An intelligent multi-sensor system for first responder indoor navigation

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Abstract
This paper presents an indoor navigation system based on sensor data from first responder wearable modules. The system combines an inertial measurement unit, a digital camera and a radio frequency identification device in a way that allows the advantages of each sensor to be fully exploited. The key to this synergy is the extracted qualitative criteria which characterizes the performance of each sensor subsystem at various first responder activities and operational conditions under certain time intervals. The accuracy of the detected walking pattern through measurements of the acceleration magnitude from the inertial sensor is utilized for the performance evaluation of the dead-reckoning algorithm. The amount of correct feature matches are linked to the three-dimensional scene representation from the camera navigation subsystem and finally, the degree of probability of each radio frequency identification location estimate is exploited as a straightforward qualitative criteria. The final fused location estimation is extracted after applying fuzzy if–then rules at each time interval. Since the inertial sensor suffers from accumulated drift, the rules of the fuzzy inference system drop the measurements from the inertial measurement unit whenever the other two subsystems perform adequately. Extensive comparison and experimental results based on the proposed architecture have shown not only a better navigation effectiveness and lower positioning error compared with other first responder navigation systems but also an increased accuracy in various and challenging operational conditions.

Keywords: indoor navigation, pedestrian localization, multi-sensor fusion, first responder

1. Introduction
First responder missions require robust and precise indoor positioning systems. The objective of such a system is multifold: to be lightweight, modular, power efficient and to provide accurate location estimates even in first responder operational conditions (Rantakokko et al 2011). Furthermore, robustness in critical operational environments such as fire, smoke and darkness should be one of the main technical challenges in creating such systems.

Since electromechanical accelerometers and gyros are becoming smaller, cheaper and more power efficient, new positioning and accurate systems are emerging. Their size and wireless interface permit placement in any part of the first respondents’ body even on their boots (Foxlin 2005). For these reasons, inertial navigation with foot-mounted sensors have been chosen to comprise the core of an indoor navigation system in global positioning system (GPS)-denied environments, since it can yield meter-level accuracies for more than 15 min. However, there is still a need for additional supporting sensors to keep the accuracy at acceptable levels throughout the duration of typical first responder operations. Complementary sensors can be magnetometers, imaging sensors, ultrasonic and radio-based sensors. A system that will utilize some of these sensors efficiently requires a careful sensor fusion design and tuning.

Simultaneous localization and mapping (SLAM) tries to estimate the trajectory along a person’s movement in an unknown environment, while it also tries to create a map of the surrounding area (Davison et al 2007). Recent SLAM
algorithms have been proposed trying to recover the structure of a scene using multiple frames (Tomono 2005). Given feature correspondences, the geometric constraints among the different views can be established. Commonly used sensors include digital cameras and laser range finders. The power consumption of camera-based SLAM is to date one of the main challenges. Furthermore, additional imaging sensors, such as night vision or infrared, are required if we need to have a stand alone SLAM system. Despite these drawbacks, image aiding is currently integrated into indoor positioning systems.

Radio-based ranging positioning approaches can achieve adequate performance during long-term operations. Pre-installed equipment in the form of access points or RFID tags would be the ideal solution, but currently this solution is considered infeasible. Recently, critical infrastructures such as hospitals and airports tend to provide such pre-deployment due to the wide use of wireless access points (Fischer and Gellersen 2010). In the case that no a priori mapping is available, portable infrastructures are brought to the scene of operations. The mapping of the vast number of Wi-Fi stations in metropolitan areas can also be exploited in order to enable Wi-Fi positioning.

In our system, we used the three heterogeneous but complementary approaches of inertial, camera and Wi-Fi positioning in order to satisfy most of the first responder requirements. The system combines the widely used inertial sensor navigation system with the two most promising indoor navigation systems: the image aiding and radio-based positioning. More precisely, a digital camera and a radio frequency identification device were utilized in a way that allows the advantages of each sensor to be fully exploited. The key to this synergy is the extracted qualitative criteria which characterizes the performance of each sensor subsystem at various first responder activities and operational conditions under certain time intervals. Since the inertial measurement unit (IMU) suffers from accumulated drift, the system drops the measurements from the IMU sensor whenever the other two subsystems are performing adequately. Fuzzy if-then rules are applied to all three subsystem measurements along with their qualitative criteria at each time interval, in order to carry out the fusion process.

