the current inertial step length and step heading. The idea here is to correct the inertial step length and heading based on the correction factor that is estimated during the previous ultrasound measurement. Basically, when the measurement is an inertial measurement, the filter does not update the state but corrects the inertial estimates. In doing so, the drift of the inertial measurements is effectively scaled based on the correction factor determined by the ultrasound measurement. In principle, if the ultrasound measurements are frequent enough, the error in inertial estimates will be minimized.

## 7. Experimental Evaluation

In this section, we first outline the test bed used for collecting data (ultrasound and inertial measurements) and the ground truth or reference system used for the evaluation purposes. We then summarize the performance of the beacon localization algorithm in Sect. V and tracking algorithm in Sect. VI.

### A. Data collection and Reference system

Twenty-one ultrasound nodes were deployed (receivers) covering an area of approximately 15x9 m. The position of deployed nodes was surveyed a priori. In all the experiments (varying from three till eight minutes) the inertial and the transmitting ultrasonic sensor were firmly attached to the user's foot. Many different paths were traversed along the deployed nodes (refer to Fig. 3).

In order to validate our tracking algorithm we need to compare the results to some ground truth. We use the results of the Ubisense Location Engine (Ubisense Technologies) (refer to our previous work (Muthukrishnan and Hazas, 2009) reporting the Ubisense performance for the same deployment area) to

report the ground truth measurements. In addition to the IMU and ultrasound node, the users also carried an Ubisense compact tag to gather the ground truth for validation purposes. Although the Ubisense estimates will have some error (also due to the fact that the ubisense tag was placed at a different location on the user when compared to the ultrasound node), they are close enough for the purposes of judging the validity of the tracking performance (especially to see the shape of the trail). For static beacon localization, the manually surveyed points are used to validate the results of MDS.

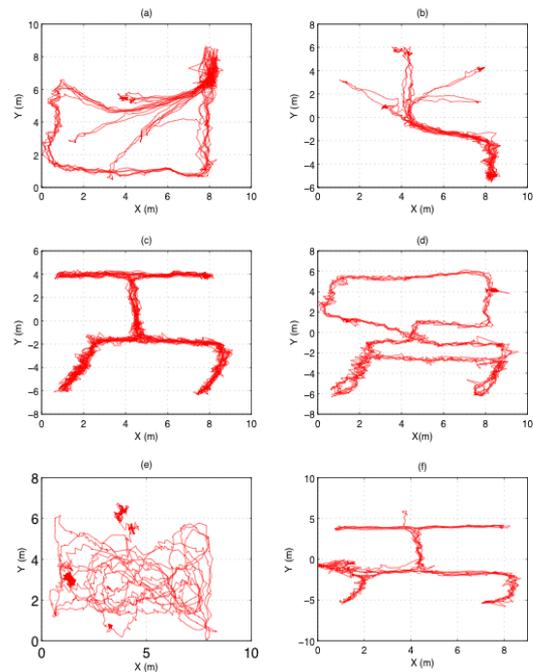


Fig. 3. Test paths, six different experimental traces ranging from three till eight minute duration.

### B. Evaluation of Beacon Localization Algorithm

In this section we evaluate the performance of MDS algorithm for the localization of the beacons (reported in Sect. V). As previously mentioned, one of the problems occurring is that not all range estimates between all beacons are available (because of the trajectory of the pedestrian, each beacon has only two neighbors). We focused our analysis on two methods to supply the missing range information (additional methods exist - for example, the authors of (Djugash et al., 2005) suggest sending robots in the network to supply missing information).

The first method we analyze is suggested by the authors of MDS in (Ji and Zha, 2004). The missing links can be replaced with the ranges computed on the shortest path (similar to the approach taken by DV distance method (Niculescuc and Nath, 2003).

