Department of Electrical and Computer Engineering

Part IV Research Report

Project Report

Project Number: 13

Localisation and Mapping for firefighters in GPS-denied Environments

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Declaration of Originality

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ABSTRACT: Several studies have developed mapping and localisation systems for firefighting environments. However, all prototypes that have been developed do not meet the strict requirements for firefighting. As a result, these systems have yet to be deployed into real firefighting. The following study is an investigation around the feasibility of lidar and inertial measurement unit technologies in a firefighting environment. A prototype consisting of these sensors was developed and tested in both the laboratory and training facility with real firefighters. It was found that the prototype met the accuracy requirements in only non-smoke-filled environments. Data relating to common firefighter motions were also investigated to observe the complex behaviour of their manoeuvres. Presented in this paper is a review of the relevant literature, development of the prototype, experimental procedures, results, and future works. This study was driven by the interests of Defence Technology Agency around lidar technology, curiosity from the New Zealand Fire service, and the lack of a commercially available mapping and localisation system for firefighters.

1. Introduction

1.1. Motivation

Firefighters rely on all their senses to navigate through unfamiliar buildings where floor plans are not available. In these environments, firefighters can easily become disoriented due to the heat, noise, and reduced visibility, which can lead to many fatalities [1]. Firefighters are also required to describe the building's environment to their commanders after a smoke dive. Due to the stress that firefighters go through while inside the building, this map is often a very poor estimate of the ground truth. A system that performs both localisation and mapping is critical for the safety of firefighters and civilians. As the global positioning system is not reliable indoors, researchers have attempted to develop localisation systems for firefighters using a variety of sensor technologies. The key challenge to this problem is finding the optimal combination and configuration of sensors which satisfies the strict firefighting requirements. Key requirements include being low-cost, lightweight, pre-deployment free, reliable, and robust. To the best of the author's knowledge, there is currently no indoor mapping or localisation system for firefighters that is commercially available which satisfies these requirements.

1.2. Research Scope and Goals

Developing a system that would be deployed into real firefighting is a challenging and multi-disciplinary task that would require many resources. The focus of this study was to investigate the feasibility of ranging technologies, specifically lidar, and inertial measurement units for a firefighting environment. Specifically, the aims were to design a system that could perform mapping and localisation for a firefighter, collect and analyse data of firefighter motions, and investigate the effects of the system in smoke. For the first prototype, it was assumed that no prior knowledge of the environment would be known, hence the use of existing infrastructure would not be allowed. Requirements such as robustness in high temperatures and other mechanical aspects were not within the scope of this study. Lastly, 3D mapping and localisation was also out of scope, with the prototype restricted to function only in 2D space. Though these requirements have been placed out of scope, the design has taken these subtleties into account. In other words, the system is modifiable, such that further development can incorporate these features.

1.3. Structure

This paper has been divided into four main sections, discussing the literature and background, prototype design, experimental procedures, and a discussion around future work. A description of the system and the associated design considerations are outlined in the prototype design section. Next, the experimental setup details the testing environments and methods of data collection in both a laboratory and training facility. The performance of the system is also presented, including mapping and location estimates for various situations. Finally, future works are discussed and conclusions are drawn.

2. Literature Review

It is widely accepted that GPS is a robust technology for outdoor positioning. However, many indoor environments are GPS-denied due to signal attenuation and interference [2]. For this reason, indoor positioning systems (IPS) have become a popular and multidisciplinary area of research, with applications including social networking, healthcare, industrial automation and emergency services. In consequence, a multitude of technologies and techniques for mapping and localisation now exist. For complex applications, sensor fusion is unarguably the required approach, where data from multiple sensors are combined to improve accuracy, reliability and robustness of a system. The key challenge is being able to combine technologies in a way that the weakness of one technology is compensated by the strength of another. This section summarises the literature review conducted at the beginning of this study, which reviewed IPS technologies and their techniques, firefighter requirements, and related existing systems [3].