The structure of this paper is as follows. In section 2, we examine the first responder environmental and operational conditions in order to assess the performance of each subsystem in such constraints. In section 3, we describe in detail the overall architecture of the proposed navigation system. In section 4, we present each navigation subsystem individually and their qualitative criteria. The fuzzy inference system for the fusion process is presented in section 5. In section 6, we present the performance evaluation of the proposed indoor navigation technique. Finally, we provide concluding remarks in section 7.

2. The first responder case

The typical operation and activity of a first responder cannot be characterized by routine occurrences and scenarios. A first responder must respond to incidents and events, the cause, severity, and consequences of which are not a priori defined. Furthermore, these incidents rarely occur at predetermined places and structures. Operations inside critical infrastructures can conceal high risks with potential life threatening situations. Indoor navigation data could significantly improve the safety of the responders operating in such critical infrastructures (Renaudin et al 2007).

Indoor navigation of a first responder is a very demanding and challenging task since the conditions and movement types are described by high complexity and high variety. Thus, first responder indoor navigation systems must be more robust than conventional pedestrian navigation systems (Sawyer et al 2004).

The first challenge corresponds to the variety of the movements that the first responder executes. Apart from the typical walking movement, other types of movements are executed from first responders, such as going up- or downstairs, crawling, side stepping, duck walking, running and climbing.

Real-time SLAM using a single camera has been extensively used in robot navigation (Davison 2003). Several approaches have also been proposed for pedestrian localization using mounted digital cameras (Kourogi and Kurata 2003a, Jirawimut et al 2003). The challenging task using this approach is the environmental conditions which are different from those where robots operate. Smoke, fire or low lightning conditions are very often in operational scenarios of first responders. Thus, stand alone camera navigation systems have been proved to be inefficient in such cases.

Utilizing protocols that provide location estimation based on the received signal strength indication of wireless access points is the best solution for RFID first responder tracking systems. The main benefit of such measurement is that the first responders must carry only one Wi-Fi tag which receives the signals from the pre-deployed wireless access points. However, in order to estimate location from the received signal strength readings, it is necessary to have a spatial statistical representation of the received signal strengths from the critical infrastructure access points (Chen et al 2006). Currently, most critical infrastructures do not provide such representations based on off-line measurements, a necessity for probabilistic location systems. Thus, this training phase must be carried out by the first responder units. Research for fast and reliable calibration procedures based on the received signal strength indication is currently one of the most active fields in probabilistic positioning community (Narzullaev et al 2010). Battery-operated beacons can be used instead of wireless access points for cases when power supply is not available. Unfortunately, even in an ideal calibration procedure, many factors that are met in first responder events can deteriorate the accuracy of the RFID measurements. Some of the radio attenuation factors that can affect the transmission and strength of radio signals inside a building are humidity, smoke, high temperature and thermal layers that could reflect or refract radio waves. What is more, when the building suffers from inside collapses the accuracy of the RFID location systems is even more deteriorated.
Figure 1. Components of the indoor navigation system include: (a) an RFID tag, a digital camera and an inertial sensor attached to a personal digital assistant, (b) deployable wireless communication nodes.

Table 1. Summary of the used sensors and their specifications.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Name</th>
<th>Vendor</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerometer</td>
<td>MTi</td>
<td>Xsens</td>
<td>Full scale: 50 m s$^{-2}$</td>
</tr>
<tr>
<td>Gyro</td>
<td>MTi</td>
<td>Xsens</td>
<td>Full scale: 1200 deg s$^{-1}$</td>
</tr>
<tr>
<td>RFID</td>
<td>T301BD</td>
<td>Ekahau</td>
<td>Wi-Fi standard: 802.11b Direct sequence spread spectrum</td>
</tr>
<tr>
<td>Camera</td>
<td>FL2G-13S2C</td>
<td>Point Grey</td>
<td>Max. Res.: 1288 x 964 Sensor: 1/3'' EXview CCD</td>
</tr>
<tr>
<td>Lens</td>
<td>DF6HA-1B</td>
<td>FUJINON</td>
<td>Focal length: 6 mm Angle of view: 1/2''</td>
</tr>
</tbody>
</table>

All the aforementioned first responder activities and operational conditions make indoor navigation a very demanding and challenging task. In our implementation, we have first examined all these conditions separately trying to estimate and evaluate qualitative characteristics for optimal subsystem operation (Amanatiadis et al 2010). Subsequently, the multi-sensor architecture will exploit these attributes in order to carry out the integration and fusion task.