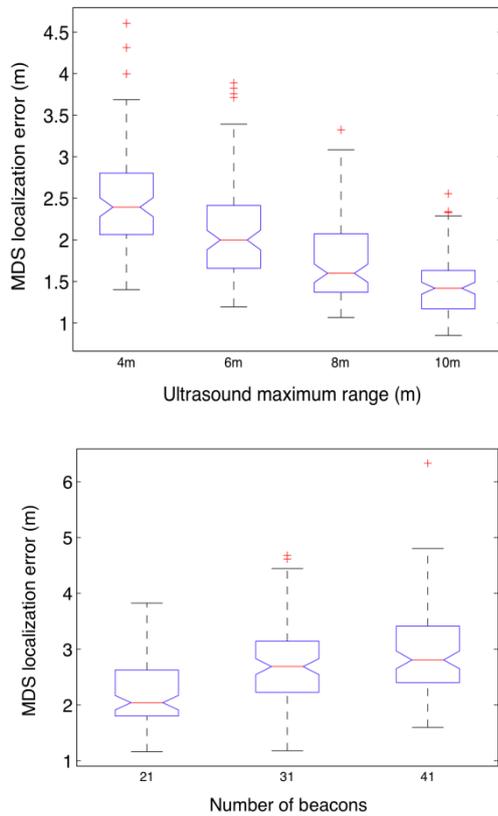


Fig. 4. Static localization errors – MDS (missing links are based on shortest path) (a) Effect of varying ultrasound transmission range; (b) Effect of varying number of beacons.

In the following, we ran hundred simulations for each metric of interest. The simulation setup we used reproduces the deployment of the beacons in the experimental setup. For the noisy ultrasound range measurements we used random samples drawn from a distribution matching the collected experimental data. We took these steps to ensure that the simulation results match the experimental setup as close as possible. The results are provided as boxplots of the mean value of the error considered for each simulated case. We chose to represent a function of the individual mean errors rather than all measurements, because we are interested in the mean behavior, while in the other case the outliers would have taken most of the space in the figure.

Fig. 4(a) shows the error characteristics for the case of real deployed beacons (uniformly over the simulated area). We simulated various scenarios where the maximum transmission range of the beacons is varied (the values on the X axis). The results indicate a mean positioning error between 1 m and 3 m. We notice a slight increase in performance with the increase of the maximum transmission range (leading an increased connectivity in the network). The deployment of the

nodes along the path or randomly across the area has basically the same effect - similar results were obtained in simulations because both setups provide a uniform coverage of the area.

Another fact arising from the simulation studies is that the noise level has little influence on the results (it is small compared to the measured distances) - this leading to the fact that the underlying topology has the highest impact on the obtained results (previous work, such as (Moore et al., 2004) describes the effects of the underlying topology graph with respect to achievable localization accuracy). In order to sustain this idea, we also evaluated the effects of beacon density, by modifying the number of beacons (“virtual” beacons were added based on a 2D uniform random distribution). As shown in Fig. 4(b) a larger number of beacons does not have any relevant benefit (in fact it increases the mean error), because adding more beacons actually decreases the ratio between known range measurements and missing range measurements. The localization error has a minimum around 20 deployed beacons (see Fig. 4(b)). Using fewer beacons will result in an exponential increase of the localization error, as studied in (Shang et al., 2003).

The second method we describe refers to using radio communication to fill in the missing links in the network. The problem of indoor radio channel modeling and distance estimation based on received signal strength indication has received significant consideration in the past (e.g. (Patwari et al., 2003)). We used the same “traditional” channel model described in (Patwari et al., 2003) (with the standard deviation of RSSI measurements  $\sigma=4\text{dB}$  and the attenuation coefficient  $n=2.3$ ) and generated the missing links (the noise is assumed to have a lognormal distribution (Hashemi, 1993) (Rapport, 1996). Fig. 5(a) shows the results obtained by varying the maximum allowed transmission range of the beacons, while Fig.5(b) shows the effects of various noise levels on the localization error characteristics.

Radio communication-based distance estimation exhibits significantly more errors than the ultrasound based one. The conclusions we can draw from the presented study is that using radio communication-based techniques leads to significantly lower accuracy. Even when changing significantly the noise level on the radio links, the achieved accuracy was still lower than the first method we proposed.

Based on these results, we conclude that using RSSI distance estimation in this scenario should be avoided when one can rely on accurate ultrasound distance measurements. As shown in the previous graphs (based on simulation results backed by data collected from the

real deployment) the static localization techniques lead to a mean positioning error between 1m and 3m. This accuracy cannot be increased by using more beacons. A slight increase can be obtained by using a more accurate ultrasound ranging hardware - just a minor improvement. This is somewhat the limit of what is feasible using static localization schemes by themselves - the choice of the centralized MDS technique guaranteeing a result very close to the theoretical limit (Costa et al., 2006).