TABLE I
TECHNOLOGIES AGAINST KEY FIREFIGHTER REQUIREMENTS

Technologies	Size/Weight	Infrastructure Deployment	Smoke Proof	Localisation Resolution	Accumulates Error	Performs Mapping
Beacons/RFID Tags	Low	Yes	Yes	cm to m	No	No
Lidar	Medium	No	Varies	cm	No	Yes
Radar/Sonar	High	No	Varies	cm	No	Yes
Ultrasonic	Low	No	Varies	cm	No	Yes
IMU	Low	No	Yes	Varies	Yes	No
Optical Camera	Medium	No	No	cm	No	Yes
TIC	Medium	No	Yes	cm to m	No	Yes
Barometer	Low	No	No	-	N/A	No
Magnetometer	Low	No	Yes	-	N/A	No

2.1. Firefighting Requirements

The requirements for firefighting are stricter than most IPS applications. It is a safety critical system where faults can endanger human lives. For general positioning systems, the major design considerations when selecting sensor technologies are cost, size, accuracy, infrastructure, complexity and general feasibility. In [4] and [5], Rantakokko surveys the requirements and technologies specifically for first responders and firefighters. It is stated that positioning systems for firefighters should be reliable, fire-proof, night-proof, lightweight, small in size, power efficient, not pre-deployment reliant, and provide meter-level accuracy. As one does not need to know exactly where a firefighter is located, errors of up to five metres, depending on the room size are acceptable. An online, non-intrusive system with low setup overhead is also required as firefighters need to focus on rescuing civilians, their oxygen intake, and own orientation.

2.2. Existing Technologies

The most recent surveys around IPS technologies presented discussions on IPS requirements, applications, technologies, techniques, trends, and challenges [6–9]. The majority of technologies utilise the electromagnetic (EM) and acoustic spectrum. Examples include Wi-Fi, RFID, thermal imaging cameras (TIC), optical cameras, sonar, and lidar. Other technologies such as accelerometers, gyroscopes, magnetometers and barometers are independent of those spectra. Table I provides a summary of potential technologies for firefighting, evaluated against key requirements. From the table, it is evident that there is no single sensor technology that can satisfy all requirements.

To add to the complexity, sensor technologies are not restricted to single measurement and localisation techniques for determining location. Measurement techniques refers to the way a sensor collects data while the localisation technique is the method to obtain location data. Often, they are closely related, but it important to make the distinction. Parameters that a technique uses depends on its application with key considerations being accuracy, infrastructure availability, and processing power. Common measurement techniques include time of flight (ToF), angle of arrival (AoA), return time of flight (RToF), cell of origin and received signal strength indicators (RSSI), while common localisation techniques include proximity detection, trilateration, multilateration, triangulation, dead reckoning, and map-matching [6], [7]. ToF methods exploit the propagation speed and time of signals to determine distance information. Similarly, RSSI models the distance but based on the strength of the signal received. Once distance measurements are found, trilateration or multilateration localisation techniques perform geometry to determine location. In AoA, the angle that signals arrive are determined via the phase difference, which are then used to determine a location through triangulation. Another common technique is fingerprinting, where a database or map of a certain variable, such as RSSI, is created either by pre-measuring or mathematically modelling the environment. The map can then be used as form of a look-up table to assist in determining location. Many measurement and localisation techniques require pre-installed infrastructure, thus, making them unsuitable for firefighting.

A select number of sensors possess the ability to perform simultaneous mapping and localisation (SLAM), namely ranging and camera technologies. Ranging technologies include lidar, sonar and radar, while camera technologies can include thermal imaging and optical cameras. For ranging technologies, an emitter sends out pulses and the signals are reflected back into a receiver. The ToF of the pulses is measured and a distance is

Table II
IPS prototypes relevant to firefighting

System	Technologies	Infrastructure Deployment	Tested with firefighter movements	Tested in smoke	Performs Mapping	Localisation Error
TOR [10]	IMU, UWB	No	Yes, up to 10 min tests	No	No	≃2m
Yuan [11]	IMU, RFID	No	Yes, up to 30 min tests	No	No	1 to 20 m
CMU [12]	IMU,UWB, long-range radio	Yes	N/A	N/A	No	N/A
Zakardissnehf [13]	Lidar, robot odometry	No	No	Yes	Yes	1 to 10 m
Chameleon [14]	TIC	No	No	Yes	Yes	≃4m
Baglietto [15]	IMU, Lidar	No	No	No	Yes	N/A

calculated. Typically, the environment is scanned in two or three dimensional space to generate a point cloud. With an initial position estimate, the data is fed into a SLAM algorithm to perform feature extraction, data association, map building, and final location estimation. Data association refers to the process of matching observed landmarks to currently tracked landmarks. The process repeats in an iterative manner constantly updating both map and position estimates. Camera technologies do not have the luxury of performing ranging, hence must perform SLAM purely by feature matching [16].