3. Multi-sensor architecture

The wearable sensors include a digital camera, an RFID tag and an IMU attached to a personal digital assistant (PDA) as shown in figure 1. Table 1 summarizes the specifications of the aforementioned sensors used in the navigation system.

The wireless communication nodes are deployed by the first responders in the critical infrastructure in order to establish the communication backbone. However, these nodes also operate as beacons for the indoor navigation system. The functions of the indoor navigation system are separated into video processing, RFID processing, inertial sensor processing and graphical user interface support. All functions are processed and implemented with the use of two host computers. The first host computer is the personal digital assistant, carried by the first responder in operations. The second host computer comprises the command center unit and is placed where the command post is deployed. Both units are equipped with a graphical user interface for better interaction.

The flowchart of the first responder indoor navigation system can be seen in figure 2.

The two host computers are connected together with a wireless high speed network. The communication protocol between the computers uses a higher level abstraction, built on top of sockets, meeting the requirements for low latency and priority handling. Apart from the libraries, the communication protocol consists of a server daemon residing on each side of both hosts and acts as a gateway to the other side. Each server daemon is in charge of delivering the messages received by the remote end to the clients in its network, and forwarding the messages received by clients in its network to the remote end, through the wireless link. The priority handling is realized by means of the cooperation between the server protocol and quality of service features such as packet identification rules, service flow classes for bandwidth reservation, latency and jitter control on the identified packets, and quality of service classes with associated service flow classes.

The data received by the inertial sensor at the PDA are firstly filtered by a complementary Kalman filter (Roetenberg et al 2005). The errors in the force measurements introduced by the accelerometer and the errors in the measurement of angular change in the orientation with respect to the inertial space introduced by gyroscopes are two fundamental error sources which affect the performance of the inertial sensor. These constant offset errors represent the ability of the sensor to reproduce the sensed rate of acceleration or turn and measured as parts per million (ppm) of
scale-factor stability. Moving bias error sources, random error sources, misalignment and nonorthogonality errors must also be investigated in order to reproduce a more advance error model. Furthermore, all inertial measurements are corrupted by additive white zero-mean Gaussian noise (Ovaska and Valivita 1998). The complementary Kalman filter is not based on the model of the process, but on a model of errors. The advantages are that this structure maintains the high dynamic response necessary for attitude state variables and most error processes in the IMUs can be described by linear processes (Brown and Hwang 1997). The four parts of the complementary filter are the a priori model prediction of the state, the error model, the Kalman filter and the state correction yielding the a posteriori state estimate (Luinge and Veltink 2005). The filtering is implemented on the PDA where the inertial sensor is attached.

The video streaming and processing present high computational burden and resource demand while it requires the full usage of certain instruction sets of a modern microprocessor. Thus, a high performance PDA was chosen with the necessary interface for a digital camera. For all the video streaming tasks, the FFmpeg video open source libraries (Amanatiadis et al 2008) were selected. The PDA video server allows multicast transmission while it sends the video stream to a fixed-destination multicast address. The services dealing with the video stream like the video player in the command center only have to listen to the appropriate multicast address, so several services can receive the same video stream without increasing bandwidth consumption. The compression was done using MPEG-4 codec, and the transmission of the video streams using the MPEG Transport Stream (Gringeri et al 1998). MPEG-TS provides many features found in data link layers, such as packet identification, synchronization, timing (clock references and timestamps), multiplexing and sequencing information. In the architecture chosen, each processing tree is executed within its own thread and is processed in parallel with other source nodes, like RFID and inertial sensor loops. In the command center, an open source video player VLC was chosen for the playback service of the video streams (Amanatiadis et al 2008). VLC is an open source cross-platform media player which supports a large number of multimedia formats and it is based on the FFmpeg libraries. The same FFmpeg libraries can decode and synchronize the received UDP packets.
The equipment was chosen carefully to ensure maximum wearability and mobility. The overall equipment does not exceed 620 g in weight, including the multipurpose PDA of 450 g. The system is designed to operate on batteries for maximizing mobility and portability. The RFID tags use their internal rechargeable batteries, and their duration depends both on the frequency of scans and the searched wireless channels. For a 1 Hz sample rate of full channel scan, the average battery duration is 10 h. The other two subsystems are powered through the PDA USB interfaces. The inertial sensor has a power consumption of 350 mW at 512 Hz update rate while the digital camera has a power consumption of 2 W while operating in a maximum frame rate of 18 frames s\(^{-1}\) in a 1296 × 964 pixel resolution. The chosen operational configuration of 15 frames s\(^{-1}\) and a 640 × 480 pixel resolution leads to a maximum of 1 W power consumption in our case. The frame rate of the digital camera in the aforementioned operational conditions is 105 Mbit s\(^{-1}\). The chosen PDA has a primary lithium-ion 3.6 V 3900 mAH rechargeable battery with an internal backup battery of 100 mAH to sustain data while swapping primary batteries. This allows first responders to carry more battery packs in order to increase the operational duration. Field tests have proved that the proposed system can hold up to 5 h in a full and continuous operation.