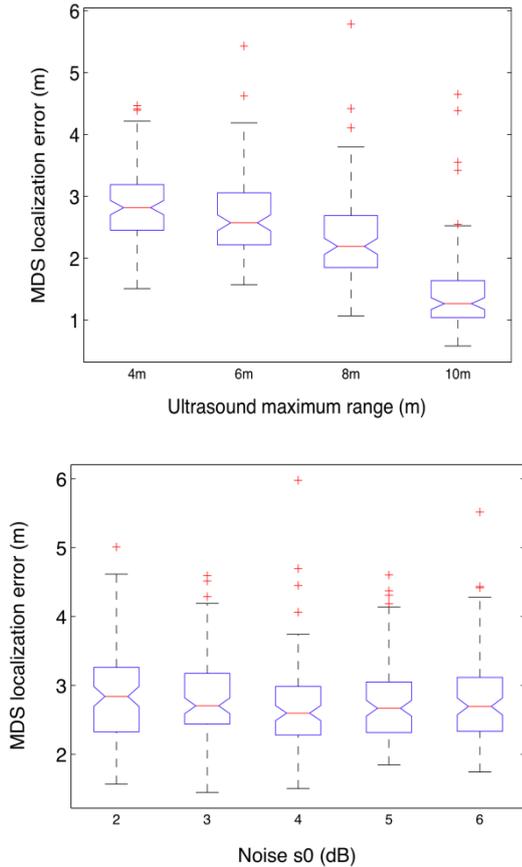


Fig. 5. Static localization errors – MDS (missing links are based on RSSI estimates) (a) Effect of varying ultrasonic transmission range; (b) Effect of varying noise level.

### C. Tracking Performance Evaluation

In this section we report the performance of the tracking algorithm presented in Sect. VI. Table 1 summarizes the performance of the tracking algorithm for all the six walking traces. The fiftieth and seventy-fifth percentile errors (inclusive of all the paths in Fig. 3) are 1.9 m and 3.7 m respectively. Inertial combined with ultrasound performs well in all cases better than inertial estimates only (refer to Fig. 6).

Path	50% conf level (m)	75% conf. level (m)
<b>a</b>	2.35	3.70
<b>b</b>	2.11	4.57
<b>c</b>	1.45	3.46
<b>d</b>	1.06	2.38
<b>e</b>	1.65	2.8
<b>f</b>	3.76	4.92
<b>Overall</b>	1.93	3.70

Table 1. Tracking performance summary. All values shown pertain to the tracking results of each of the six walking traces shown in Fig. 3.

Fig. 6 shows the estimated path of the tracking algorithm with Ubisense estimates plotted for the purposes of comparison. In most cases, we notice that the shape of the resultant trail matches to the Ubisense result and the PDR only trail is significantly impacted by the heading errors. Also one can notice that there is a difference in the performance of the PDR among all the traces. This may be due to the internal calibration algorithm used by the Xsens IMU, as it has been reported that the internal calibration algorithm adapts to the characteristics of the users movement (Xsens Technology). Comparing our results with the ground truth, we observe that the Ubisense results are much smoother than the presented algorithms, re-assuring that the ground truth we have used is more likely closer to the real path. Also, from the Fig. 6 we see that the algorithm can perform well for the intended application of locating the user within room-level. The other benefit of fusing multiple modalities comes with regard to the update rate; since ultrasound measurements are sampled only every 5 Hz approximately while the inertial sensors are sampled at high rate (typically 100 Hz), fusing multiple modalities by using SCAAT based algorithm, increases the update rate of the resultant tracking algorithm. The performance of the algorithm will improve if the beacon measurements are supplied more frequently and will deteriorate for lower beacon densities and for error in the beacon position.