2.3. Existing Systems

Many existing systems rely on floor plans or access points within a building. It is true that a system should take advantage of infrastructure and make use of available information. However, many firefighting environments are unknown, hence the system's core should not be depend on such information. Few systems have been tested in smoke-filled environments and with complex firefighter motions. Meanwhile, systems that investigate firefighter movements and smoke, tend to not have mapping functionality and floor plans are typically provided [10], [11]. A summary of existing systems relevant to firefighting, along with their characteristics, is presented in Table II. Each system has at least one major shortcoming, preventing them from being deployed into real firefighting. To this day, research is still being conducted to develop firefighter positioning systems. For example, Carnegie Mellon University recently received a grant, to develop a localisation-only system using inertial measurement units and radio technology [12].

3. Proposed solution

Initial investigations were carried out to understand firefighting procedures. Volunteers from New Zealand Fire explained that in search and rescue, and smoke-diving operations, firefighters operate in pairs with breathing apparatus lasting thirty minutes. Traversing along the walls, firefighter activities include walking, stomping, running, crawling, and climbing. After completing a dive, firefighters are tasked with reconstructing a map either verbally or by drawing, explaining areas they searched. To perform mapping and localisation for this application, it was decided to trial lidar and inertial measurement unit sensors. The prototype is designed around a hard hat, as shown in Fig. 1. The devices attached to it include two Thunderboard Sense (TS) boards [17], one Scanse Sweep lidar [?], a Raspberry Pi 3 (RPI), and a battery pack. Sensor data is collected, fed into an RPI, and transmitted via Wi-Fi to a remote machine where further processing is performed to produce a map and location estimate.

Figure 1: System overview

3.1. Hardware considerations

The RPI was chosen as the processing unit for the data collection system to reduce development time. It provided a friendly prototyping environment with multiple interfacing options for sensors and wireless capabilities to communicate with the remote machine. The design considerations around the IMU and lidar will now be discussed.

3.1.1. Inertial Measurement Units

The inertial measurement unit (IMU) has been incorporated into the system because it is a low-cost, lightweight, and fundamental technology for localisation systems. Each TS has an ICM-20648 inertial measurement unit (IMU) on board which includes a three-axis accelerometer and three-axis gyroscope. The accelerometer and gyroscope provide linear acceleration and angular velocity information, respectively. One IMU provides orientation information of the head, while the other is attached to the back solely for the step detection algorithm. The rationale behind this is that the back area exhibits less spurious movement in contrast to areas such as the limbs of firefighters.

An alternative IMU, the Xsens MTi [18], was also considered. It is a popular IMU due to its high accuracies and is used by many localisation systems, such as in the Chameleon system [14]. Though they have higher specifications than the ICM-20648, preliminary experiments concluded that the Xsens units available for this study had Bluetooth connectivity issues and the ICM-20648 was sufficient for the metre-level accuracy required by firefighters. As the Xsens units must operate wirelessly and with Xsens software, TS boards were chosen over Xsens MTi, which exhibit multiple interfacing features, including both wired and wireless options.

3.1.2. Lidar

The selection of lidar technology was mainly due to its reduced setup time and ability to quickly generate maps. This is in contrast to using thermal imaging cameras that are expensive, both in terms of cost and computational complexity. Ultrasonic sensors were also an option, however, due to their lower accuracy and sampling rates, ultrasonic ranging devices would be challenging to implement for an initial prototype. In addition, the sponsor of this project, Defence Technology Agency, were interested in understanding what lidar technology could achieve for human navigation.

The lidar sits on a 3D-printed plate and is screwed onto the top of the helmet for a 360-degree field of view. Though infrared light cannot penetrate thick smoke, a previous study has shown promising results with lidar not being affected by thin smoke and able to detect features up to a few metres in dense smoke. It was hypothesised that the system may be able to take advantage of firefighters travelling along walls, allowing the lidar to detect close features. The Scanse Sweep lidar was selected for its high 40-metre maximum range to cost ratio. This is in contrast to lidars in the same price range such as the RPLidarA2, which exhibits a 12-metre range [19].