The synchronization dilemma of whether to use polling or events was considered in our implementation. Apart from the fact that the choice is mostly dependent on the user programming environment, several other considerations were examined. When using the polling method, the system continuously or at a certain interval queries the sensor subsystems if a new location estimate has been calculated. When queried, the subsystems will immediately return the most recently calculated estimates. The polling method is useful when the query function runs in a loop at a certain update rate and each time location data are needed, the system just needs the latest data and not necessarily every single location estimate. When using the events method, instead of continuously querying the sensor subsystems, the event notifies the system when new data have been calculated and is available for retrieval with the appropriate functions. We chose the polling method since it ensures that we always get the latest available location estimate when we ask for it. The polling method allows the other processes in our software to be asynchronous with the sampling rate of each subsystem, and we can synchronize the data with our processes.

The concurrency and parallelism were considered in the programming of the navigation system by using a multi-thread model. The fusion run time model is using the \texttt{wait.until.done()} function, before a following read of subsystem location estimates can be initiated. The following runtime model was chosen for the fusion class:

\begin{verbatim}
Thread 1 (fusion)
fuzzy.location_estimate()
wait.until.done()
do other things
\end{verbatim}

\begin{verbatim}
Thread 2 (monitor)
periodically wake up
check wait.until.done flag
read.new_subsystem_location_estimate()
if (new_subsystem_location_estimate != old_subsystem_location_estimate)
old_subsystem_location_estimate=...
...fuzzy.location_estimate(new_subsystem_location_estimate)
\end{verbatim}

4. Proposed indoor navigation system

The overall architecture of the proposed indoor navigation system is shown in figure 3. Position estimates from all the three subsystems are introduced to the fuzzy inference system for a fused estimation. The key features for the fusion process are the qualitative metrics from each subsystem which correspond to the accuracy of each measurement in a certain time frame. Since the INS navigation subsystem suffers from accumulated drift, a compensation is achieved by using the previous fused location estimates in the position estimation model of the INS subsystem.
4.1. Inertial sensor subsystem

In the proposed system, the inertial sensor is placed on a foot in order to exploit the zero velocity updates. When the foot comes to rest, zero velocity updates reduce the time window of INS predictions to less than a second, ultimately leading to significantly improved navigation performance. However, the accuracy of the PDR system degrades gracefully with extreme modes of legged locomotion, such as running, jumping and climbing, since the foot rest cannot be determined efficiently. For automatic detection of the foot rest, we analyze the signature of the accelerometer signals (Godha and Lachapelle 2008). Since the sensor is placed on a foot, the accelerometer signature demonstrates specific repeatability corresponding to each phase of the gait cycle as shown in figure 4.

More precisely, for a high confidence identification, the following two conditions should be met. First, if the variance between consecutive measurements of the acceleration magnitude ($\sigma_k, \sigma_{k-n}$) are within a predefined threshold value ($\sigma_{\text{threshold}}$), then a stance phase can be identified with more accuracy. The $n$ parameter is tightly coupled with the sample rate of the inertial sensor. Empirical signal analysis tests have shown that for a sampling rate of 100 Hz, three samples ($n=3$) are adequate (Godha and Lachapelle 2008). The sampling rate also affects the second condition that must be met. The second condition checks for the minimum time separation $\Delta t$ between the current time $t_k$ and the start time $t_s$ of the last step as $\Delta t < t_k - t_s$. The time separation $\Delta t$ is determined by the sampling rate of the inertial sensor and a value of 30 is adequate for a 100 Hz sampling rate, based on the empirical analysis of the gait cycle (Kidder et al. 1996).