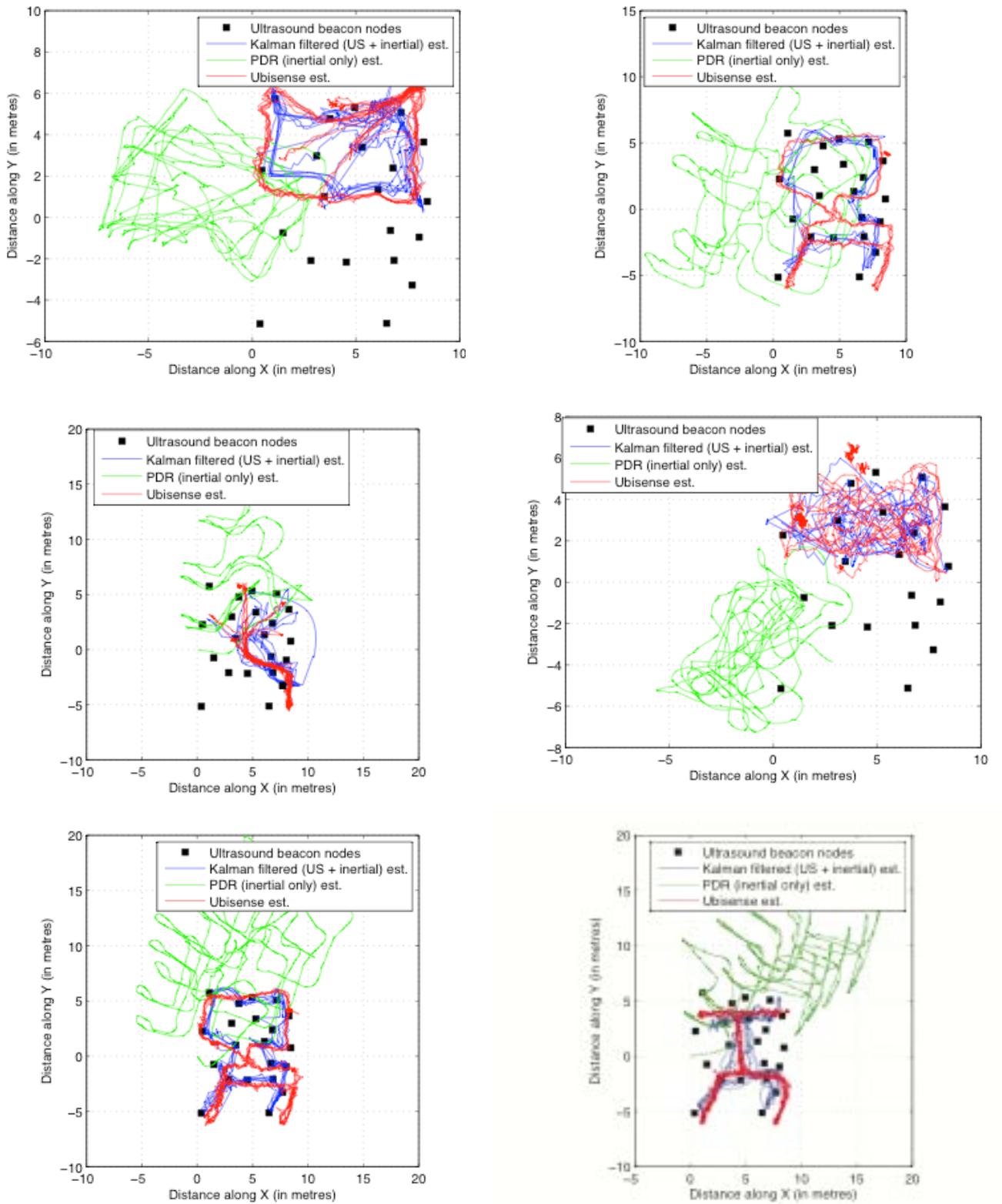


Fig 6. Path estimated by Kalman filtered ultrasound-inertial and inertial-only measurements.

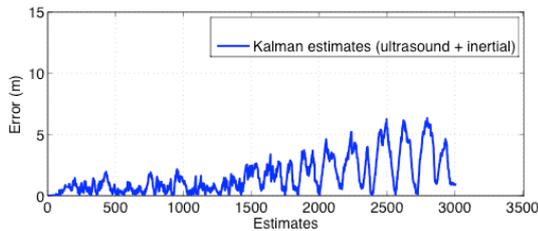


Fig 7. Error with respect to Ubisense (reference) estimates

Fig. 7 shows the results of tracking performance for one of the paths (c) that we illustrate in Fig. 3. From Fig. 7 we observe that in general the error in the estimates decrease periodically, confirming that the moving device was getting closer to the deployed ultrasound nodes.

**MDS computed position:** As reported earlier applying MDS to estimate the deployed beacons position results in an average positioning error of 1 to 3m. While, we have used the perfect location of the deployed nodes for the analysis in Fig 6 and Table 1, Fig. 8 shows the results of Kalman tracking when we use the MDS computed beacon positions in place of the perfectly known beacon positions. Comparing with Fig 6, the trajectory is slightly pulled in the direction of the newly computed beacons. This shows that there is a tight requirement for computing the beacon locations as accurately as possible. One possibility to improve the accuracy of the beacon position is to use the results of MDS as a first approximation and then obtain a refined position by extending Kalman filtering as explained in (Djugash et al., 2005).

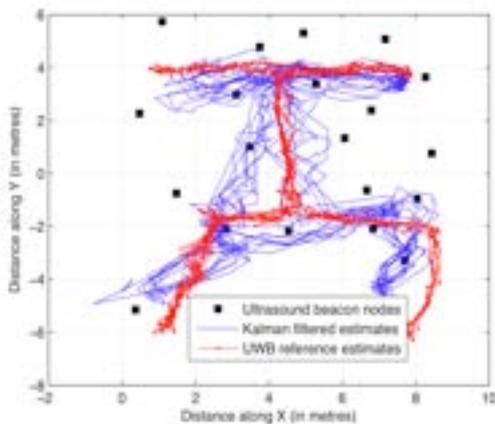


Fig 8. Path estimated by Kalman filtered ultrasound measurements (using MDS estimates).