3.2. Software considerations

The system utilises the open source Robot Operating System (ROS) framework, a set of well-documented software libraries, tools, and algorithms for robotic applications [20]. ROS allows seamless real-time wireless communication between devices and is compatible with the RPI, lidar, and TS hardware. The framework is not restricted to robots and key concepts such as methods of communication, data structures, and packages have been used extensively in the development of this system.

An overview of the system describing the key software components is shown in Fig. 2, along with the flow of key information. After the pre-processing stages within

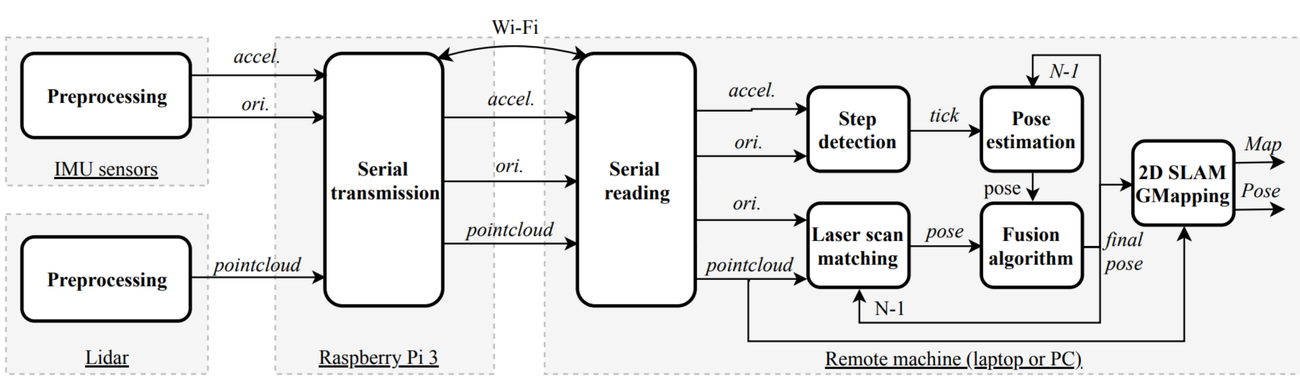


Figure 2: System architecture and information flow

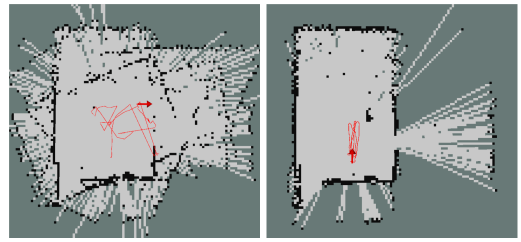
sensors, the data is converted into ROS messages and communicated to a remote laptop. This includes linear acceleration and orientation information from the IMUs and point clouds from the lidar. All within the ROS framework, the remote machine reads the data, processes the information and performs mapping and localisation. Data from both IMUs are used to perform step detection where a position and orientation, or pose [21], is calculated. Point cloud information from the lidar is input into a laser scan matching algorithm which provides another pose estimate. The algorithm also receives additional orientation information from the IMU for better convergence. The two pose estimates are input into a simple fusion algorithm which aims to find the best pose estimate. Finally, the SLAM algorithm receives the final pose estimate and point cloud data to generate a map around that pose. The mentioned algorithms will now be discussed in further detail.

3.2.1. Preprocessing stage

Aside from slight modifications around communication and interfacing options, both the IMU and lidar sensors run pre-installed software from the manufacturers. For this study, these off-the-shelf algorithms have been treated mostly as black boxes. On the TS board, all features such as bluetooth capabilities have been turned off for lower energy consumption. The gyroscope and acceleration information from the IMU is pre-processed within the ICM-20648 on an embedded digital motion processor (DMP), which acts to offload computation of motion processing algorithms from the TS's microcontroller. The DMP uses a complimentary filter to fuse angular velocity and linear acceleration data to determine orientation [22]. For the Scanse Sweep lidar, the time of flight approach is used. Micro-pulses of unique patterns of infrared light are emitted and reflected back to a receiver. A built-in correlation algorithm identifies the unique light pattern from noise and determines the distance to the object. The Sweep uses an optical encoder to measure the angle of the rotating sensor head, such that it can provide an angle measurement relative to the sensor for each distance measurement [23].