The dead-reckoning algorithm uses this step event in order to determine and track the absolute position of the first responder. The heading and position are calculated from the previous location states and the step parameter as follows:

$$\theta_t = \theta_{t-1} + \delta \theta$$

$$x_t = x_{t-1} + l \times \cos \theta_t$$

where $\theta_{t-1}, x_{t-1}, y_{t-1}$ are the final fused values of the overall navigation system, $\delta \theta$ the change in heading between the previous and current steps from the noisy inertial measurements, after the complementary Kalman filtering, and $l$ the step length.

4.2. Structure from the motion subsystem

Structure from motion (SfM) algorithms refer to the problem of recovering the structure of the scene using multiple 2D images taken by a moving camera and motion information of the camera. The motion information is the position, orientation and intrinsic parameters of the camera at the captured views. Given feature correspondences, the geometric constraints among the different views can be established. Thus, the projection matrices that represent the motion information can be recovered.

Existing algorithms can be classified in two families (Guilbert et al. 2006), namely batch algorithms (Poelman and Kanade 1997, Aanaes et al. 2002), which recover all pose and structure parameters in one step, and sequential algorithms where the parameters are recovered progressively as new views become available. Besides, significant effort has been put into
the so-called auto-calibration (VanGool et al 1998), where the initially unknown intrinsic parameters of the camera are recovered together with the pose.

The method used in our system belongs to sequential algorithms where the parameters are recovered progressively as new views become available and consists of the following steps.

- Extract and track feature points through the image sequence. A fast, invariant and robust feature description framework that consists of a detector and a descriptor (Bay et al 2008) is used together with a correlation-based tracker, similar to the KLT tracker (Baker and Matthews 2004).
- Eliminate outliers using the constraints imposed by the epipolar geometry. For sequences where the matching of the individual frames is difficult, for instance due to excessive noise, the RANSAC paradigm is used to eliminate the outliers.
- Recover the structure and motion parameters using the factorization scheme (Poelman and Kanade 1997), achieving an initial estimation of Euclidean structure and motion parameters.
- Refine the Euclidean structure and motion using bundle adjustment (Strasdat et al 2010).

Since video transmission is a prerequisite for first responder missions, we had to choose a configuration that satisfies the tradeoffs between quality in the transmitted video, accuracy in the feature extraction algorithm and limited processing power. A camera resolution of $640 \times 480$ pixels at 15 frames s$^{-1}$ was transmitted to command center. However, the extraction of feature points at such frame rates would lead to a potential lack of processing power. Thus, only 2 frames s$^{-1}$ were used for the feature extraction algorithm resulting in an average of 79% of correct matches.

The qualitative criterion, which will determine the efficiency of this subsystem, is the number of correct matches along the image sequence. Since the geometric constraints among the different views are tightly coupled with the number of correct matches, this metric can be defined as a fine quality measure.

4.3. Radio-frequency identification subsystem

In order to overcome the RFID aforementioned problems, we used a probabilistic positioning framework, where the world is taken to be probabilistic and not deterministic, accepting the fact that the measured signals are inherently noisy. Our solution can be applied in infrastructures that provide spatial statistical representations of their indoor signal strengths. The formula used is an example of an application of a mathematical theorem known as the Bayes rule (Ekahau 2003). Based on probability theory, the theorem gives a formal way to quantify uncertainty, and it defines a rule for refining a hypothesis by factoring in additional evidence and background information, and leads to a number representing the degree of probability that the hypothesis of the location estimate is true.

The probabilistic model which assigns the probability for each possible location $L$, in continuous space, given observations $O$ consisting of the RSSI of each channel is as follows:

$$P(L|O) = \frac{P(O|L) \times P(L)}{P(O)},$$

where $P(O|L)$ is the conditional probability of obtaining observations $O$ at location $L$, $P(L)$ is the prior probability of location $L$ and $P(O)$ is a normalizing constant.

The final location in such techniques is strictly defined by the highest calculated probability. However, even in cases with poor quality signals and calculations, the location system must choose a final position based on the overall highest probability. The fact that the chosen location is defined by the highest probability among possible low overall estimations is transparent to the user; however, it identifies a higher uncertainty. This leads to the conclusion that the measure of the calculated probability can be used as a metric to the overall accuracy of the positioning RFID method.