**Parameters and its effect:** One of the issues arising with Kalman filter is that the system model is not well known, and the modelled noise values need to be increased in order to account for the errors. The specific parameters we used in the tracking algorithm for the

process noise covariance ( $Q$ ) and measurement noise covariance ( $R$ ) were chosen empirically and does not reflect to measurable noise values. We observed that with increasing values of the measurement noise covariance and process covariance, the accuracy of our algorithms degrades. In future, adaptive Kalman filters that have the capability of tuning the thresholds automatically based on the current measurement will be explored.

#### Comparison with ultrasound only Kalman filtering:

It is interesting to compare the performance of our tracking algorithm with ultrasound-only Kalman filtering approach to showcase the benefit of multimodal fusion. Raw ultrasound measurements are noisy (especially bearing), thus using raw measurements directly to estimate the position of the mobile node will give a rough trail. Here, the state vector is both the position variables and velocity variables. We transform the reported range/bearing measurement to Cartesian coordinates. After any discrete time step, the filter has an idea of its state and how confident it is in that state. The filter then corrects the predicted state based on the most recent measurements (range/bearing converted to position) and its internal state. Fig. 9 reports the performance comparison between both the tracking algorithms. Inertial measurements combined with ultrasound measurements perform well in all cases better than ultrasound only tracking, and accuracy is typically improved by about 1.5 m.

Although there are other ways to combine the heterogeneous data (Djugash et al., 2005, Fischer et al., 2011) the results show that our approach is well suited for the problem at hand and analyzing the trade-off among different approaches is a subject of future work.

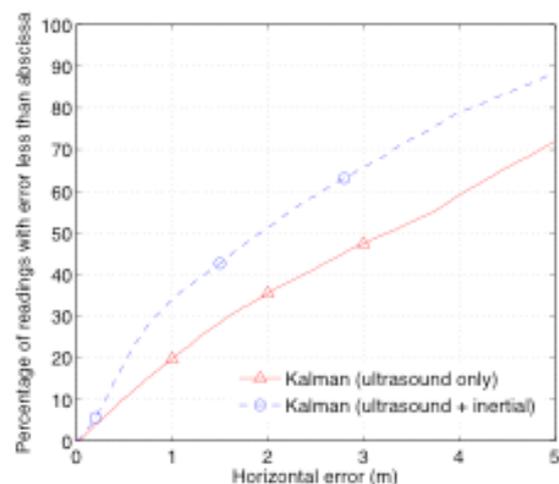


Fig. 9. Tracking performance of Kalman filtering – ultrasound and inertial measurements and ultrasound only (all test path included).

## 8. 8. Conclusions

In this paper we have focused on the use of a sensor network to provide positioning and tracking capabilities that can directly support firefighters. Although application of sensor networks to support emergency response and in particular firefighting has been explored in a range of projects by pre-deploying positioning infrastructure, our research in contrast focuses on a sensor network approach that does not require any pre-deployment of infrastructure. We have addressed the use of ultrasound and inertial sensing technologies to aid firefighters by providing positioning and tracking solutions. Based on the understanding of the errors encountered in the PDR estimates, we have looked into complementary technologies that can correct for the drift. Specifically, we have used ultrasound sensors, which have the capability to measure relative range and bearing.

We have used the algorithm based on multi-dimensional scaling (MDS) for estimating the position of the beacons. Two methods were analyzed to fill in the missing links needed for MDS, shortest path and radio communication based approach. For tracking, we have used an extended Kalman filter based algorithm. The results of the ultrasound fused with inertial sensors are clearly a win over only inertial data. We also showed how ultrasound fused with inertial measurements have improved accuracy over Kalman filtered ultrasound-only measurements. This is because the error in inertial estimates starts to grow gradually, and periodic corrections from ultrasound estimates will help in minimizing the drift. The fusion of ultrasound combined with inertial not only improves the accuracy, but increases the update rate of the overall system. However, the increased processing also consumes more of the mobile device's resources. Analyzing these tradeoffs and usage of other probabilistic algorithms such as particle filtering or variants of Kalman filtering such as unscented Kalman filtering is a subject for future investigation. We strongly believe that such a combination of modalities (inertial and ultrasound) can be extended to provide a fully functional ad-hoc positioning system for tracking and guiding the emergency responders.

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