3.2.2. Laser scan matching algorithm

The point cloud data from the lidar is input into an iterative closest point algorithm to produce a position and orientation estimate [24]. The algorithm finds the optimal transformation between subsequent point clouds that minimises the difference between them. As optimisation is involved, the initial guess is a critical factor in ensuring the algorithm converges. For quick translations and rotations, the algorithm has difficulty converging to a solution if only the lidar is used. To assist with convergence, the IMU attached to the helmet provides a better initial guess based on the change in orientation and translation experienced by the IMU. This involved editing the algorithm's source code because it did not properly cater for this. The effects of this is shown in Fig. 3, where the subject is continuously walking backwards and forwards.



(a) Lidar only *(b)* Lidar + IMU

Figure 3: Effects of improving intial guess

3.2.3. Fusion algorithm

Due to time constraints, sensor fusion techniques to fuse the two calculated pose estimates have yet to be formally explored. In addition, the current step-detection and step-length algorithms are in their early stages and not yet ready to be fused in that way. Currently the system toggles between the two algorithms under different scenarios. For example, if the head is tilted too far the pose fed into GMapping would only be from the step detection algorithm. However, the step detection algorithm cannot be used for long periods of time as the error can rapidly drift off.

3.2.4. GMapping

In the current prototype, the popular Rao-Blackwellized particle filter is used to create a map from the laser scan data [25]. High-level parameters for the Gmapping package were configured, and the internal process was treated as a black box.

3.2.5. Step detection algorithm

The typical usage of the IMU involves dead reckoning, where the position is calculated by updating the previous position based on estimated velocities of the object. This process can be achieved through techniques such as double integration or step detection. In an ideal world, a single IMU can provide location data with perfect accuracy. Through double integration of the acceleration and integration of the angular velocity, a change in position and orientation can be determined. However, in practice, accelerometers and gyroscopes have finite resolutions, biases, and electrical noise. These imperfections lead to an important concept called drift, or integration drift, which is the accumulation of error as time progresses.

An alternative solution, which was used in this prototype, is step detection and step-length estimation. Using a moving average, the variance is calculated for every point in order to amplify the peaks. Next, a step is detected through thresholding and peak detection. After a step is detected, a heading angle based on orientation is used to help find the change in position. A constant step-length model is used in this prototype. Step estimation is still a form of dead reckoning, thus it is still prone to drift and additional information is required to reset the position, for example from the lidar. To detect steps, only the acceleration along the axis aligned with gravity and orientation around that axis were considered. The challenge with the step-detection technique is the robustness of the algorithm with complex motions. Typically, this technique is applied to walking pedestrians who exhibit regular motions. Data collection of the complex motions are further discussed in Section 4.2.2.

4. Experimental Results

After laboratory experiments, the system was tested in the field with volunteer firefighters. As the system only collects data from the environment, the information was processed both online and offline. In co-operation with the Devonport Fire Brigade (DVFB), experiments were undertaken at a training facility during training sessions. This section outlines the experiments conducted, prototype performance and key findings.

4.1. Laboratory

The experimental procedure involved collecting data and testing the system in various scenarios. Key findings in the laboratory include the effects of windows, hallways, and head-tilting. Fig. 4 shows the floor plan of the laboratory area.

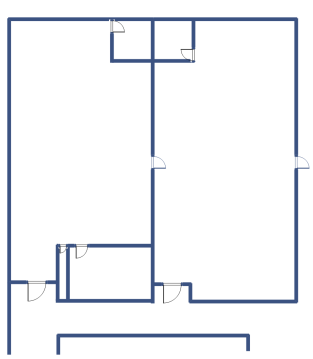
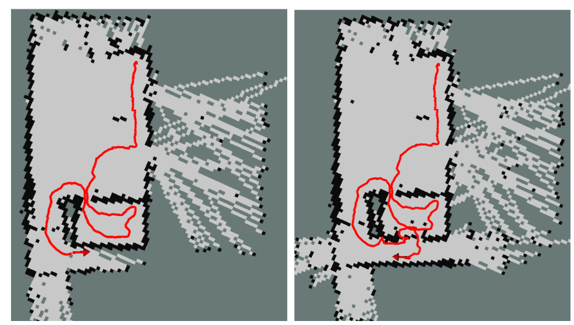