5. Fuzzy inference system

We first define as $R_{\text{INS}}$, $R_{\text{SFM}}$ and $R_{\text{RFID}}$, the qualitative measures of inertial sensor, structure from motion and radio-frequency identification subsystems, respectively. In order to derive the weight which will define the proportional contribution of the current location estimate, we present the qualitative components as three separate inputs to a fuzzy Mamdani-type inference system. The fuzzy inference system consists of three triangular membership functions (TMFs) for all the input components, three TMFs for the three subsystem output weights and five TMFs for the overall system weight output, as shown in figure 5. The first input variable is the $R_{\text{INS}}$ which indicates the similarity of the pre-defined walking pattern from the estimated one and ranges from 0 to 100. The input variable $R_{\text{SFM}}$ denotes the number of used features used in the image sequences, and its value ranges between 0 and 128. The input variable $R_{\text{RFID}}$ is the highest probability extracted by the probabilistic positioning technique of the RFID subsystem and ranges from 0 and 1.

The parameterization was developed in a way that only two membership functions will overlap for any input variable. The overlapping TMFs are tightly coupled with the overall timing performance since a three-function overlap would make the design more complicated and time demanding. The defuzzification method utilized is that of the centroid. The three inputs are cross-connected to the output through a set of 27 if-then rules as presented in table 2. The linguistic rule premises were attained after extensive comparisons with results from straightforward calculations.

Since Wi-Fi and image sensor technologies do not suffer from accumulated errors, we designed the rules of the fuzzy inference system in order to integrate INS measurement. More precisely, when both the Wi-Fi and camera subsystems are performing accurately, based on their qualitative attributes, we drop the location estimation from the IMU sensor and apply the final weighted averaging method only to RFID and SFM location estimates. At this timestamp, the location
estimation from the IMU sensor is set equal to the location estimated only by the other two subsystems, initiating a new starting point for future IMU location estimates. This integration was realized by the following three rules as follows: where $R_{SFM}$ and $R_{RFID}$ are high then (do not use $W_{INS}$), $W_{SFM}$ is high and $W_{RFID}$ is high.
The current localization estimation in PDR(t) is given by

\[ FusedM(t) = \frac{\sum M_{\text{subsystem}(t)} \times W_{\text{subsystem}(t)}}{\sum W_{\text{subsystem}(t)}} \]  

for all subsystem \( \in \{ \text{‘INS’}, \text{‘SfM’}, \text{‘RFID’} \} \).

The final localization technique weight \( W \) represents the efficiency of the overall location estimates and determines the accuracy of the estimated location in each time state \( t \). A proportional weight of the previous location estimation is used in order to maintain the consistency of the position, when the current state estimation suffers from high uncertainty. The formula used is as follows:

\[ \text{FinalFusedM}(t) = W \times FusedM(t) + (1 - W) \times \text{FinalFusedM}(t-1), \]  

where \( t \) represents the current time state and \( 0 < W < 1 \).

### 6. Experimental results

To verify the feasibility of the proposed indoor navigation system, several tests were performed on two floors inside the university’s laboratory building. The two laboratory floors consist of several areas with different environmental and operational conditions as shown in figures 6(a) and 7(a). In order to evaluate the performance of the navigation system, some rooms are characterized by low lighting conditions. In these rooms, the performance of the digital camera subsystem will be deteriorated since there will be not enough correct matches for the efficient structure from motion. The intelligent system must understand the current environmental conditions assigning less weight to localization measurements from the structure from the motion subsystem. The staircases will deteriorate the inertial measurements leading to false INS location estimates. However, the ascending and descending stair pattern will not match the predefined patterns of the walking first responder; thus, with the help of the intelligent navigation algorithm, only the other two subsystems will contribute to the final location estimation. Rooms with no beacons exist also in the floors in order to evaluate operational conditions with no or low radio frequency identification support. There, the proportional weight of the RFID navigation subsystem must be low, in order not to contribute with false estimations to the final positioning of the first responder.

The results obtained through the experimental sessions from the first and second floor are shown in figures 6(b) and 7(b), respectively. The solid trajectory indicates measurements from the inertial navigation subsystem while the dashed trajectory illustrates the route calculated from the RFID measurements. The location estimations using the camera structure from the motion algorithm are shown with solid circles. It can be seen that the dash–dot trajectory which corresponds to the route computed by the proposed fusion algorithm is closely aligned with the reference trajectories. However, this was quite expected since in normal conditions the fused path is an average estimation of the three independent location subsystems. The superiority of the proposed intelligent system is apparent when it is tested under different operational conditions. In such cases the position estimation is still closely aligned with the reference trajectories.