Figure 4: Laboratory floor plan

In Fig. 5, the test subject was tasked to navigate around the laboratory with minimal head movements. In this situation, the system relied on the lidar and only the IMU for orientation correction. As infrared light from the lidar penetrates glass, windows appear on the map as doors or openings. In firefighting, this would create confusion for the commanding officer as they would ask firefighters to investigate that area further. The system also has difficulty when subjected to long corridors. As a corridor has minimal features, this results in the laser scan matching algorithm receiving very similar point clouds. Due to non-ideal optimisation in the algorithm, the laser scan matcher outputs a position in the same location, in other words, there is no transformation because of the subtle difference between point clouds. However, GMapping continues to build a map around the position using the laser scan data it receives. As a result, the wall at the end of the corridor is pushed further back, as shown at the bottom of Fig. 5. Aside from the windows and hallways, the accuracy of localisation and mapping was well within the metre-level requirements specified by firefighters.



(a) Before hallway *(b)* After hallway

Figure 5: Laboratory experiment example

4.2. Training Facility

The fire brigade co-ordinate different types of training sessions for firefighters, ranging from search and rescue operations in abandoned tunnels to house fire simulations by setting old houses on fire. For this study, the prototype was tested with volunteer firefighters at a training facility; a floor plan is shown in Fig. 6 which served to simulate a typical household. The middle of the facility includes a staircase which is not within the scope of this study. A series of experiments were conducted in this facility to test the effects of firefighter motion and smoke on the system.

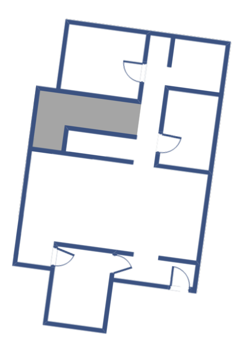
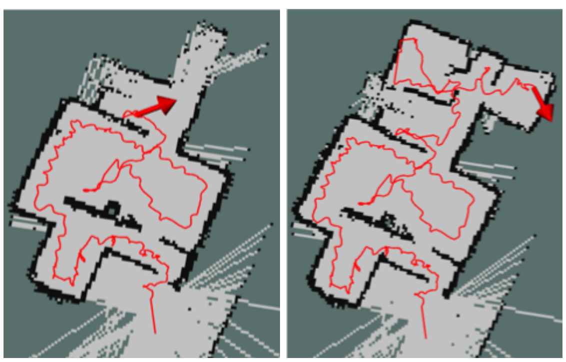


Figure 6: First level of training facility

4.2.1. *Standard house fire operation*

In this experiment, the prototype was attached onto a firefighter who was asked to execute standard training procedures in the dark, without smoke. The firefighter traversed along the walls with a partner around the first floor of the facility. Fig. 7 shows promising results of the final output of the map and position estimate. By visual inspection, localisation performance meets the accuracy requirements for firefighters. It should be noted that the map is constantly updating as time progresses. As the map is adjusting to new features observed, the previous positions are not recalculated. Therefore, the position estimate at a given point in time is only relative to the map produced at that instance. The result is that after a period of time the history of location estimates drifts off. The effect of this drift can be understood by observing the slight difference between the paths at the entrance of the building in Fig. 7. The experiment was repeated with the lights on to observe the manoeuvres performed and another with the firefighter asked to minimise the movement of their head. All experiments produced similar results.



(a) After 4 minutes *(b)* After 8 minutes

Figure 7: Performance over time without dry ice

A dry ice generator was used to simulate a smoke-filled environment. The room was completely filled with smoke to the point where there was only a few centimetres of visibility for the human eye. In this environment, the same experiment was repeated. Fig. 8 shows the mapping and localisation results. As suspected, infrared light is scattered by the small particles in the environment, resulting in erroneous results due to the inaccurate time of flight measurements the lidar. After analysing the point cloud data offline, it was concluded that even the walls that were half a meter away could not be detected, thus falsifying the original hypothesis. The system in its current configuration is only functional in non-smoke-filled environments. Further developments would be required for the system to be robust to smoke, as will be discussed in Section 5.