More precisely, when the first responder enters the rooms with low lighting conditions, the number or the features extracted from the digital camera algorithm are below the defined thresholds, leading to a very small proportional contribution to the final estimations. The localization is then defined mostly from estimations from the inertial and RFID subsystems. The same process but in different conditions is realized in the rooms with low radio frequency signal. There, the probabilistic positioning system is characterized by low probability estimations. The indoor navigation system now relies on the other two subsystems. Finally, when the first responder ascends or descends stairs, the walking pattern is not identified, forcing the intelligent system to count on the other two subsystems which work adequately. Based on the experimental results, fusing INS information, SfM information and RFID measurements has several advantages. First, it improves the performance of the whole system in terms of positioning, and secondly it allows accurate estimation
when one or two subsystems are unavailable due to special conditions and first responder activities. A first responder real case scenario has been realized in the Madrid Calle 30 tunnels, where we also had the opportunity to test the performance of our indoor navigation system. The M-30 is a motorway around the most central districts of Madrid; it has a length of 32.5 km with an average radius of 5.17 km. Furthermore, it has three lanes and route runs over 30 m deep and at some points reaches 70 m underground.

Accuracy statistics from both the two university floors and the real case scenario are shown in table 3. The average location error is the average of all errors of all
Figure 7. (a) Second floor test area with different environmental and operational conditions. The marked path illustrates the reference trajectory. (b) Results from the three different sensor subsystems and from the proposed fusion algorithm.

Table 3. Accuracy statistics in different evaluation sessions and comparisons with other proposed methods.

<table>
<thead>
<tr>
<th>Map</th>
<th>Distance traveled</th>
<th>Time traveled</th>
<th>Average error</th>
<th>90% error</th>
<th>Zone accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laboratory first floor</td>
<td>94 m</td>
<td>1.4 min</td>
<td>2.58 m</td>
<td>5.10 m</td>
<td>100%</td>
</tr>
<tr>
<td>Laboratory second floor</td>
<td>102 m</td>
<td>1.7 min</td>
<td>2.70 m</td>
<td>5.48 m</td>
<td>100%</td>
</tr>
<tr>
<td>M-30 tunnel</td>
<td>1150 m</td>
<td>13.8 min</td>
<td>7.88 m</td>
<td>12.48 m</td>
<td>100%</td>
</tr>
<tr>
<td>Rugged terrain</td>
<td>953 m</td>
<td>13 min</td>
<td>19.90 m</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

(Ojeda and Borenstein 2007)

location estimates. The 90% error shows that nine out of ten measurements were below that distance. Based on first responder experience, the main target goal of such navigation systems is to be able to locate correctly the zone that a responder lies in. This criterion is defined by zone accuracy and corresponds to the percentage of location estimates that were located inside the correct zone such as room, hallway, entrance and stairs. All evaluation sessions included mostly walking and light running patterns in almost all the locations of the zones. Individual system performance as well as the final fused weighted-averaging performance can be seen in table 4.

Table 4. Individual technique performance and the final weighted averaging.

<table>
<thead>
<tr>
<th>Map</th>
<th>Inertial sensor</th>
<th>Image sensor</th>
<th>Wi-Fi sensor</th>
<th>Average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laboratory first floor</td>
<td>2.2 m</td>
<td>3.4 m</td>
<td>1.24 m</td>
<td>2.58 m</td>
</tr>
<tr>
<td>Laboratory second floor</td>
<td>2.5 m</td>
<td>2.2 m</td>
<td>1.73 m</td>
<td>2.70 m</td>
</tr>
<tr>
<td>M-30 tunnel</td>
<td>24 m</td>
<td>10.4 m</td>
<td>3.47 m</td>
<td>7.88 m</td>
</tr>
</tbody>
</table>
7. Conclusion

In this paper, we used three heterogeneous but complementary technologies along with a weighted averaging technique which led to an enhanced system in terms of positioning performance. The system is designed to meet most of the first responder needs; thus, different types of first responder activities and operational conditions were examined and classified according to extracted qualitative attributes. In order to derive a proportional contribution of each navigation subsystem, we present the calculated qualitative components to a fuzzy inference system. The final location estimate is calculated by applying different weights to each subsystem coordinates depending on their current time state performance quality. Laboratory and field tests have shown a better navigation effectiveness and lower positioning error compared with the used stand alone navigation systems.

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