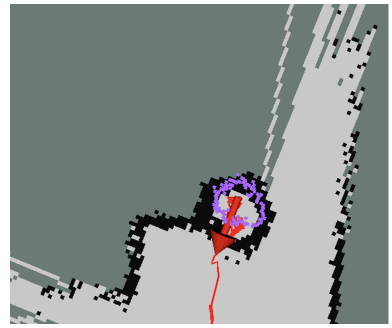
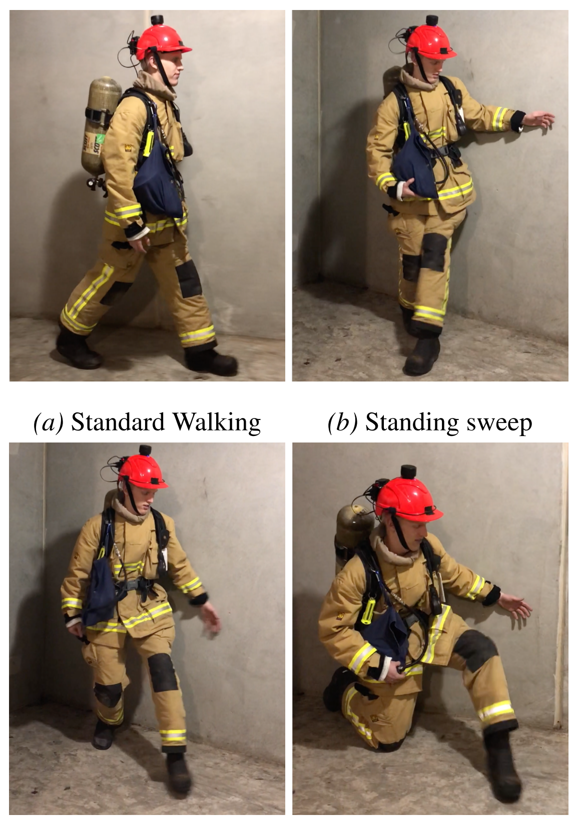


Figure 8: Performance with dry ice

4.2.2. *Firefighter motions*

In contrast to pedestrians, firefighter motions are complex and constantly changing. To understand the motions of firefighters, short straight-line experiments were conducted to collect linear acceleration and orientation data for four common firefighter manoeuvres. The actions are demonstrated by a volunteer firefighter in Fig. 9. As expected, the standard walking motion is similar to normal pedestrians. In the sweeping action, the firefighter uses one leg to sweep the area in front of them to check for obstacles. Similarly for the two types of stomping actions, the firefighter uses one leg to stomp the floor to check its structural integrity.

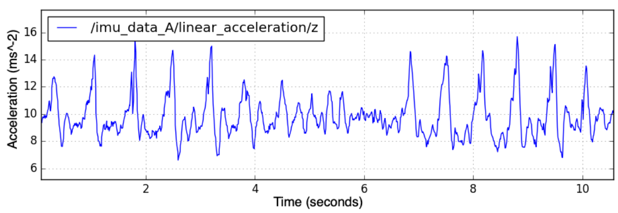


(a) Standard Walking *(b)* Standing sweep

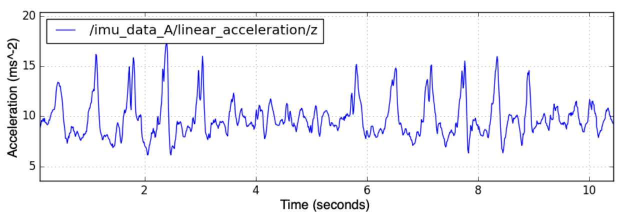
(c) Standing stomp *(d)* Kneeling Stomp

Figure 9: Firefighter movements

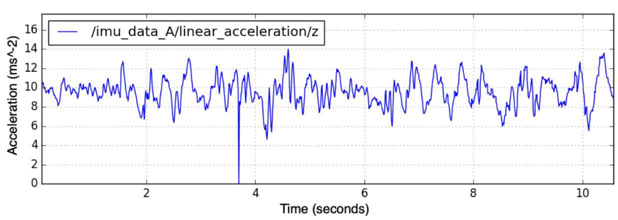
The acceleration along the axis of gravity for one of the IMUs is shown in Fig. 10. It is evident that there are visually well defined patterns for standard walking and sweeping due to their less spurious motions. Note that the gap in the middle corresponds to the firefighter turning around. After calculating the variance, steps can be detected using the current thresholding technique. However, for motions involving stomping, the signals are difficult to analyse with the current technique. Further enhancements to the thresholding technique are required.



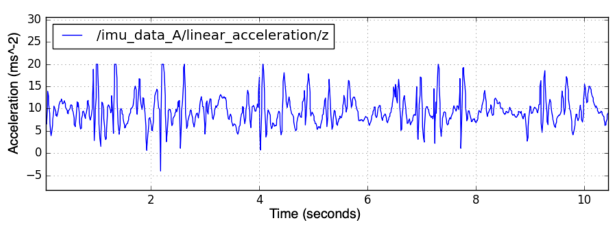
(a) Standard Walking



(b) Standing sweep



(c) Standing stomp



(d) Kneeling Stomp

Figure 10: Acceleration of firefighter movements

4.2.3. *Error quantification*

Error quantification is a non-trivial task as the ground truth is very difficult to procure. The location estimate at every instance in time is required and typically studies resort to a rough estimate of the truth. From the straight-line tests of the firefighter motions, the position estimates were evaluated against an estimate of the ground truth. The error was approximated by quantifying the perpendicular deviation from the straight line, simply the closest distance to that line. The errors across all experiments were combined and a histogram was plotted. As shown in Fig. 11 the localisation error for all tests were less than half a metre, well below firefighter requirements.

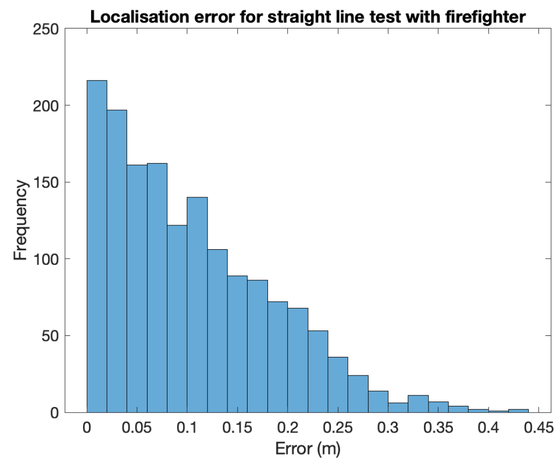


Figure 11: Histogram of error from straight-line tests

5. Future work

For this prototype to be deployed and used by real firefighters, more investigation is required in multiple areas. As the system is still in its early stages, only the tasks in the immediate future will be presented.

For the IMU, the key area of focus should be on investigating additional approaches for modelling the firefighter's motions to perform step detection. This would involve detecting the type of motion the firefighter is performing and then finding the optimal algorithms for each type of motion. Additional IMUs can also be attached to various parts of the body to collect more data and potentially identify patterns between the acceleration and orientation signals. The current implementation assumes a constant step-length for each step, hence a varying step-length model can be introduced in the future for a more accurate estimate.

As the Scanse Sweep lidar does not work in smoke-filled environments other technologies that can perform mapping should be investigated. In comparison to lidar, ultrasonic sensors have a lower range and poorer accuracy, however, as fireman traverse along walls, it may be a feasible option. Though the ultrasonic sensor has lower resolution, the lidar performance is well below firefighter requirements. This means accuracy resolution can simply be traded off for improved robustness in smoke-filled environments.

6. Conclusions

This paper presented an investigation around the feasibility of lidar and IMU technology for mapping and localisation for firefighter navigation. As the prototype is in its early stages, this study serves as a starting point for future development. The system was subject to a series of experiments which produced a variety of results.

The current system, when attached onto a real firefighter, meets the accuracy requirements in the training facility in a non-smoke-filled environment. It has also been demonstrated that sensor fusion within the laser scan matching algorithm improves the performance of the system, in contrast to using the lidar alone. However, the hypothesis regarding the lidar's ability to detect close features such as the walls in smoke has been rejected. Further development is still required to allow the mapping component to work in smoke-filled areas, which may be achieved through ultrasonic or thermal imaging camera technologies.

The investigation also involved collecting acceleration and orientation data for various common firefighting manoeuvres. For the step detection algorithm, the system is able to detect steps for normal walking motion with reasonable accuracy. However, the current implementation has been unsuccessful in detecting steps for complex firefighter motions that are difficult to model.

To conclude, this study suggests that the current prototype can be used by firefighters during training sessions in the absence of smoke. Future work around alternative mapping technologies and step detection algorithms is necessary before the system can be ready for real firefighting.

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